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Psychomotor Profiling with Bayesian Neworks

Prediction of User Abilities based on Inputs of Motorized Wheelchair Parameters

Meike Jipp, Christian Bartolein, Essam Badreddin
Automation Laboratory
University of Heidelberg
Mannheim, Germany
meike.jipp@ziti.uni.heidelberg.de

Ciamak Abkai, Jürgen Hesser
Experimental Radiation Oncology
University Medical Center Mannheim
University of Heidelberg, Germany
ciamak.abkai@medma.uni-heidelberg.de

***Abstract*—A high level of psychomotor abilities often is essential for successfully operating many technical systems and especially medical and rehabilitation devices. This paper introduces an approach to enable a technical system to automatically assess its user's level of psychomotor abilities, so that it can adapt its level of automation and provide the user with more or less assistance depending on the individual user profile. For this purpose, a study has been conducted during which the motor abilities of the participants have been assessed and their wheelchair control behavior recorded. Bayesian Networks (BN) and Structural Equation Models (SEM) have been applied to model the relationships between the wheelchair control behavior and the motor abilities of the participants. The BN demonstrate usefulness and magnificent advantages compared to the SEM for modeling uncertainty in structure and parameter dependencies, which are shown by validation experiments. Although only a small amount of data samples (23 participants) was available for model generation, a target variable reflecting the user's precision ability was successfully classified based on real data input in more than 82% of cases.**

***Keywords*—Human-Technology Interaction, Bayesian Networks, Psychomotor Abilities, Adaptive Automation**

I. State of the Art

A. Human-Centered Technology: Adaptive Automation

Due to major developments in the computer technology, automation systems got more and more sophisticated in the last decades, so that they were enabled to take over a broad range of highly intelligent tasks, which were originally executed by a human operator. It was the vision that applying these systems significantly enhances the dependability of human-technology systems and reduces the (negative) impact of the "human factor". However, the practical experience with these technology-centered automation systems demonstrated that they could not fulfill these expectations [1]. As reasons therefore, researchers discussed a reduced situation awareness of the human operator, an incorrect/incomplete mental model about the technical system and a resulting incapability to intervene, if necessary [2]. In order to avoid such problems, the importance to keep the human operator in the loop of such systems was highlighted [3].

Such human-centered technology (HCT) systems aim essentially at optimizing the performance of a joint system consisting of the technical system and its operator. One way to achieve this goal is to define different levels of automation (LOA) [4] and to choose the LOA which – when active – results in the best performance when cooperating with the human operator. While some researchers propose a static definition of these LOAs ([5], [6], [7]), others prefer a dynamic definition ([8], [9], [10], [11]). This dynamic approach should take into account performance variations of the human operator, thus, supporting him/her with automation when he/she is incapable of executing a specific task with a high level of dependability and letting him/her execute the given task, when he/she has the capabilities in order to achieve a required performance level. The capability of the human operator to achieve a required performance level has been defined on the basis of his/her situation awareness level, or of the current workload, both of which have been associated of being highly predictive with regard to performance differences (see e.g., [12], [13], [14]).

B. Bayesian Networks

Causal relations in the field of HCT do not need to be expressed only in terms of stochastic mean values, as done by population modeling, regression analysis or structural equation modeling (SEM) [15][16]; Bayesian Networks (BN) are offering a flexible alternative with decisive advantages e.g. structure and parameter learning, reasoning and prognosis. A BN is a probabilistic graphical model for stochastic causal modeling consisting of an acyclic graph (nodes and arcs) and a representation of conditional dependencies between nodes of the network given by conditional probability distributions (CPD), which are not restricted to be Gaussian as in many other modeling approaches [17]. In discrete cases a CPD can be described by a conditional probability (lookup) table (CPT), which is capable to represent any arbitrary distribution generally and thus leads to more freedom in modeling. Therefore, BN have been used in many scientific domains e.g. system modeling and risk analysis. In the field of HCT and human-machine interaction BNs are increasingly used in many applications during the last years, e.g. for prediction of user (internal) states and intention estimation [18]. Additionally BN can be used as a real-time inference engine after the structure and parameters have been learned or adjusted by designer knowledge, as done e.g. for human stress monitoring [19].

A general methodology to assess psychological and cognitive profiles with BN based on well-founded methods from psychology was shown in 2008 [20], where the

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advantages of BN over SEM modeling were clearly observable and the feasibility for real-time application was proofed. We apply a similar approach to describe a new model for psychomotor abilities, which will provide a framework to access individual user ability parameters from the human-machine interaction interface of a powered wheelchair. BN will be used for the first time for such an approach according to the state of literature.

