Interpreting Symptoms of Cognitive Load and Time Pressure in Manual Input

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Abstract

Users of computing devices are increasingly likely to be subject to situationally determined distractions that produce exceptionally high cognitive load and/or time pressure. The question arises of how a system can automatically interpret symptoms of such cognitive load and time pressure in the user's manual input behavior while taking the user's knowledge of the system into account. An approach to this problem is presented which the results of relevant previous research are used as the basis for the construction and manipulation of a dynamic Bayesian network.

Keywords

Adaptive systems, User modeling, Manual input, Bayesian networks, Time pressure, Cognitive Load

1 Introduction

A user's available time and working memory can vary considerably, even within a given interaction with a system. The situational variability of these user "resources" seems to be increasing since more and more portable computing devices are used in the everyday busy environment. In this paper possible symptoms of manual user input are analyzed and investigated. A three-step framework that is implemented with Bayesian networks (Pearl, 1988) is presented. To implement a system that can reason about its user's resource limitations within a given type of interaction, we require knowledge about the relevant causal relationships, i.e., the causes and consequences of the resource limitations in that type of interaction. Lindmark (2000) presents a wide-ranging analysis of symptoms and symptomatic behaviors involved in human-computer manual input.

1.1 System and Example Domain

We illustrate our approach in the context of the system READY (Jameson, Schäfer, Weis, Berthold, & Weyrath, 1999). In the scenario of the second phase of the project, the airport scenario, READY serves as a hand-held assistance system that offers a traveler various types of help, such as: describing the location of airport facilities and giving route descriptions; helping with the planning of travel to or from the airport; giving instructions about standard procedures or the use of airport facilities, and explaining access restrictions.[1]

In the airport scenario, the traveler's time restrictions can be severe. Likewise, a high working memory (WM) load can arise—for example, when the traveler tries to remember a route description while dealing with obstacles in the airport. The system has to take into account not only the long-term limitations of the user's WM but also the user's current situation (competing tasks, distractions, and emotional pressure)—as well as static variables, such as the user's familiarity with the airport situation, that likewise influence WM load.

1.2 Example Interaction

Figure 1 illustrates the type of behavior that we want READY to be able to interpret: The user $\mathcal{U}$ has asked the system $\mathcal{S}$ "Where can I change money?", and $\mathcal{S}$ has presented a screen with the five icons shown in the figure. $\mathcal{U}$ can now click on an icon to get more information about one of the banks. Suppose $\mathcal{U}$ first clicks forcefully on *Dresdner Bank* and then immediately on *Deutsche Bank*. $\mathcal{S}$ should infer that $\mathcal{U}$ may have really wanted information on *Deutsche Bank* but erroneously clicked on another icon; and $\mathcal{S}$ should make inferences about $\mathcal{U}$'s current resource limitations, taking into account both the incorrect click and the high force that $\mathcal{U}$ exerted.

In this paper, we first present our modeling framework and then give a concrete example of its use.

2 Modeling Framework

2.1 Basic Concepts

Figure 2 gives a simplified overview of the modeling framework that we are using to handle the inference task described above.

The circles in the bottom row correspond to *symptomatic behaviors* which $\mathcal{S}$ can recognize relatively straightforwardly. The three variables at the top include the two *resource limitations* that $\mathcal{S}$ wants to make inferences about—time pressure and cognitive

[1]Such a system would have to get much of its information and computing power via a wireless connection to a server. The actual development of the READY prototype is being done on a normal workstation that includes a simulation of the airport context.

Figure 1: “Please select an icon”

load—as well as a third relevant resource limitation called *lack of knowledge*, i.e., $\mathcal{U}$’s unfamiliarity with the system.

In principle, it would be possible to design a Bayesian network that included only these variables as nodes, with links directly connecting them. For the sake of greater generality and comprehensibility, we include an intermediate level of classes of *symptoms* (see the second row in Figure 2). These are categories of errors and other behavioral phenomena which have been studied by researchers on human-computer interaction and human performance more generally. On the basis of this previous research, we can make educated guesses about the relationships between symptoms and resource limitations (i.e., between the second and first rows of variables in the figure).

In the other direction, we can often classify a particular symptomatic behavior as an instance of a particular symptom. Then, when $\mathcal{S}$ observes the symptomatic behavior, it can instantiate the corresponding node for the symptom. Such classification relationships are represented in the figure with gray lines (not to be confused with the links in a Bayesian network). In some cases, a particular symptomatic behavior can belong to two or more symptom classes. For such cases, we construct nodes that correspond to the logical disjunction of two or more symptom classes.

