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Probabilistic Estimation of Human Interaction Needs in Context of a Robotic Assistance in Geriatrics

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Abstract: The key purpose of assistance robots is to help people coping with work-related or everyday tasks. To ensure an intuitive and effective support by an assistance robot, its expectation conform behavior is essential. In particular, when using assistance robots in geriatrics to assist elderly patients, special attention to the human-robot interaction should be paid. In order to help elderly patients maintain their independence and abilities as much as possible, the robot should only intervene when its support is needed. Therefore, the continuous estimation of the patient's need for interaction is of particular importance. For enabling suitable models to estimate this need, we elaborate the use of Bayesian Networks. The analysis of our results seems promising, yielding a robust and practical approach.

Keywords: Bayesian Networks, Virtual Evidence, Robotics, Gerontology, Social Robot, Assistance Technology.

1 Introduction

For the European Union, the transition towards an older population structure due to an increasing life expectancy and low birth rates can be observed. In 2017, the population was estimated at 511.5 million people, from which $19.4\,\%$ were aged 65 and more. By the year 2080, this share is expected to rise by a further 10.5 percentage points to a share of $29.9\,\%$. Over the same period, the proportion of European people aged over 80 will double [1]. While this transition results in medical as well as technological challenges, it also opens up new opportunities for research and development in these areas [2]. Geriatrics (healthcare of elderly people) and AI-based technologies like assistance robots are among these. New findings in these areas may help to bridge the expected gap between the number of professional caregivers and elderly patients in the future.

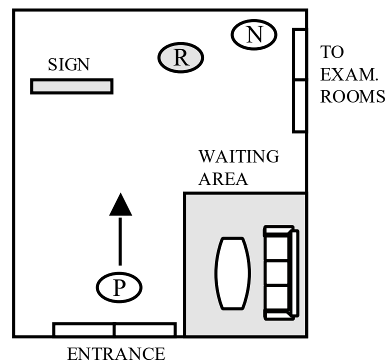

Fig. 1: Top view of the considered application case: An elderly patient (P) has to find his way to the appropriate examination rooms in a geriatrics department. For assistance, the patient may interact with a robot (R). Also present is a waiting area, a sign with directions and a nurse (N).

When using assistance robots to support elderly patients, special emphasis should be placed on human-machine interaction: In general, to ensure an intuitive and effective assistance, an expectation conform robot behavior is essential [3]. In context of geriatrics, also the acceptance of the robot by the elderly plays a key role [4–6].

At best, in order to maintain the independence and skills of elderly people as much as possible, assistance by the robot should only be offered when it is needed. The basis for this is the continuous estimation of the patient's need for interaction. For enabling suitable models to estimate this need, this contribution elaborated the use of Bayesian Networks for an exemplary application.

2 Technical Application

In our study, we investigate an exemplary application of robot assistance in a geriatrics department of a hospital, cf. Figure 1. In the considered scenario, an elderly patient arrives at the department and has to find his way around the building. While some patients prefer to move around the department on their

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own, others may need assistance as they may e.g. not be able to read or understand signs in the building. Patients in need can be supported by a robot that accompanies them to the desired examination room. It is also possible that this robot interacts with patients during a waiting period before their examination, serving as a distraction and acting as a companion.

3 Fundamentals

Bayesian Networks have been shown to be a viable means for assessment and prediction in context of uncertainty [7, 8]. For assistance in diagnostic processes or surgical interventions in which more and more observation values are added over time, we could show that tailor-made Bayesian Networks are very suitable [9]. Similar models are also well suited for the problem presented here, since the probability of the patient's need for interaction may be calculated by successively adding observation values derived from the robot's environmental sensors through time. Thereby, fragmentary values and, inter alia, uncertainty originating from pre-processing algorithms must be taken into account. Furthermore, Bayesian Networks allow us to incorporate expert knowledge of the underlying process directly, tackling the challenge of the lack of training data and thus differing from models such as common artificial neural networks [10].

A Bayesian Network is a probabilistic graphical model. Therefore a Bayesian Network over the random variables $X^{0:N} = X^0, \dots, X^N$ is given by a tuple

$$B = (P, G)\,,$$

whereby P is a joint probability distribution

$$P(X^{0:N}) = \prod_{n=0}^{N} P(X^n|\mathrm{Pa}(X^n))\,,$$

and

$$G = (V, E)\,,$$

corresponds to a directed, acyclic graph (DAG) [11–13]. This DAG G, also known as the structure of a Bayesian Network, is used to define dependencies between random variables $X^{0:N}$. Thereby, the vertex set V represents the set of random variables. While a directed edge $V_k \to V_m$ within the set of edges E represents a direct dependency between two variables, the independence of two variables is symbolized by a missing edge [10].

