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EXPERT SYSTEM SHELL ARCHITECTURE BASED ON DECISION NETWORK

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Abstract: *Presented paper deals with preliminary design of an empty expert system suitable for system monitoring in various engineering applications. Discussed expert system is rule-based with the possibility of importance factor definition within each rule. The deduced result can be composited from more than one possible hypothesis based on different confidence level. The core of the system is based on Bayesian decision network and simple autonomous mobile robot use-case is used for results presentation.*

Keywords: Expert System, Decision Network, Knowledge Engineering.

1. Introduction

Development of reliable mobile robot system highly depends on capabilities of used onboard diagnostics. There are various robotic systems which have lack of any onboard diagnostic (Masek, 2015). These robots count on usage reliable components itself and in case of mechanical, electrical or other failure this system crashes. Such system are used as a toys or experimental devices (Gibbons, 2009 and Krejsa, 2010) with no impact on user/operators health. Other kinds of robotics machines have off-line diagnostics, which can be used while searching for failure causes. The most advanced diagnostic subsystems are used for on-line full system diagnostic with possible failure prediction (Buchanan, 1984).

This paper describes the diagnostic expert system, which is running independently on other onboard systems on mobile robots. This diagnostic tool is designed as an empty expert system and can be used in different fields e.g. smart homes (Vechet, 2016). The main idea behind the expert system is that the expert system is probabilistic and has the ability of simultaneously deduce various hypothesis with different likelihood. The user can support the decision process with answering given questions or the expert system can get adequate answers directly from the system in question itself.

2. Expert system architecture

The architecture for the expert system is based on traditional expert system shell described by Merritt (1989). The traditional concept was also used in MYCIN or EMYCIN (Melle, 1984) and consists from:

– knowledge base which holds the information of an expert about selected domain,
– inference engine which derives possible solutions for given inputs,
– user interface which interacts with the user,
– working storage of domain specific data structures for temporal/long term usage.

Further described expert system uses this traditional paradigm, however the implementation of selected parts differs in order to enable following behavior:

– it starts as an empty expert system which can be used as a state-of-the-art system regardless the type of the problem to be solved,

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– multiple hypothesis can be deduced simultaneously with various level of confidence,
– each hypothesis can be supported or negated with additional information gathered from user/system under observation,
– information presented to the expert systems are ternary (e.g. {Yes, No, Unknown}, {True, False, None}, ...),
– the expert system can adapt in time to new conditions using user interaction.

To provide such behavior we implemented the knowledge base as a set of independent naive Bayesian networks with decision node. The decision node takes into account the reward for doing or not doing deduced action and it is used for changing the internal believe in the hypothesis and thus it evolves in time. The decision network is implemented on paradigm described by Korb (2010).

2.1. Decision network structure

The decision network can be described as direct acyclic graph. The core concept is shown in Fig. 1. Even that the decision network is defined as a naive Bayesian network, the resulting decision process can be chaining using recursion where a selected hypothesis can be used as an input for next decision to be made.

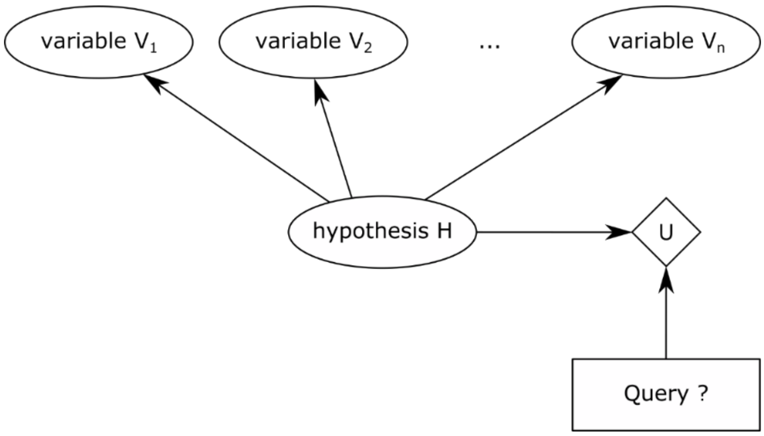

Fig. 1: Single decision network structure as a core of the expert system.

Tab. 1: Utility node reward definition. H-hypothesis, Q-query, U-utility.

H	**Q**	**U(H,Q)**	**Notes**	**Outcome**
True	Yes	100	System state changend and ES prove it.	Excelent
True	No	50	System state changed, however ES didn't prove it.	Poor
False	Yes	-100	Nothing to prove and ES proved wrong hypothesis.	Terible
False	No	100	Nothing to prove, no hypothesis in scope.	Excelent

3. Architecture evaluation

The evaluation of designed expert system was performed using a concept of question/answering system meant to help a customer with online assistance when solving malfunctioning autonomous mobile service robot originally developed via Bender Robotics company (Hrbacek, 2010, Masek, 2013 and Krejsa, 2014).