The network is instantiated as follows: After each action of $\mathcal{U}$, for each symptomatic behavior observed, the corresponding node is instantiated accordingly.

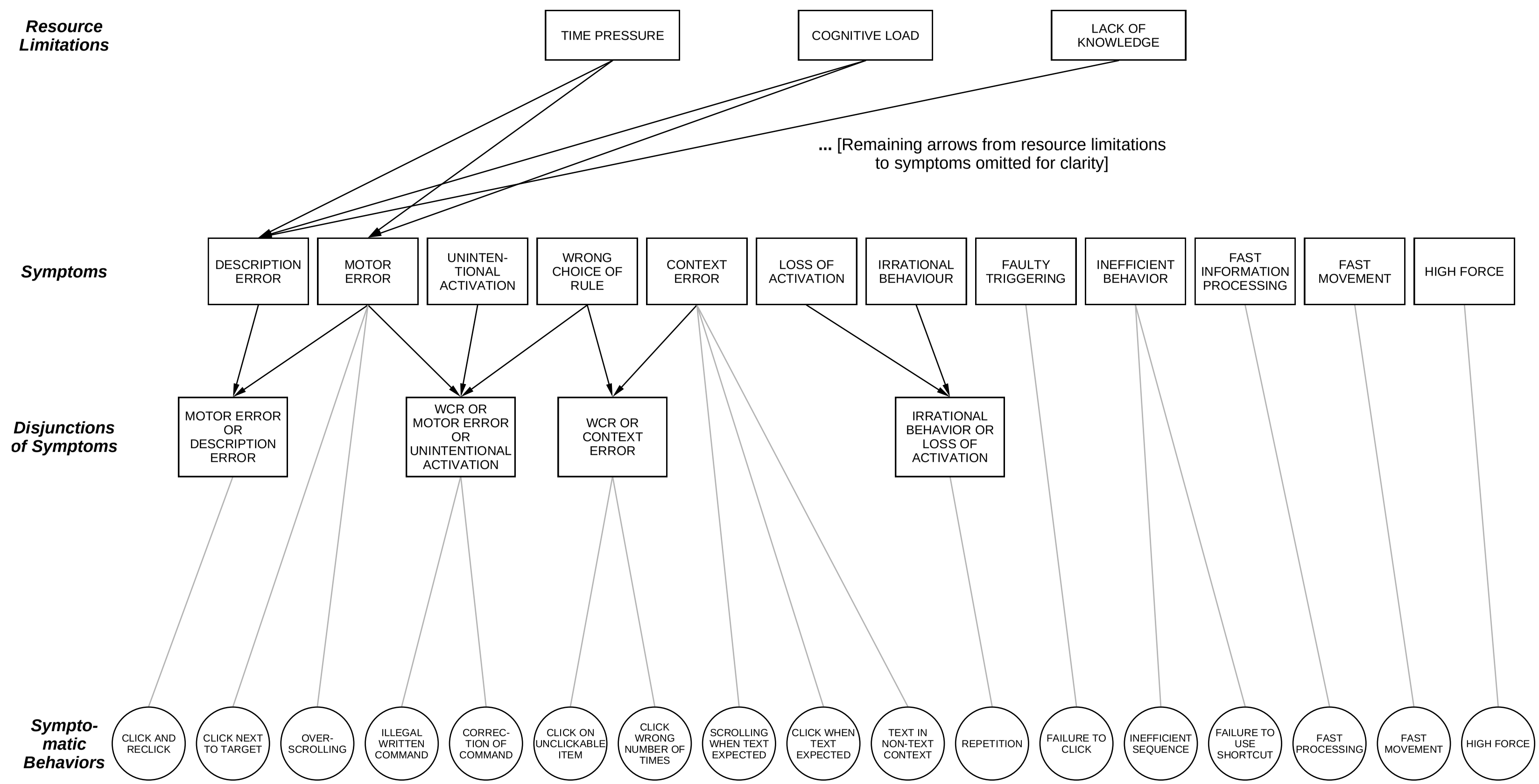

Figure 2: Overview of the modeling: Rectangular boxes are nodes in a Bayesian network, and black arrows are links in this network. The circles at the bottom stand for symptomatic behaviors, and the gray lines connect them to the symptoms of which they are instances.

2.2 Variables Representing Resource Limitations

Time Pressure (TP)

Performing actions under scarce time conditions is a situation that occurs all the time in our society. The concepts of time pressure and human stress have been widely studied. The perspective of deadlines and time limitations can, however, vary dramatically, from instant reaction time studies to scarcity of time in important decision making in life-critical situations. The basic assumption in the READY prototype is that given a time-pressured situation, the user prefers to shorten the execution time of an action, even though the result is affected. Hence, time pressure is a variable that reflects the short-term subjective cost of the user's time.

