An Ambient Intelligent Agent Model using Controlled Model-Based Reasoning to Determine Causes and Remedies for Monitored Problems

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Abstract

This paper addresses the design of an ambient agent model that incorporates model-based reasoning methods for the analysis of internal causes of observed undesired behaviours of a human, and for determination of actions that remedy such causes. The models used are based on causal and dynamical relations and integrate numerical aspects. By the model-based reasoning methods hypotheses, observations and actions are generated. Control parameters within these processes are described that allow the ambient agent to focus the reasoning. These control parameters are related to each other and to specific domain and situation characteristics, such as time pressure, or criticality of a situation.

1. Introduction

Within Ambient Intelligence software/hardware agents are developed that contribute to personal care; cf. [1;2;12]. Such agents can be based on possibilities to acquire sensor information about humans and their functioning, but more intelligent agents make use of knowledge for analysis of human functioning. If knowledge about human functioning is explicitly represented in the form of computational models in an ambient agent, it can (re)act by undertaking actions in a knowledgeable manner that improve the human's wellbeing and performance. In recent years, human-directed scientific areas such as cognitive science, psychology, neuroscience, and biomedical sciences have made substantial progress in providing an increased insight in the various physical and mental aspects involved in human functioning. Dynamic models have been developed and formalised for a variety of such aspects and the way in which humans (try to) manage or regulate them. Such models can be used in dedicated model-based reasoning methods that allow an agent to derive relevant analyses from these models and available sensor information, and generate intervention actions that make sense.

This paper addresses the design of an ambient intelligent agent that has knowledge about human behaviours and states in the form of explicitly represented models of the causal and dynamical relations involved. Such models are represented in a logical format that also integrates numerical aspects; cf. [6]. Reasoning methods are described making use of such models, to obtain an analysis of (internal) causes of observed undesired behaviours and actions that remedy such causes. The reasoning methods can generate larger sets of hypotheses, observations or actions. To obtain a more efficient reasoning pattern, control parameters are used to focus on specific hypotheses, observations or actions. It is shown how these control parameters relate to each other and to specific domain and situation characteristics, such as time pressure, or criticality. The reasoning methods addressed cover causal and numerical simulation, qualitative reasoning, and abductive reasoning [9].

Section 2 describes the (uncontrolled) model-based reasoning patterns that are used to relate problems to causes and causes to remedies. Next, in Section 3 the control parameters are discussed. Section 4 addresses how these control parameters can be related to domain and situation characteristics. Section 5 illustrates how these reasoning methods can be used, by performing simulation experiments in two example case studies. Section 6 concludes the paper with a discussion.

2. Problems, Causes and Remedies

The type of ambient intelligent agent considered in this paper has as its goal to monitor whether the human functions well, and if detected that he or she does not, to analyse what is the cause of the problem and how it can be remedied. To this end it is assumed that causal models are available (1) from possible causes to problems, and (2) from possible remedies to causes. In Figures 1 and 2 below, an example causal model of an operator (and environmental)'s process is shown. Here on the right hand side the observable aspects of the process are depicted: observations of the human's actions performed, their results and sensor data on the human's body state and environmental state. On the left hand side the aspects are depicted that can be changed from outside the process: input for the human and/or certain environmental aspects. In the case of problems, the reasoning pattern is as follows. The information indicating that there is a problem is located on the right hand side (a combination of properties). The causes, however, usually are in the middle area (as a combination of properties). Remedies have to be found (as a combination of properties) on the left hand side.

Model-based reasoning from problems to causes

By a model-based reasoning pattern the causes for problems observed are determined, by making use of the middle and right hand part of the model..

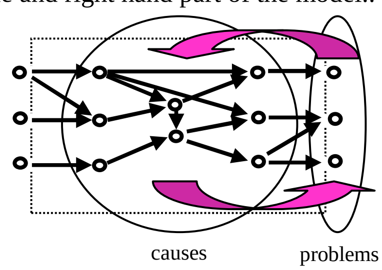

Figure 1. Reasoning from problems to causes

Backward model-based abductive reasoning generates hypotheses for causes and forward deductive model-based reasoning derives observable consequences by which such hypotheses can be tested

Model-based reasoning from causes to solutions

Next remedies for the causes of problems are determined, making use of the middle and left hand part of the model: backward model-based abductive reasoning to generate candidate remedies for causes and forward deductive model-based reasoning to test such candidate solutions.