The expert system should help to identify the problem while asking the user questions based on system state. Typical use case is demonstrated on basic situation: considering the robot OS is running and GUI interface successfully shows the map and a position of the robot inside the map, however the robot is not moving. The user is asked if the data from laser range finder (LIDAR) are present, which implicates the hypothesis that the LIDAR is not connected properly. The second thought (hypothesis) of the expert system is that in case the LIDAR is working, the reason for not moving robot is motor driver (which is unreliable component). The partial (removed all occurrences where *RobotNotLocalized* is False) decision process for hypothesis *LidarNotConnected* is shown in Tab. 2 where the expected utilities are calculated.

The probabilities used in this sample case are defined as:

$$P(RobotNotLocalized=T|LIDARNotConnected=T) = 0.9 \quad (1)$$

$$P(WrongMap=T|LIDARNotConnected=T) = 0.6 \quad (2)$$

$$P(DataNotShown=T|LIDARNotConnected=T) = 0.95 \quad (3)$$

The definition for expected utility is based on Korb (2010) and is given as:

$$EU(Q|E) = \sum_i P(O_i|E,Q)U(O_i|Q) \quad (4)$$

where E is available evidence, Q is action/query with possible outcome O_i, $U(O_i|E)$ is the utility of each outcome or reward (see Tab. 1), $P(O|E,Q)$ is the probability over possible outcomes given evidence E and query action Q performed.

The results shown in Tab. 2. were calculated using equations (5 – 8) which are based on Bayesian conditional probability theory.

Tab. 2: Expected utility calculated as a reaction to given evidences presented to the ES.

Evidences	**EU (Query=Yes)**	**EU (Query=No)**	**Decision**
True True True	**51.1**	25.85	Do
True True False	-1.1	5.15	
True True None	**50**	31	Ask
True False True	**33.9**	17.4	Ask
True False False	-3.9	6.6	
True False None	**30**	24	Ask
True None True	**85**	43.25	Ask
True None False	-5	11.75	
True None None	**80**	55	Ask
False - -	...	...	...
None True True	**55**	30.5	Ask
None True False	-35	39.5	
None True None	20	70	
None False True	**35**	22	Ask
None False False	-55	58	
None False None	-20	80	
None None True	**90**	52.5	Ask
None None False	-90	97.5	
None None None	0	150	

Presented decision network results in three possible outcomes {*do*,*ask*,*none*}. Where *do* means, that the result cannot be more supported with any other evidence or additional information from system (all supporting evidences are known and *True*).

The decision *ask* means, that this hypothesis is likely, however more information from the user or the system is needed. The decision *none* handle hypothesis that are unlikely to appear or there is not enough information available.

In case we have measured all needed evidences the joint probability is calculated as a product of equations (1 – 3) using (4) where:

$$P(LIDARNotConnected{=}T|RobotNotLocalized,WrongMap,DataNotShown) = 0.513 \quad (5)$$

$$P(LIDARNotConnected{=}F|RobotNotLocalized,WrongMap,DataNotShown) = 0.002 \quad (6)$$

Expected utility calculated using all above defined equations:

$$\mathrm{EU(Q{=}Yes)}{=}P(LIDARNotConnected{=}T)^{*}\mathrm{U(H{=}T,Q{=}Yes)}+ P(LIDARNotConnected{=}F)^{*}\mathrm{U(H{=}F,Q{=}Yes)}{=}0.513^{*}100 + 0.002^{*}(-100) = 51.1 \quad (7)$$

$$\mathrm{EU(Q{=}No)}{=}P(LIDARNotConnected{=}T)^{*}\mathrm{U(H{=}T,Q{=}No)}+ P(LIDARNotConnected{=}F)^{*}\mathrm{U(H{=}F,Q{=}No)} = 0.513^{*}50 + 0.002^{*}(100) = 25.85 \quad (8)$$

4. Conclusions

We present a preliminary design of an expert system which is able to generate multiple hypothesis with different probabilities and via query/answer interface is able to deduce most likely hypothesis which is presented to the user.

Since the query/answer mechanism is not limited to interaction with the user, the additional information can be obtained directly from monitored system itself. Thus the expert system can be used for online diagnostic of various mechatronic systems from autonomous mobile robots to smart houses.

The actual and future work on presented expert system is focused on advanced human-machine interaction to ensure it can be naturally used in various engineering applications.

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