Hard evidence (also known as regular evidence) is a common way allowing for observation values to be incorporated into a Bayesian Network. With the use of hard evidence, a particular value x of a variable X^n can be specified as observation $\lambda_{X^n}(x) = 1$ when x is the observed value of X^n and $\lambda_{X^n}(x) = 0$ otherwise [14].

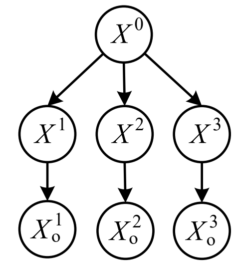

Fig. 2: In this example, the nodes $X^1, X^2,$ and X^3 are not directly observable. Observation nodes are used to model virtual evidence, i.e., evidence with uncertainty, by using the corresponding probability distributions $P(X^i_o|X^i)$.

In cases where a direct observation of variables is not possible, different approaches can be used to model uncertain evidence – e.g. fuzzy evidence [15], soft evidence [16] or virtual evidence [17]. The latter can colloquially be described as "evidence with uncertainty", whereas (e.g.) the second-last can be regarded as "evidence of uncertainty". The careful differentiation is important, because the terms are sometimes confused e.g. in application software [14].

Virtual evidence on a variable X^n can be modeled by adding a node X^n_o to the Bayesian Network representing undisclosed observations. Figure 2 shows the structure of a naive Bayesian Network incorporating three random variables X^1, X^2, and X^3 which are not directly observable. Virtual evidence is modeled by auxiliary nodes X^1_o, X^2_o, and X^3_o incorporating the probability distribution $P(X^n_o|X^n)$.

4 Modeling Approach

Figure 2 shows our modeling approach. Our model, a Bayesian Network which estimates the human interaction need, consists of a root node, three child nodes, and three observation nodes. The root node X^0 represents the estimated probability of the patient's need for interaction with the robot. It is a binary node and its unconditional probability table states maximum uncertainty:

$$\begin{aligned} &\textit{Need for interaction: } X^0 = \{\textit{Yes, No}\}, \\ &P(X^0 = \textit{Yes}) = P(X^0 = \textit{No}) = 0.5. \end{aligned} \tag{1}$$

The estimated probability of the patient's need for interaction depends on the patient's focus of attention, on his behavior, and on his position with respect to the robot. To model the patient's focus of attention, we firstly introduce a child node X^1. In our current approach, we explicitly model three possible attention foci: The robot itself, a sign in the surrounding

Tab. 1: Exemplary conditional probability table associated with observation node X_o^3 if the distance estimation algorithm detects the patient's distance with a probability of 70% as high. This table represents virtual evidence and changes according to the algorithm's detection results.

Distance	Low	Medium	High
Yes	0.05	0.25	0.7
No	0.95	0.75	0.3

area which might indicate where to find certain examination rooms, and another person. All other possible attention foci are grouped as unknown:

$$\textit{Focus of attention: } X^1 = \{\textit{Robot, Sign, Person, Unknown}\}. \quad (2)$$

Secondly, we use the child node X^2 to model the patient's current activity. For our setting in the entrance area, we chose the three possible activities walking, standing, and sitting. A fourth activity, waving, is additionally chosen as a way to introduce a patient to the robot or to say goodbye to it. Other possible activities are again grouped as unknown:

$$\textit{Activity: } X^2 = \{\textit{Walking, Standing, Sitting, Waving, Unknown}\}. \quad (3)$$

Thirdly, we use the child node X^3 to represent the distance between the patient and the robot. In order to being able to adapt to different surroundings, we do not choose concrete distance ranges but use the three states low, medium, and high:

$$\textit{Distance to robot: } X^3 = \{\textit{Low, Medium, High}\}. \quad (4)$$

When a patient is standing far away from the robot, the probability of him wanting to interact with the robot is generally lower than when he stands closer to it, regardless of the patient's particular activity. To model this, we add a directed edge from X^2 to X^3 (not depicted in Figure 2). Next to the child nodes, further nodes have to be added to the network. The child nodes described above cannot be observed directly, but algorithms, e.g. for activity recognition or distance estimation, must be used. Since these algorithms only provide a probability distribution over possible variable assignments,

hard evidence where $\lambda_X(x) = 1$ for exactly one value x cannot be used. Instead, we incorporate virtual evidence by adding an observation node to each child node, namely $X_o^1, X_o^2,$ and X_o^3 in Figure 2. Table 1 shows an example of how to integrate information of a distance estimation algorithm.

To initialize the Bayesian Network, we incorporate expert knowledge by estimating the probability of a patient performing a certain activity while having the need for interaction or not.