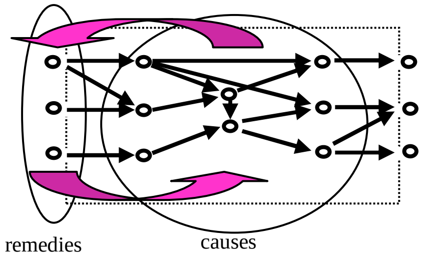

Figure 2. Reasoning from causes to remedies

Model-based reasoning methods

The model-based reasoning patterns sketched above are modelled using a model representation format leads_to_after(X, Y, D), which indicates that the occurrence of some state property X at some time point t will lead to the occurrence of state property Y within time duration D, i.e., at time point t+D. In [4] such methods have been described and formalised.

3. Control Criteria for the Reasoning

The model-based reasoning methods described in Section 2 may generate several options for causes and remedies. To make them more efficient, control parameters are built in that steer the reasoning process.

Multi-criteria selection

A selection strategy is used for choosing:

- observations to be performed (to detect problems),
- hypotheses to be evaluated (to determine the causes),
- actions to be performed (to select one of the remedies).

In order to do this effectively, a multi-criteria strategy is used for each part of the reasoning process. This means that for each observation, hypothesis and action values for a number of criteria are defined that may affect the desirability of its selection. The final desirability of selection is calculated as a weighed sum:

$$\text{value} = w_1 \cdot c_1 + w_2 \cdot c_2 + ... + w_n \cdot c_n \text{ where } \Sigma\, w_k = 1$$

The *weights* w_k of the criteria can be varied depending upon the domain (see Section 4). The following are examples of criteria that are distinguished in the model.

Observation Determination

- Time (time it takes to perform the observation).
- Quality (how high is the quality of the observation)
- Cost (associated with performing the observation).
- Information gain (does the observation deliver a lot of possibilities to distinguish between hypotheses).

Hypothesis Selection

- Criticality (how urgently a hypothesis needs attention).
- Impactability (in case the hypothesis holds, to what extent are there options for changing the situation, i.e. remedies).
- Cost (to determine a hypothesis, e.g., computation).
- Plausibility (is there information that makes it likely that the hypothesis is the case).

Action Selection

- Time (how long does it take to perform the action).
- Cost (how much does it cost to perform the action).
- Impact of success (if successful, what is the impact and what are the side effects of the action).
- Likeliness of successfulness

4. Relating control criteria to situation characteristics

Control of the reasoning process of the ambient agent has to fit to the situation in which the human functions. This implies that the weights for the different control criteria relate to the characteristics of the situation in which the human is functioning. One important aspect is the human's task. Other aspects are the environmental circumstances, e.g. the availability of resources or externally imposed constraints. In the model the following characteristics are distinguished: *time pressure* (the situation requires that operations are done fast), *criticality pressure* (it is very important that the operations are done), *quality pressure* (the operations should be done very good), *impact pressure* (the effectiveness of the operations should be high), *cost pressure* (the costs of the operations should be minimal), and *information quality* (the operations should be based on reliable and valuable information).

The characteristics of the situation have implications for both the functioning of the ambient agent and of the human, and consequently for the view of the agent on the human. Figure 3 indicates what the effect of the situation characteristic is on the weighting factors of the criteria that represent priorities for selection of the observations, hypotheses and actions (see the arrows starting from the left side of the figure). A minus next to an arrow indicates a negative influence, and a plus a positive influence. In addition to the direct effect of the situation characteristics on the priorities for the criteria, there is also an effect of priorities of one criterion on the priorities of other criteria. These are also shown in Figure 3 (the solid lines starting from actions, observations or hypotheses). An example of such a relation is the following:

between action criteria

- if "chance of success" pressure is high, then "side effect" pressure is lower

rational: if you want successful actions, then you don't bother too much about side effects

These rules result in additional information as a basis for the weighting factors.