II. PROBLEM STATEMENT

While especially cognitively demanding tasks will require its operator to have a high level of situation awareness and a medium-level of workload in order to achieve a required level of performance; other tasks will require different abilities and capabilities. A good example is the operation of a powered wheelchair, which is especially demanding regarding the fine or psychomotor abilities of its user, as was confirmed by a variety of studies ([21], [22], [23], [24]). Motor skills are with regard to a dynamic definition of a LOA important, as e.g., spasticities vary depending on the stress level of its user and are not constant over time. Hence, if a wheelchair user has strong spasticities due to a stressful situation, the wheelchair should apply a high LOA in order to ease the life of the person in need and in order to reduce the probability of an accident. If, however, the user has only minor spasticities, the LOA of the powered wheelchair should be low, so that the user actually trains his/her motor skills and they do not diminish. In order to achieve such an intelligent wheelchair system, methods need to be developed, which allow a technical system to continuously judge on the motor abilities of its user. The research paper at hand aims at providing and evaluating such methods on the basis of BN and SEM and, thus, at complementing existing research with regard to the dynamic definition of a LOA.

III. SOLUTION APPROACH

In order to provide a cognitive model which enables an electrically powered wheelchair to judge on the current motor abilities of its user, a study was conducted to assess the motor abilities of its participants, to measure the wheelchair motion and the joystick inputs. The data analysis focused at developing a SEM and a BN, at validating both and choosing the one, which enables the better judgment on the motor ability level of the user.

This study and its results will be introduced and thoroughly be discussed in the following.

A. *Description of the Conducted Study*

The study took place in a realistic office environment (see Fig. 1 for its floor plan) and lasted on average between 60 and 90 minutes. Within the office environment, obstacles (tables), goal positions and a course were identified, which allowed to gather data on how participants manage to maneuver in cramped areas but also on how they move in free space.

The goal positions were defined, such that reaching them resembles behavior which would be necessary if the participants actually worked in this environment. For this purpose, the goal positions were linked to objects distributed in the environment, which are listed in the following (see numbering in the floor plan in Fig 1.):

1. A specified position at a wall (reflecting a movement in a less cramped environment)
2. An office cupboard (the participants had to drive next to it so that they could theoretically open it and withdraw something from it),
3. A drawing board (which required maneuvering around tables and boxes),
4. A table in a narrow environment reflecting a work place (leaving the table required the participants to turn in a very narrow space/on the spot),
5. A printer located on a table (the participants had to drive besides the table, which was in a narrow area so that maneuvering was required in order to reach the printer).

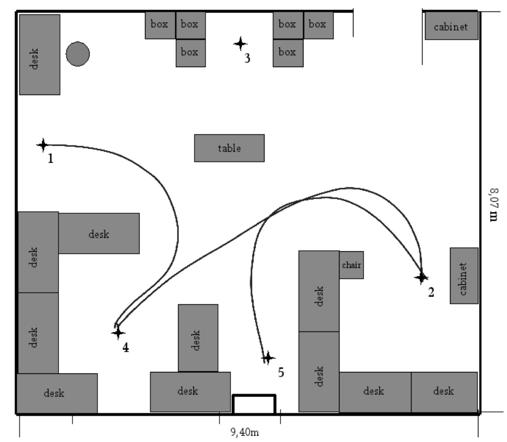

Figure 1. Floor plan of the office environment, in which the study took place also showing the way a participant required to drive to the first three goal positions of the complete course.

As this description already shows, driving to these goal positions and maneuvering through the environment evoked critical behaviors from the participants. For wheelchair users it is important to master these behaviors in order to be able to use their assistive device in everyday behavior. These critical behaviors are also tested in wheelchair skills tests (see e.g., [25], [26]) and refer to “turning on the spot/very narrow space”, “driving straight for a specified distance”, “driving around corners in different angles”, “driving besides an object”. In order to evoke many of these behaviors, a course was defined within this environment. This course consisted of driving to the specified goal positions in the order 1 – 4 – 2 – 5 – 2 – 4 – 3 – 1 – 5 – 3 – 2 – 1 – 5 – 4 – 1, which are 14 sections in total.

In order to drive through this course, the participants used a powered wheelchair from Otto Bock Healthcare GmbH (type B600), which was further equipped (as thoroughly described in [27]) with ultrasonic sensors for measuring the distance to other objects in the environment and a control PC, which was mounted underneath the seat in order to collect and store the data of the wheelchair movement. The wheelchair was controlled with a standard joystick by the participants.