Cognitive Load (CL)

Cognitive load and working memory are the terms often used for the resource bottleneck of human information processing. In the READY project, the WM is viewed as one component that can store a certain capacity and the limitation is therefore one of the constraining factors. A high cognitive workload will restrict the user in the interaction with the system (Jameson et al., 1999). The available WM for the current task can be decreased, for example, when the user performs another action simultaneously or is distracted by something in the environment.

Lack of Knowledge (LK)

It is also important to pay attention to the factor of the user's prior knowledge. Behavior characteristics can otherwise be misinterpreted as signs of stress, when they are in fact signs of lack of knowledge of how to perform a task. Olson and Olson (1990) discuss the importance of extending cognitive modeling to include individual differences in skill and knowledge.

3 Example Bayesian Network

On the basis of the schema in Figure 2, the READY prototype constructs a new time slice of a dynamic Bayesian network every time a behavior of $\mathcal{U}$ has been observed.[2]

Figure 3 shows a part of the network that is created for the example given above. It can be seen that, for each variable, three discrete levels are distinguished. These are, from top to bottom None, Mild, and Severe (corresponding to the numerical labels 0, 1, and 2).[3]

[2]Within each time slice, inferences about the most recent behavior of $\mathcal{U}$ are made. To accumulate the results of such inferences over time, $\mathcal{S}$ needs to construct a series of connected time slices. (See, e.g., Schäfer & Weyrath, 1997, or Jameson et al., 1999).

[3]In Figure 2, it was implicitly assumed that each variable was Boolean, to simplify exposition.

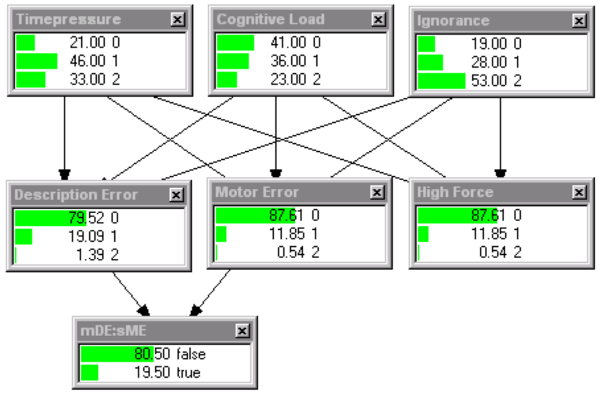

Figure 3: Example Bayesian Network: Before any observation

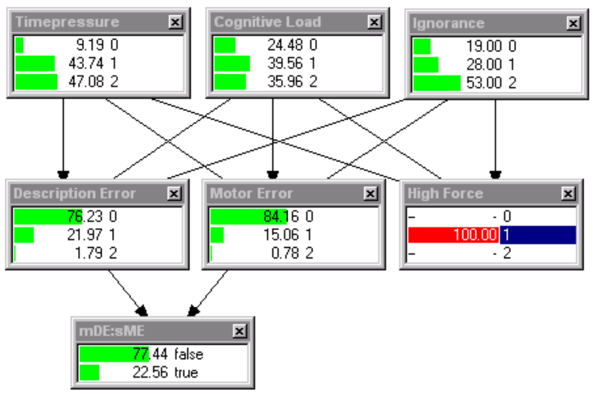

Figure 4: Example Bayesian Network: After observation of HIGH FORCE

The a priori probabilities of the user 's resource limitations could be interpreted as follows: "The user is currently most likely under medium time pressure, most likely under low cognitive load but has most likely a high degree of lack of knowledge of the system." These values seem plausible in the airport scenario.

This can be seen as a typical default for the overall scenario of an airport guidance manual input device, as introduced in the READY system.