Finally, during the reasoning process there are also propagating effects of *specific actions, hypotheses and observations* on the weighting of the criteria. In Figure 3 these are depicted as dashed arrows. An example is the following:

from hypothesis criteria to observation criteria

- if "urgency" of an *hypothesis* is high, then "time" pressure for observation is higher and "cost" pressure for observation is lower (for all dimensions)

urgent hypothesis have to be evaluated quickly, while the costs of evaluation are less relevant (for this hypothesis only)

5. Detailed Design

In order to demonstrate the approach, the ambient agent model described above has been formally

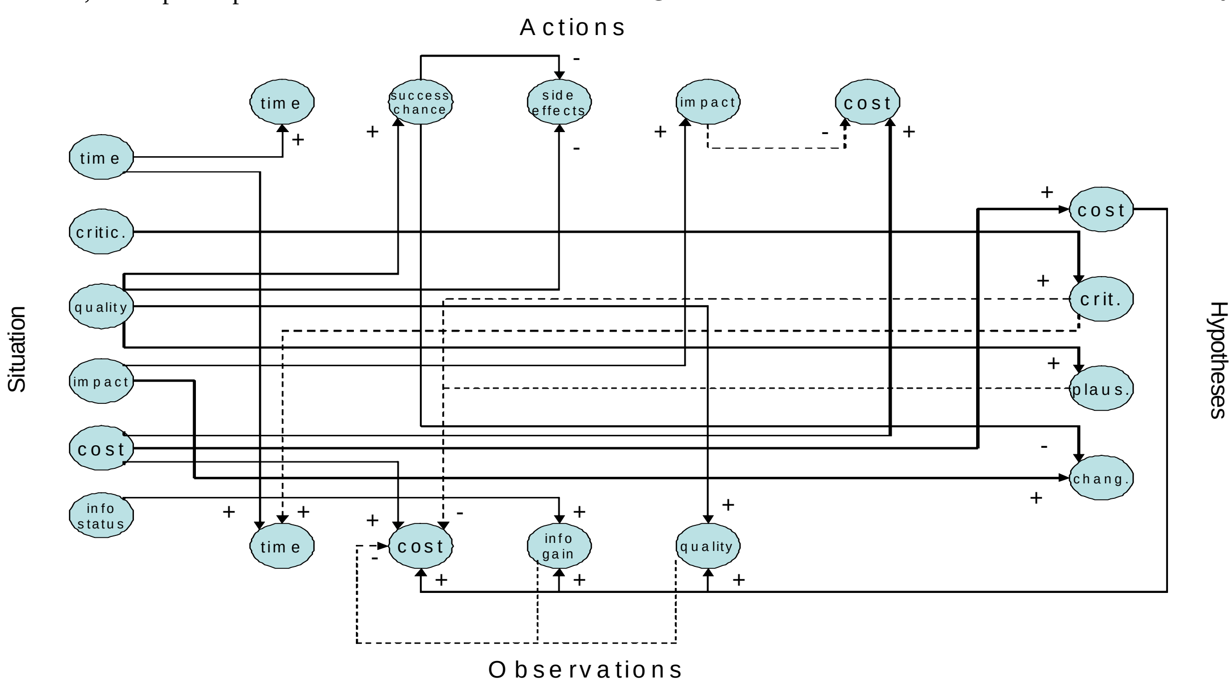

Figure 3. Dependencies between weights of criteria (criteria explained in text)

specified and implemented using the component-based agent design method DESIRE and its software environment [7]. The architecture consists of two main components, namely *hypothesis determination*, in which the appropriate hypothesis are selected, and tested (from problems to causes), and *plan determination*, in which actions (from causes to remedies) to be performed are derived. Below, the key specifications for each of the subcomponents within *hypothesis determination* are described.

Generate Possible Hypotheses

This component takes care of the reasoning process specified in Section 2 concerning the model-based reasoning from problems to causes. It is activated in case a problem has been monitored. In that case, the component receives observation results. Based upon that information and the temporal leads_to_after relationships of the causal model (for an example, see Figure 4) it derives what hypotheses are possible given the current observations (using a temporal backward reasoning method, cf. [4]). In case a state is derivable, and it is an intermediate state within the model, then this is a possible hypothesis. The possible hypotheses are then forwarded to the components *observation determination* and *calculate hypothesis values*.

Observation Determination

In the component *observation determination*, for each of the possible hypotheses the predicted observations are determined. This is done using a temporal forward reasoning method. The predictions are then forwarded to the component *calculate hypothesis values*.

Calculate Hypothesis Values

In this component the mechanism using the criteria for hypothesis and observations in the form of a weighted sum as presented in Section 3 is used. Hereby, the weights for each of the criteria are forwarded from a coordination component that derives the weights from situation characteristics. In this case, the criteria for hypothesis and observations are both calculated. If a hypothesis has been rejected, the cost of this hypothesis will not be calculated, resulting in the hypothesis no longer being considered. The results of the calculations are forwarded to the component *select best hypothesis*.