Before the participants drove through the course, they had the chance to practice with the wheelchair system for an unlimited time in order to allow skill acquisition to take place before the actual data collection started.

While driving through the course, a variety of data on the wheelchair movement and joystick inputs were collected. More specifically, the times (t_), the average velocities (v_) and the distances (d_) driven were recorded for the passages driven forward (_fw), backward (_bw) and for rotating on the spot (_r). In addition, the number of input commands given (defined as the number of excursions from the zero position of the joystick) were calculated (inp), as was the number of times the wheelchair started to drive backward when standing (bw), the number of directional changes (i.e., the number of times the participants change their movement direction from right to left or vice versa while driving) (dc), the means of the translational and rotational inputs given via the joystick and the variance of the translational and rotational input commands. Last, the integral over the spectrum of the user input for frequencies of above 0.2 Hz was calculated (fft), reflecting correction behavior of the user.

These variables were calculated for all 14 sections, standardized and treated as if they were derived from independent participants. This procedure was taken due to the small number of participants which could be tested with the wheelchair system (see also Section B).

After the participants had completed the complete course, they filled in a biographical questionnaire and completed a test (motor performance test, see [28]) measuring their psychomotor abilities and most specifically their precision ability.

B. *Description of the Sample*

The study took place at the Universities of Mannheim and Heidelberg (Germany) with N = 23 students (n = 11 were male, n = 12 were female). The majority of the participants studied psychology (n = 20), the others (n = 3) were enrolled in computer engineering. They were all between 19 and 34 years old (average age: 23.1 years). None of the participants has ever depended on a wheelchair (this is why the participants received unlimited training time in order to avoid skill acquisition effects). As a reward for participation, the participants have either received 5 € or a certificate for participation, which is required by some students to complete their degree.

IV. Modelling

In order to predict the psychomotor abilities on the basis of the wheelchair movements and the joystick input, two models were developed on the basis of the SEM methodology ([15]) and the BN methodology, which are described in the following.

A. *Structural Equation Models*

In psychology, SEMs are applied in order to test theoretically expected relationships with empirically derived variance/covariance relationships [15]. It is an extension of the general linear model enabling applying a set of regression equations simultaneously.

In order to set up a SEM, theoretical knowledge about the expected relationships between the measured variables and unmeasured factors, which can be derived on the basis of factor analytic procedures by absorbing the covariance of highly correlated variables, is required in order to define a model as a starting point. This theoretically derived model is then tested with the empirical data and goodness-of-fit indices and χ^2-tests applied in order to test whether the model fits the data or not. For this purpose, the statistical inference scheme follows an inverted hypotheses-testing approach: The null hypothesis tests the – from the researcher – desired assumption that the empirically derived relationships match the theoretically proposed ones. The alternative hypothesis expects a difference, which means that the theoretical knowledge and the model are falsified. Hence, in this case, a non-significant result is good.

In order to account for variance, which cannot be explained by variables assessed, errors and disturbances are included as variables in the model and their impact on the measured variable judged.

To set up a SEM, the variables reflecting the wheelchair movements and the joystick input were inserted, as was the precision variable, which is expected to be predicted on the basis of the wheelchair and joystick data. Theoretical relationships were proposed on the basis of known, physical relationships (e.g., velocity driven is correlated to the time driven) and on relationships, which can be assumed on the basis of the theoretical definition of precision. According to [29], precision is defined as the ability to implement small deviations from a desired and an actual route. For this purpose, information on performance had to be collected continuously, which needed to be processed and very fine motor movements had to be defined and realized, which corrected the current behavior. As this description already demonstrates, a relationship between the precision and the wheelchair data should be apparent. After having set up the SEM accordingly, its fit was tested with χ^2-tests. In order to yield a good-fitting model, the approach of nesting models [30] was applied and the degrees of freedom (df) reduced of one from one model-test to the next and the difference of the resulting χ^2 values tested for significance with df = 1. If this difference reached an appropriate significance level ($\alpha = 0.05$), the model with less degrees of freedom was accepted and continued with. This procedure of nesting modeling was repeated until a model was identified, which had a non-significant χ^2 value. This indicates that the empirically found relationships match the model itself and which receives goodness-of-fit indices where the size matches the rules-of-thumb [16].

