Automatic IO Device Selection for Ambient Environments

Brigitte Kupka[1*], Jonathan Steinhart[1], Miroslav Sili[1], Matthias Gira[1], Christopher Mayer[1,2]

[1]AIT Austrian Institute of Technology GmbH, Health & Environment Department, Donau-City-Straße 1, 1220 Vienna, Austria; *brigitte.kupka@ait.ac.at

[2]Department of Analysis and Scientific Computing, Vienna University of Technology, Wiedner Hauptstraße 8-10, 1040 Vienna, Austria

SNE Simulation Notes Europe SNE 26(1), 2016, 17-22
DOI: 10.11128/sne.26.sw.10323
Received: January 10, 2016; Revised: February 15, 2016;
Accepted: March 20, 2016;

Abstract. Active and Assisted Living (AAL) aims at providing services for elderly or disabled people in their homes using modern smart home technology and AAL software. The accessibility of user interfaces for such systems is of particular interest. This article proposes a model-based solution for selecting the best device and modality for user interactions of AAL services using the Ambient Assisted Living user interfaces (AALuis) framework. The best device and modality for a given situation depends on context information provided by the AAL system. An exemplary household was modeled as a Bayesian Network, incorporating a selection of devices and their modalities, together with relevant context information regarding the user and the environment. Each entity of the network is assigned with a probability. For devices and modalities these probabilities represent a measure of their suitability for output for the user, given the context. This model was then used to simulate different scenarios, in order to review the results of this selection mechanism.

Introduction

Active and Assisted Living (AAL) Environments use modern technology to provide services specifically tailored to elderly or disabled people and their caretakers [1]. Those services include telecare, telecommunications, comfort services and emergency prevention and detection [2]. They have, in general, the objective of promoting and maintaining physical and psychological health, and assistance in daily life. AAL middleware unites common household electronics and specialized smart home hardware components with AAL service software. AAL services are meant to be integrated into the live of the user as seamlessly as possible. Therefore the user interfaces (UIs) are of particular interest in AAL environments [3]. The project Ambient Asssisted Living User Interfaces (AALuis) [4] is concerned with the flexible creation of accessible UIs for AAL services.

The model-based Automatic IO Device and Modality Selection for AALuis has the objective of selecting the best device and modality combination for any AAL service, given the context. Context information, regarding the user, the devices and the environment is provided by the AAL framework and serves as a basis for the selection. A user interaction typically consists of input and output. This work is concerned with the selection mechanism for only the output part of UIs.

This paper first describes the problem of the Automatic IO Device Selection for AALuis and follows with a brief introduction to the chosen method, Bayesian Networks. Then, the modeling process is presented, followed by the results of evaluating this method for solving the given selection problem. Next, the results are discussed and finally the paper closes with a conclusion and a brief outlook on further topics of interest in this context.

1 Automatic Output Device Selection for AALuis

New devices, each with their individual features, are constantly being introduced. It is desirable to also make them available to AAL systems. However, AAL service developers cannot anticipate all device's possibilities and constraints regarding the UIs at design time. AALuis can help to use them to their full potential.
The idea of AALuis is to provide open AAL systems with innovative UIs. It frees service developers from

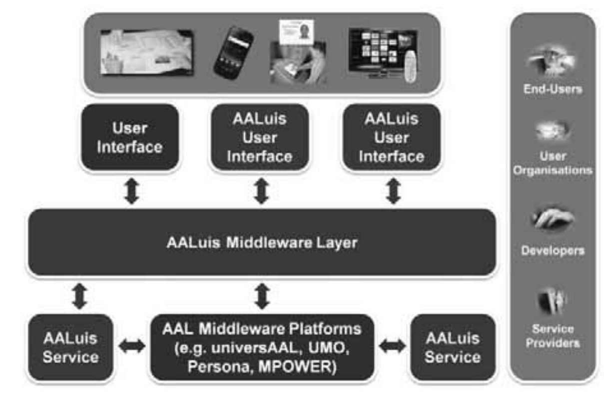

Figure 1: The AALuis middleware [4].

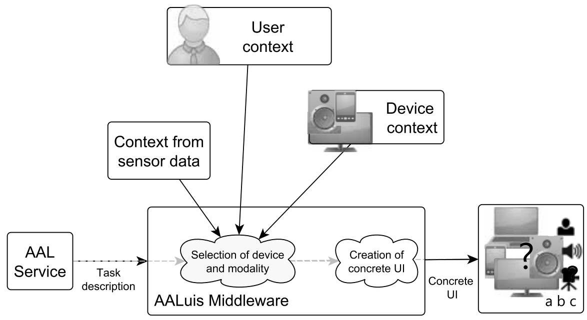

Figure 2: The device and modality selection problem in context of the AALuis UI creation process.

the task of designing the specific UIs, by linking the AAL system with the available devices and generating accessible interfaces for the services. The AALuis middleware operates from between another AAL middleware platform and the devices, as shown in Figure 1.