5 Evaluation

In order to evaluate our model, we investigate the following scenario: A geriatrics patient is detected far away from the robot. A nurse stands in sight of the patient near the exit to the examination rooms. The patient walks towards the robot and introduces himself. As the patient wishes to leave, he waves the robot goodbye and walks away.

For the evaluation, we divide this scenario into 14 triples of the form:

$$(\textit{Focus of attention, Activity, Distance to robot}). \quad (5)$$

Since the values of these triples cannot be directly incorporated into our model as hard evidence, we created virtual evidences. Therefore, we assigned a high probability to a chosen state of a variable, while equally distributing the remaining percentages on the other states.

E.g., the sentence "A geriatrics patient is detected far away from the robot." was transformed into the following triple:

$$(\textit{Unknown, Unknown, High}). \quad (6)$$

The focus of attention as well as the activity is set to unknown because the patient is too far away for the recognition or detection algorithms to give a more concrete result. The other 13 triplets were generated as described above. We created suitable conditional probability tables for the three observation nodes of all triplets and used Bayesian inference to estimate the patient's need for interaction. The result is shown in Figure 3. The probability of the need for interaction rises as the distance between the patient and the robot decreases (c.f. data points 2 to 4 in Figure 3). When the activity changes from walking to standing in data point 5, the estimated probability of interaction is nearly tripled. The highest probability is estimated when the patient shifts his focus of attention from the nurse to robot, cf. data points 6 and 7. The probability decreases as the patient waves the robot goodbye, cf. data point 8, and further decreases as the patient focuses on the nurse and walks away (data points 9 to 14).

6 Conclusion

In this work, we presented an approach based on Bayesian Networks for estimating human interaction needs in the context of robotic assistance. The technical application is a scenario in geriatrics, in which an elderly patient might need support to find his way in a hospital building. In order to estimate the patient's need for interaction with the robot, we consider various uncertain observation data obtained from the algorithmic analysis of sensor values, such as the patient's focus of

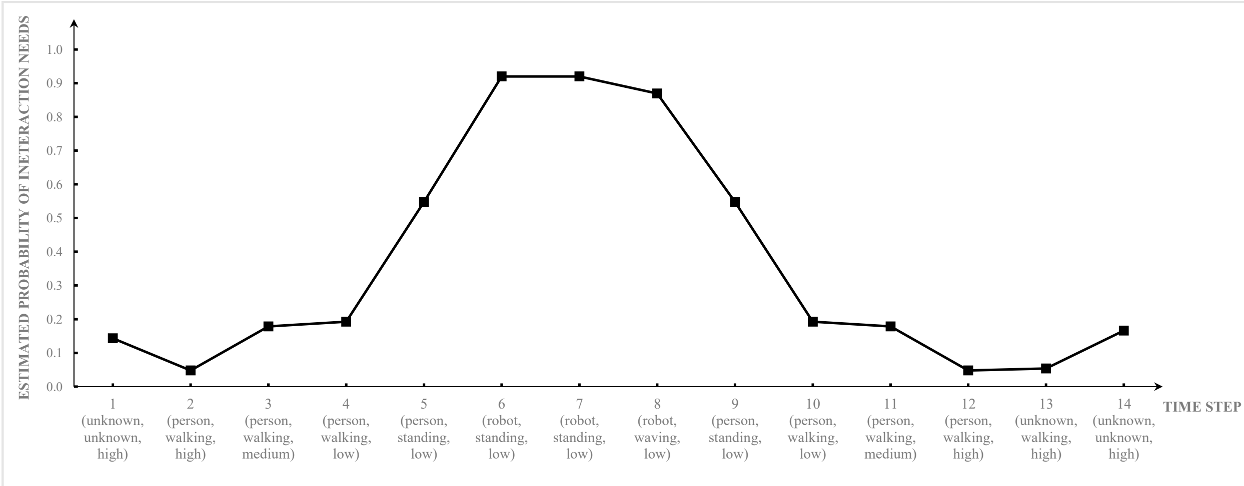

Fig. 3: Result of the probabilistic estimation of the human interaction need, using the presented approach. The abscissa shows the observed triples: the patient's focus of attention, activity, and distance to the robot. The ordinate shows the estimated probability.

attention, his activity and his distance to the robot. While the presented approach is a first step in estimating human interaction needs in the described scenario, we plan to extend our model in the future, e.g. by considering interaction needs of several people in a scene and by adding further observations that can be derived from the obtained sensor values.

Author Statement

Conflict of interest: Authors state no conflict of interest. Informed consent: Informed consent has been obtained from all individuals included in this study. Ethical approval: The research related to human use complies with all the relevant national regulations, institutional policies and was performed in accordance with the tenets of the Helsinki Declaration, and has been approved by the authors' institutional review board or equivalent committee.

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