The resulting model is depicted in Fig. 2: Its validity is reflected in χ^2 (df = 3) = 3.76, p = 0.29 (not significant). In addition, the goodness-of-fit indices [31] are also positive: With regard to the comparative fit indices, the model reaches a normed-fit index (NFI) = 0.99 (with NFI = 1 reflecting an ideal fit) and an incremental-fit index (IFI) of = 1.00 (with IFI = 1 reflecting an ideal fit). With regard to the population-based fit indices, the model yields a root mean square error of approximation (RMSEA) = 0.03 (rules of thumb indicate that the RMSA should be smaller than 0.05 to reflect a good fit) and an Akaike's Information Criterion (AIC) of = 27.76 (smaller numbers reflecting better fits).

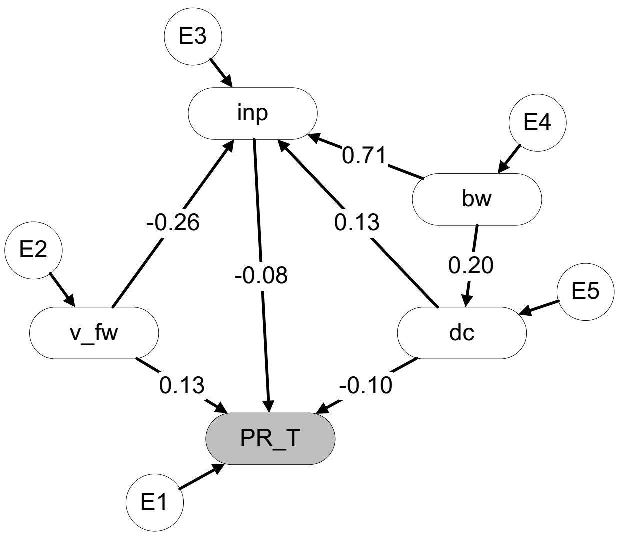

Figure 2. Structural Equation Model which yields a good fit to the data and which was derived from the nested modeling approach (inp: number of total number of joystick excursions out of the zero-position, v_fw: average velocity driven forward, bw: number of times the participant drove backward when standing, dc: number of directional changes while standing, E1-E5 error variables, PR_T: precision ability).

The standardized estimates (see Fig. 2) demonstrate the influence of one variable on another. This shows that, for example, bw (number of commands given to drive backward when standing) has a high influence (i.e., $\beta = 0.71$) on inp (i.e., the total number of joystick excursions out of the zero-position) and that the biggest influence on precision (PR_T) is given by the mean forward velocity v_fw (i.e., $\beta = 0.13$). The influences of the error variables (E1 – E5) on the endogeneous variables v_fw, inp, bw, dc (i.e., the number of the directional changes given while driving) and pr_t are not listed, as they were judged a priori.

B. Bayesian Networks

As mentioned before, one essential advantage of BN is the possibility to learn the structure and parameters of the network from real data. Various techniques are known in this area and target different purposes. We apply the PC structure learning algorithm, which is belonging to the constrained based structure learning algorithms and is based on stochastic dependency/independency tests. By this method the network designer can contribute additional (pre-) knowledge during the structure design phase by defining constrains for the PC algorithm. The network structure (defined by arcs) is adjusted in correlation to a significance level, which describes the amount of statistical dependency. Therefore, one has the knowledge how strong the influence of one node to another is. After the structure of the network is known the parameters can be learned, e.g. by EM algorithm. The fact that the number of participants was very small was reflected in the significance level of the structure learning algorithm. Here, the statistical correlation between the measured variables (e.g. v_fw, fw, dc and fft) was to a factor of 10^3 higher than among those and the target variable PR_T. Therefore, we take representative nodes of each highly correlated clique to reduce the network complexity. The result is a hierarchical BN with 3 layers, as shown in Figure 3. The first and second layers are less correlated than the second and third layers according to the small amount of learning data. Although the third layer is not necessary to infer the results for the node of interest PR_T, the additional nodes can be used to estimate evidence states in the second layer if those data are missing, which is an important point for future implementation in real systems. We apply different discretization strategies to maximize the level of significance, e.g. by dynamic and hierarchical discretization methods. After inference was applied on the network a simple maximum likelihood classifier is used to determine the state of interest.

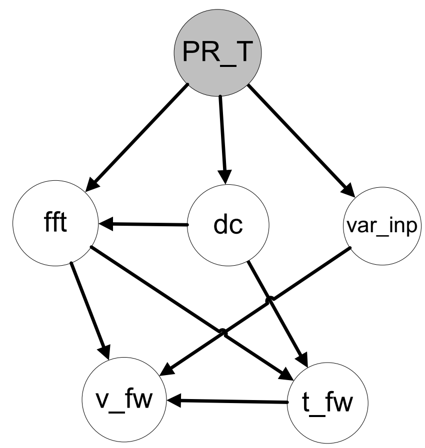

Figure 3. BN based on the PC structural learning algorithm. (dc: directional changes, var_inp: variance in joystick input, t_fw: time for forward movement, v_fw: forward velocity, fft: power spectrum density above frequencies of 0.2 Hz).