Each device supports one or more modalities. A modality is the communication channel used to transport a message between a human and a computer. Audio or text are output modalities, speech or text would be the corresponding input modalities [5].

AAL services initiating a user interaction contact the AALuis middleware with an abstract description of the task. It describes one user interaction and does not make references to a specific device or modality. During the following step AALuis shall automatically select the best combination of device and modality available, based on context and device information provided by the AAL middleware, and create an abstract UI description. On this basis, a concrete UI is created and sent to the selected device for rendering. Figure 2 shows this process and highlights the part of selecting a device and modality, which is the main focus of this article.

The context of an AAL system includes the user, the user's capabilities and constraints, personal preferences, the available devices, and the situational context, like surrounding noise, ambient light, temperature and current activities [6]. In different contexts, some modalities and devices might be preferable over others, for example, text output on a small device is not ideal for a person with visual limitations.

A number of additional requirements for the Automatic IO Device and Modality Selection for AALuis were identified. Input data from sensors, providing context information, might not be available at all times. Also, new devices can be added to a smart home at any time, others might become unavailable. Still, the selection mechanism has to produce a result every time.

Due to this flexible nature of the target systems, it is not possible to collect any training data for a classifier.

2 Bayesian Networks

Bayesian Networks were chosen as a method to solve the selection problem given the constraints stated above.

A Bayesian Network [7] is a directed acyclic graph and constitutes a compact representation of a probability distribution. The graph's nodes stand for discrete random variables and its edges represent causal relationships between them. Each node is assigned with the probability for each value the random variable can take.

Bayesian Networks can incorporate the subjectivist interpretation of probability, as opposed to the commonly known frequentist interpretation.

Traditionally, probability is based on the frequency at which certain events occur during repeated statistical experiments. There are situations however, where it is not possible to conduct an experiment multiple times in order to determine the frequencies of its outcomes. In the subjectivist interpretation of probabilities [8], probability is a numerical value, representing the degree of belief in the occurrence of an event A, given prior knowledge E (Evidence). This definition enables one to utilize expert domain knowledge and assign probabilities to events that are conditioned on E.

In a single Bayesian Network, both interpretations can be used conjointly.

2.1 Independence Assumption in Bayes Networks.

In a Bayesian Network, an edge connecting two nodes represents a causal relationship between them. Therefore, two nodes that are not connected are considered independent. This property is essential for using a Bayesian Network to compactly represent a probability distribution of n random variables. Expanding the definition of conditional probability $P(A|B) = \frac{P(A \cap B)}{P(B)}$ to multiple variables leads to the Chain Rule, shown in Equation 1, to calculate the joint probability distribution of the variables.

$$P\left(\bigcap_{k=1}^{n} A_k\right) = \prod_{k=1}^{n} P\left(A_k \middle| \bigcap_{j=1}^{k-1} A_j\right) \tag{1}$$

For two independent random variables the following holds: $P(A|B) = P(A)$.

This property, together with the assumption that there is no causal relationship between two not connected nodes, is utilized in a Bayesian Network, resulting in the Chain Rule for Bayesian Networks [8], shown in Equation 2.

$$P(A_1, ..., A_n) = \prod_{i=1}^{n} P(A_i | Pa_G(A_i)) \tag{2}$$

where $Pa_G(A_i)$ denotes the parent nodes of A_i in the graph G.

This means that after assigning each node of the Bayesian Network with the Conditional Probability of the represented random variable, given its parents, the Network contains all the information needed to calculate the joint probability function of all random variables.

2.2 Inference on Bayesian Networks

The states of some of the modeled random variables in a Bayesian Network can be observed in the real world. Using an inference algorithm, the graph structure can be exploited, to calculate the posterior probability of any random variable $P(A|E = e)$, given the observed evidence.

For this work, the junction tree algorithm by Shenoy and Shafer [9] was used for inference. This algorithm uses techniques of graph theory to convert the graph to a a simpler structure, the eponymous junction tree. After Evidence was observed, the probabilities in the model are updated. When the algorithm has completed, the probability of each single variable can be found through marginalization of a relatively small table. There is no need to calculate the entire joint probability distribution using the Chain Rule for Bayesian Networks, shown in Equation 2, to obtain the value for a single variable anymore.