3.1 Bayesian Inferences

The first network (Figure 3) shows the prior expectations of the symptoms and the hidden variables. In the second network (Figure 4) HIGH FORCE has been instantiated to *medium*. $\mathcal{S}$ slightly increases its assessment of $\mathcal{U}$'s TP and CL to *medium*. The third network (Figure 5) shows that CLICK AND RECLICK can be an instance of at least two different types of errors:

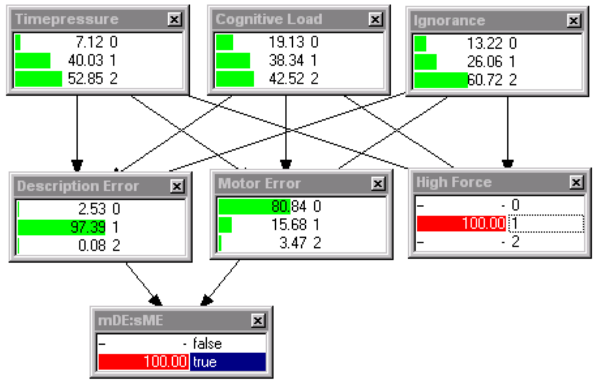

Figure 5: Example Bayesian Network: After observation of CLICK AND RECLICK

A DESCRIPTION ERROR, defined as "ambiguous or incomplete specification of the intention" (see, e.g., 'b=Norman83), is essentially a case where $\mathcal{U}$ has inadequately distinguished between two objects, because of their similarity. In this case, the two icons in question are fairly similar, so if $\mathcal{U}$'s confusion of them is due to a DESCRIPTION ERROR, it is a mild description error. A MOTOR ERROR involves a poorly controlled hand movement by $\mathcal{U}$. In the present case, the two icons in question are quite far apart; so if $\mathcal{U}$'s CLICK AND RECLICK is due to a motor error, it is a very severe one. The symptomatic behavior CLICK AND RECLICK causes the disjunctive node MDE:SME (mild description error or severe motor error) to be instantiated. The probability of both of the hypotheses increases by more than 4 times, but because of prior expectations, "severe motor error" still has only a probability of 3.47 %. In other words, $\mathcal{S}$ "explains" the mistake as a DESCRIPTION ERROR, because such a severe MOTOR ERROR would have been unlikely.

3.2 Defining the CPTs

As with all Bayesian networks, the question arises of where the numbers come from. In the long run, it will be desirable to conduct empirical studies concerning the particular causal relations described here. But on the basis of previous theory and empirical results, it is possible to specify roughly the likely relationships between the three uppermost variables and the symptom classes (see Table 1). The reasoning behind these assessments is given by Lindmark (2000).

To translate these assessments into conditional probability tables (CPTs) for the Bayesian networks, we first assume that the likelihood of a symptom given a particular configuration of the parent variables is given approximately by a binomial distribution of the form binomial$(2, p)$, where p is a probability between 0 and 1.[4] The higher p is, the greater the likelihood of either a mild or severe occurrence of the symptom. For each

[4] For example, binomial$(2, 1/6)$ gives the expectation of the number of 6es that you will get if you roll a pair of dice: [25/36, 10/36, 1/36] for 0, 1, and 2 6es, respectively

Symptom	Time Pressure	Cognitive Load	Lack of Knowledge
Description error	medium	high	medium
Motor error	high	low	low
Unintentional activation	medium	high	medium (negative)
Wrong choice of rule	high	high	medium
Context error	high	high	medium
Loss of activation	medium	high	low
Irrational behavior	high	high	medium (negative)
Faulty triggering	medium	high	medium
Inefficient behavior	low	high	high
Fast information processing	high	medium (negative)	medium (negative)
Fast movements	high	medium (negative)	medium (negative)
High force	high	medium	low

Table 1: Rough estimates of the influence of three resource limitations on the likelihood of occurrence of types of symptoms

symptom, we specify p as a function of the values of the three parent variables, according to the following formula:

$$\max(0, (a \cdot \text{TP} + b \cdot \text{CL} + c \cdot \text{LK}))/6) \tag{1}$$

Since each of the variables TP (time pressure), CL (cognitive load), and LK (lack of knowledge) has a numerical value of 0, 1, or 2, this quantity is always between 0 and 1. The information of Table 1 is translated into the CPT variables a, b, and c as follows: “high” is mapped to 0.2, “medium” is mapped to 0.1 and “low” is mapped to 0.0, which means that the influence is neglected. For “negative” influences, the sign is negative.

For example, the CPT for the symptom HIGH FORCE is defined by:

$$\text{binomial}(2, \max(0, (0.2 \cdot \text{TP} + 0.1 \cdot \text{CL} + 0.0 \cdot \text{LK}))/6) \tag{2}$$

4 Summary and Outlook

We have introduced a first framework for interpreting symptoms of cognitive load and time pressure in motor behavior, while taking into account the user’s knowledge of the system. Although the initial model, which was developed on the basis of previous published research, can take into account a wide variety of symptomatic behaviors, an important future step is to acquire empirical data on to which to base the CPTs, as has already done for speech input (Großmann-Hutter & Müller, 1999; Müller, 2000).

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