Select Best Hypothesis

The hypothesis with the highest evaluation value is selected in this component, and in case there are multiple highest ones, an arbitrary hypothesis is chosen. This information is forwarded to the component *test hypothesis*.

Test Hypothesis

Within the *test hypothesis* component, the hypothesis with the best evaluation value (i.e. the one received from *select best hypothesis* is evaluated. The rules within the component are shown below.

```
if      selected_hypothesis(at(S1:STATE, I1:integers))
 and predicted_for(at(S2:STATE, I2:integers),
                   at(S1:STATE, I1:integers))
 and not observation_result_available(S2:STATE)
then to_be_observed(S2:STATE);

if      observation_result(at(S1:STATE, I1:integers), neg)
 and selected_hypothesis(at(S2:STATE, I2:integers))
 and predicted_for(at(S1:STATE, I1:integers),
                   at(S2:STATE, I2:integers))
then to_be_rejected(S2:STATE);
```

In case a certain hypothesis has been selected, and a particular observation result is predicted given this hypothesis, and this has not been observed yet, then this will be observed. In case an observation result has been predicted for the selected hypothesis, and the opposite is observed, then the hypothesis is rejected

Besides selecting the appropriate hypothesis, another element is to determine what action to undertake, performed by *plan determination* (see Figure 2). This process follows the same line of reasoning as the selections of hypotheses, and is therefore only briefly explained. In the sub-component *generate possible actions* temporal reasoning methods are applied to generate what action could potentially solve the cause of the problem (i.e., the "from causes to solutions" part specified in Section 2). Thereafter, the possible actions are sent to the component *calculate action values* that performs calculations using a weighed sum of the various criteria for selecting the actions (following Section 3). Finally, in the component *select best action* the action with the highest evaluation value is chosen.

6. Case Study

The formally specified and implemented model has been evaluated by means of a case study. For this, the causal model that is shown in Figure 4 is used. This model describes the relation between stress of a human, his experience, and the quality of the task execution. It specifies that there are two starting points: the level of the task, and support provided for the task. These two situations can be modified by an ambient agent offering explicit task support, or taking away tasks of the human using a task allocation agent. In case there is a high task level, and no task support for a human, this leads to a potentially stressful situation. In case the human does not have experience and such a situation occurs, this results in a stressful situation without experience. This situation can be observed (i.e., a problem is detected) by indicators measuring stress, and a sloppy task execution. In the case where the human does have experience, the state stressful situation with experience occurs, resulting in indicators measuring stress, but not in sloppy task execution.

Table 1. Deriving weights from situation

	criterion	imposed by situation	consequ-ences	final criteria	quan titati ve
obs.	time			low	0
	cost	medium	high	high	0.5
	quality		medium	medium	0.25
	information gain		medium	medium	0.25
hyp.	urgency			low	0
	plausibility			low	0
	cost	medium		medium	1
	changeability			low	0
actions	cost	medium		medium	1
	time			low	0
	chance of success			low	0
	impact of success			low	0
	side effects			low	0

Table 2. State characteristics

	State	Characteristic
observations	indicators_measure_stress	cost = 1 information gain = 0.1 quality = 0.2
	sloppy_task_execution	cost = 0.1 information gain = 1 quality = 0.5
hypotheses	stressful_situation_without_ experience	cost = 1
	stressful_situation_with_ experience	cost = 0.2
	potentially_stressful_ situation	cost = 0.3
	experience	cost = 0.1
action	time_pressure	cost = 1
	guidance_by_pda	cost = 0.1

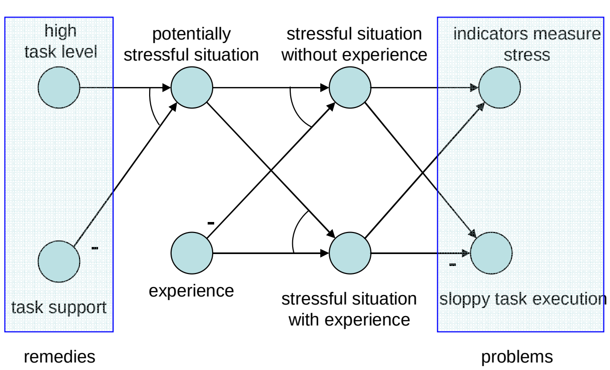

Figure 4. Case Study Causal Graph

This causal model has been used to analyse the reasoning process in the following scenario. The relations in Figure 3 are used to determine the weights of the criteria in the reasoning process. The scenario starts with a situation in which there is a high cost pressure. By default, all weights of the criteria are set low. Applying knowledge as described in Table 1 results in the cost factor for observations, hypotheses, and actions being set to medium, as shown in the third column of Table 1. Also the indirect effects described in Section 4, are taken into account for a number of criteria (fourth column). Eventually, this results in priorities for the criteria (listed in the fifth column). These priorities are translated into weight to order the actual observation, hypotheses and actions, thus forming a selection strategy. Here the qualitative measure is translated into a quantitative measure, the outcome of which is shown in the last column.