3 Modeling

In order to solve the Output Device and Modality Selection for AALuis using a Bayesian Network, an example household was modeled as a template for any real household using AALuis. This section gives a brief introduction on the included elements and how they were combined in this model.

3.1 Elements of the Bayesian Network

Devices. For each known device, one node with the possible states *yes* and *no*, representing the subjective probability that the device is a good choice, was included. Each device has a parent node, indicating the device's current availability. Battery operated devices were additionally assigned a parent node, indicating the battery status of that device, with the possible values *low* and *OK*. In the modeled sample household, motion sensors provide the AAL middleware with information about the user's proximity to each device. To incorporate this information into the Bayesian Network, for each device node a proximity indicator was added as a parent. The subjective probability of every possible state of each node was assigned during the modeling process. These probabilities are used during inference, if the real value of the corresponding node was not observed. Figure 3 shows an example for a device called *smartphone*. Table 1 shows the corresponding conditional probability table for the device. It holds a probability for the values *yes* and *no*, for each possible state of the parent nodes.

For all entries, where the node *available* takes the value *no*, signaling that the device is currently not available to the system, the probability for the device node evaluating to *yes* was set to 0, thereby excluding the device from the selection process.

Modalities. Each modality supported by any of the known devices is represented as a single node in the

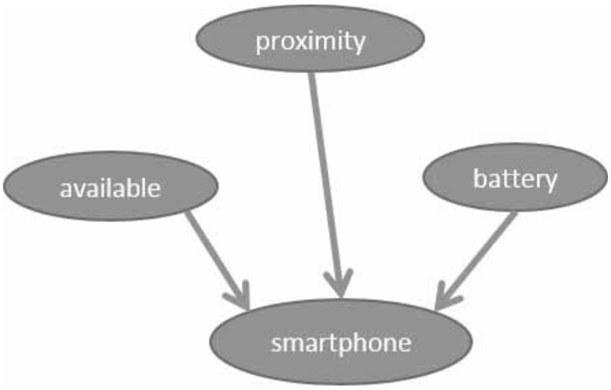

Figure 3: The nodes for a smartphone, with its properties battery status, availability and user's proximity.

available	battery	proximity	smartphone	
			yes	no
yes	OK	same room	1.0	0.0
		different room	0.5	0.5
	low	same room	0.1	0.9
		different room	0.1	0.9
no	OK	same room	0.0	1.0
		different room	0.0	1.0
	low	same room	0.0	1.0
		different room	0.0	1.0

Table 1: The Conditional Probability Table for the smartphone node of Figure 3.

Bayesian Network. The instance values *yes* and *no* represent how well the use of this modality would suit the current situation. The parents of a modality node are all the influencing factors from sensors or the user profile that have the potential of reducing the suitability of this modality.

User Profile and Sensor Data. For the modeled template household and AAL system, it was assumed that there was a user model, retrieving information about the user from a user profile. Four exemplary properties, indicating the user's abilities were included in the model: *hearing*, *visual acuity and sensitivity*, *field of vision* and *language reception*. Two items of sensor data were also included: *noise* and *ambient light*.

Result Nodes. Finally, for each possible combination of modality and device, a so called result node was added. It merges the probabilities of its parents so that the probability assigned to its value *yes* reflects the level of agreement for that combination, given the evidence. A minimal working example including only one device and one modality is shown in Figure 4.

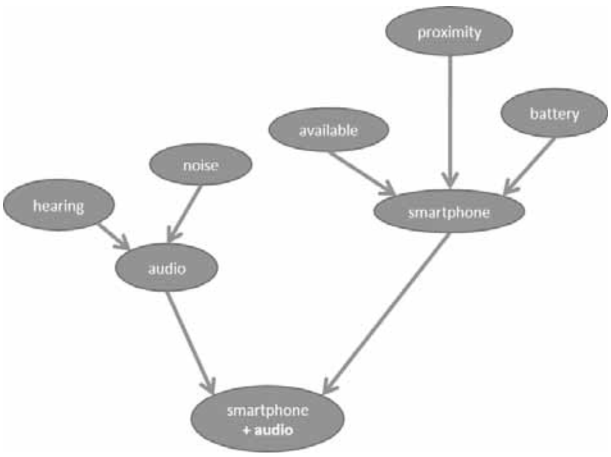

Figure 4: A minimal example of a household with only one device, which supports exactly one modality.

3.2 Inference on the model

When a selection is initiated by AALuis, evidence is set for all nodes which have been observed and inference can be performed. After completion, each result node is queried for the probability now assigned to its instance value *yes*. By ranking the result nodes according to their updated level of agreement, the best device and modality combination is found.

4 Results

To review the described approach's suitability to solve the Automatic IO Device Selection for AALuis, the example household was used to simulate different situations. Two example scenarios, will be presented below.

Scenario 1. A graphical summary of Scenario 1 is shown in Figure 5. It includes a user with good visual acuity and impaired hearing abilities. A TV is available in another room, and a touchtable is situated near the user. The level of noise is currently high, and the ambient light is of medium intensity. In this scenario, combinations using the touchtable are rated

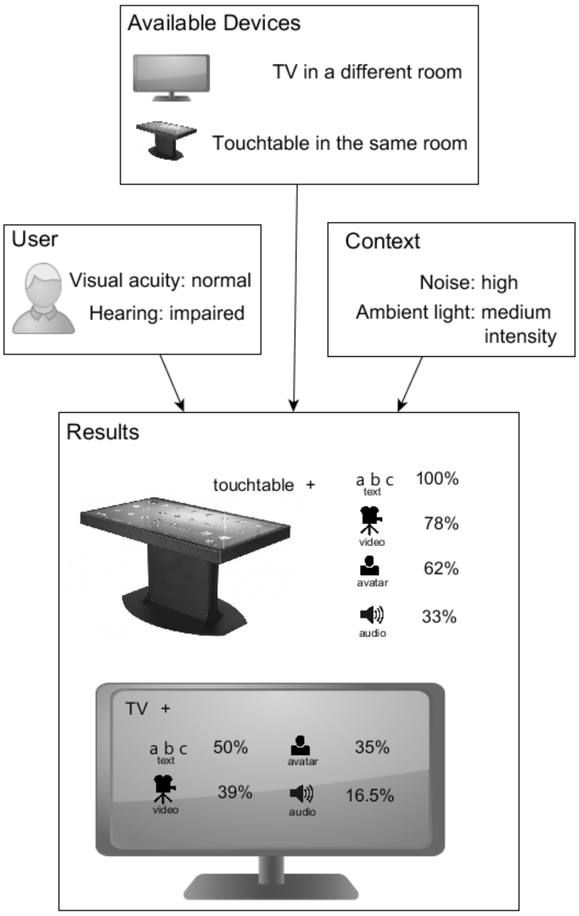

Figure 5: Scenario 1

overall higher than the options for the TV. The combination of touchtable and text output receives 100% agreement, while audio output on the TV receives only 16.5% agreement.

Scenario 2. The second scenario represents a user with severe impairments in hearing and their field of vision. Their visual acuity is also impaired, while the language reception was rated as normal. There are four devices present, including a TV in a different room, a laptop with good battery status in a different room, a smartphone with low batteries in the same room and a touchtable in the same room. The sensors report high noise and low ambient light. In this scenario, no result combination receives an agreement of more than 34%. Audio output on the smartphone scores only at 0.33%.

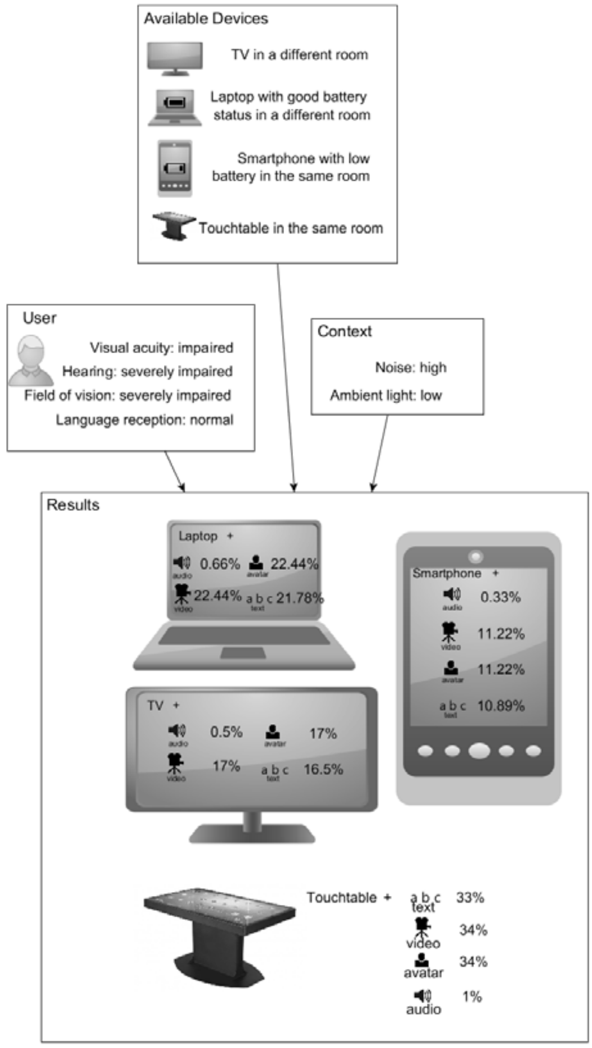

Figure 6: Scenario 2

5 Discussion

This section will review the simulated scenarios presented above and provide a short interpretation of the individual results.