The value of the states in the case study, for each of the non-zero criteria the value for these criteria are specified in Table 2. Note that in case the cost indicated are higher, this means that they comply better with the cost criterion.

Below, a selection of the output of the components is shown for this scenario ordered on time. First, the component *generate possible hypotheses* derives the hypotheses that are possible given the observation:

generate_possible_hypotheses
Input:
observation_result(at(indicators_measure_stress, 10), pos)
Output: possible_hypothesis(X) with
X = at(and(potential_stress, experience), 8), at(and (potential_stress, not(experience)), 8), at(experience, 8), at(not(experience), 8), at(potential_stress, 8), at(stressful_with_experience, 9), at(stressful_without_experience, 9))

Thereafter, *observation determination* derives the predictions for the observations.

observation_determination
Input: (see output previous component)
Output: predicted_for(at(sloppy_task_execution, 10), at(and(potential_stress, not(experience)), 8))
etc.

Now the cheapest hypothesis is calculated, given the costs specified before. In this case the hypothesis stressful_without_experience is evaluated as the best:

calculate_hypothesis_values
Input: (see output previous two components)
Output: best_hypothesis(stressful_without_experience)

Since there is only one best hypothesis, this is selected in the component *select best hypothesis*:

select_best_hypothesis
Input: (see previous component)
Output: selected_hypothesis(stressful_without_experience)

In the component *test hypothesis* it is determined whether observations need to be derived. In this case, the sloppy_task_execution is derived as an observation that needs to be performed:

test_hypothesis
Input: (see output previous component)
Output: to_be_observed(sloppy_task_execution)

As a result a new observation arrives from the world, which specifies that the state sloppy_task_execution is the case at time point 10. Since this fully complies with the predictions, the hypothesis is confirmed, and the *plan determination* component is activated. Within the component, the subcomponent *generate possible actions* generates the actions that would result in a change of the current unwanted situation:

generate_possible_actions
Input: active_hypothesis(at(stressful_without_experience, 9))
Ouput: possible_action(change(at(high_task_level, 7)))
possible_action(change(at(not(task_support), 7)))

Since the cost of changing the high_task_level are a lot better than changing the task_support, this action is eventually selected.

6. Discussion

The agent model described is a basis for agent-based ambient intelligence applications aimed at assisting humans in critical or demanding tasks. The model has been designed and formally specified using the component-based agent design method DESIRE cf. [7]. The prototype application has been developed within the DESIRE software environment. Within the agent model reasoning processes were specified that make use of causal, dynamical models of the human's functioning. The latter models were specified in LEADSTO format (cf. [5]). To use such causal models in reasoning processes within an agent model, a formal mapping has been made of the language LEADSTO into the language DESIRE. This mapping comprises (1) a mapping of the representation format, using a leads_to_after predicate introduced in DESIRE, and (2) a mapping of temporal reasoning methods that can be applied to LEADSTO specifications into DESIRE rules. In this way a kind of (meta-)interpreter for LEADSTO specifications has been explicitly represented in a logical manner within the language DESIRE. The resulting intelligent agent model has a high representational and reasoning power, where, e.g., also the reasoning can be controlled based on domain and situation characteristics, as has been shown.

The main process performed by the agent described in this paper is model-based diagnosis [8;10]: causes of malfunctioning are determined and remedies are proposed, using a model of system to be diagnosed. This paper focuses on the implementation of diagnosis in an ambient agent, which controls the process based on characteristics of the situation.

Within agent-systems, several personal assistant agents which maintain user-models, and utilize them, have been proposed. In [3] a virtual secretary agent is shown that incorporates a user-model to enable a more dedicates assistance. The reasoning process of the model is however not tailored towards the situation, such as addressed in this paper. Furthermore, agents have also been developed that learn the user models (see e.g. [11]). Such a learned model could be the input of the agent architecture proposed in this paper.

7. References

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