Scenario 1. Scenario 1 was shown in Figure 5. The results show that all modalities, including an audio component, namely audio, avatar and video, were penalized because the user was observed to have impaired hearing abilities. All combinations including the TV were rated significantly lower than the ones including the touchtable. This result is plausible because the TV is in a different room. Output on this device would require the user to move closer to it, which should be avoided if possible.

Scenario 2. Scenario 2, shown in Figure 6, stands out because of the overall low agreement for all possible output combinations. The numerous negative influences present in this scenario influence all options heavily. This behavior, while being undesirable for successful user interactions, is in accordance with the concept applied during the modeling process. If one of the possible output combinations would receive a good score under these disadvantageous conditions, it would mean that none of the possible influences are connected to it. Regardless of the observed conditions, such a combination would always receive the exact same agreement level and possibly distort the selection mechanism. An occurrence like this could indicate that the model might not include causal relationships that should be considered.

The scenarios show that overall changes in the simulated input lead to plausible changes in the results. Single negative influences affect specific result combinations. The output of the selection mechanism in general reflects the intentions and assumptions that were the basis for the assignment of the probabilities for each node.

6 Conclusion and Outlook

The presented work described one possible approach to solve the Automatic Output Device Selection for AAluis with the use of Bayesian Networks. This method is capable of producing a result, even when the input data is incomplete, because it relies on the probabilities assigned during the modeling process in those cases. The use of subjective probabilities also eliminates the need for training data. If training data were obtained, it can easily be used to adjust the assigned probabilities.

The results confirm that Bayesian Networks in this setting produce satisfactory results in general. The specific probabilities assigned to the individual nodes however are crucial to the success of this method in real-world applications. To validate the assumptions made during the modeling process, the model has to be tested in a live setting by users belonging to the target audience of AAL systems.

Moreover, a successful user interaction typically consists of both output and input. So far, this work has only covered the selection of output device and modality. It remains to be seen, if the same method proves to be practical applied to the selection of an input device and modality, and if both parts can be joined in a meaningful way.

Acknowledgement

The project AALuis is cofunded by the AAL Joint Programme (REF. AAL-2010-3-070) and the following National Authorities and R&D programs in Austria, Germany and The Netherlands: bmvit, programm benefit, FFG (AT), BMBF (DE) and ZonMw (NL).

References

[1] Belbachir AN, Drobics M, Marschitz W. Ambient Assisted Living for ageing well–an overview. *e & i Elektrotechnik und Informationstechnik*. 2010; 127(7-8):200–205.

[2] Kleinberger T, Becker M, Ras E, Holzinger A, Müller P. Ambient intelligence in assisted living: enable elderly people to handle future interfaces. In: *International Conference on Universal Access in Human-Computer Interaction*. Springer. 2007; pp. 103–112.

[3] Mayer C, Zimmermann G, Grguric A, Alexandersson J, Sili M, Strobbe C. A comparative study of systems for the design of flexible user interfaces. *Journal of Ambient Intelligence and Smart Environments*. 2016; 8(2):125–148.

[4] Mayer C, Morandell M, Gira M, Hackbarth K, Petzold M, Fagel S. *AALuis, a user interface layer that brings device independence to users of AAL systems*. Springer. 2012.

[5] Obrenovic Z, Abascal J, Starcevic D. Universal accessibility as a multimodal design issue. *Communications of the ACM*. 2007;50(5):83–88.

[6] Dey AK. Understanding and using context. *Personal and ubiquitous computing*. 2001;5(1):4–7.

[7] Pearl J. *Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference*. San Francisco, CA, USA: Morgan Kaufmann Publishers Inc. 1988.

[8] Koller D, Friedman N. *Probabilistic graphical models: principles and techniques*. MIT press. 2009.

[9] Shenoy PP, Shafer G. Propagating belief functions with local computations. *IEEE Expert*. 1986;1(3):43–52.