V. RESULTS: VALIDATION OF THE MODELS

In order to validate both models, a two-step procedure was applied: First, the derived models were used to estimate the precision values (i.e., PR_T) and calculate the number of correct estimations on the complete data set. Second, 50 participants were deleted from the data set, the model was replicated with the reduced data set and the model was applied in order to estimate PR_T of these 50 participants. Again, quality measures were calculated to validate the models. The SEM introduced above was generated with the continuous data, which were derived from the wheelchair control behavior, from the joystick inputs and from the motor skills test. As, however, the BN was calculated with the discretized data, two types of quality measures were derived for the SEM: First, the standard error was calculated reflecting the standard deviation of the estimated and actual precision values; second, the numbers of correct and false classifications were calculated on the basis of a-posteriori, discretized estimated and measured precision values.

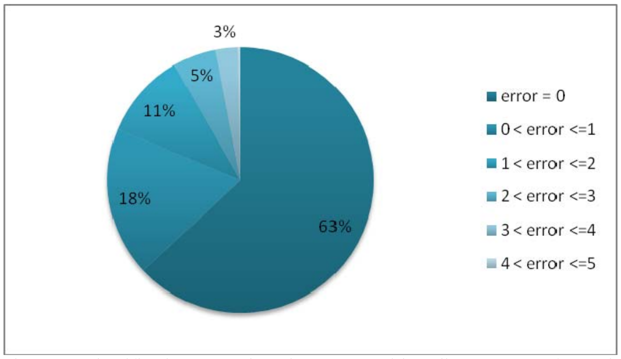

Figure 4. Classification errors based on a BN with 6 discrete states for each node (e.g. including additional intermediate states between low, middle and high for the node PR_T): 63% of the classifications in the evaluation phase where correct and 18% within a discrete range of one.

With regard to the first validation experiment, i.e. the one for which the precision values of the complete data set were estimated and compared with the measured ones, a standard error of SE = 10.24 was achieved, which equals about one standard deviation. This result is also reflected in the number of false/correct classifications: Only 48% of the classifications made were correct, as shown in table 1. The number of correct classifications for the same number of discrete states (3 classification states for the precision value PR_T: low (bellow 42), middle (between 42 and 56) and high (above 56)) was for the BN model higher than 72%. Additionally a model with higher discretization was build, which lead to a higher failure rate and a smaller error-free classification of 63%, as shown in Figure 4. These errors can be explained with the small number of learning data which leads to a model underfitting, while 18% of the classifications have a discrete step difference of one. Many classification errors occur due to model underfitting of different states having the same (maximum) probability after inference.

With regard to the second validation experiment, i.e., the one where a random sample of n = 50 participants was deleted from the data set, the modeling procedure was repeated for the reduced data and the resulting model was applied to the deleted n = 50 participants. Again, the difference between the estimated and actually measured precision values was calculated, on which basis the standard error was derived. In this case, the standard error refers to SE = 9.27, which is slightly better than for the first validation experiment. In order to make the results comparable to the ones of the BN validation experiments, the same validation sample, as was used for the BN. It was conducted on the basis of the estimated and measured PR_T. Again, the numbers of false and correct classifications were calculated: Out of 50 a-posteriori classifications, 21 were correct, 29 were incorrect, which equals 42% (compared to 82% for the BN classifier) and is slightly worse when compared to the first validation experiment (see Tab.1).

According to the low significance level of the real data to the target node PR_T, it was not surprising that the total error for BN was still approximately between 20% and 30% for wrong classifications, although due to higher degrees of freedom in modeling, BN were still a better adaptation to the real data.

TABLE I. VALIDATION RESULTS: TRUE CLASSIFICATION RATES BASED ON SAMPLES FROM REAL DATA

Number of learning samples	Number of validation samples	SEM true classifications	BN true classifications
322	322	48%	72%
272	50	42%	82%

VI. DISCUSSION, CONCLUSIONS, AND FUTURE WORK

The results introduced in the previous section with regard to the ability to predict wheelchair users' fine motor abilities and especially precision revealed the following conclusions:

First of all and most importantly, the derived BN outperforms the SEM, which is especially evident when evaluating the validation experiments: The classification accuracy of the BN is better when compared to the SEMs. This is especially interesting, as the goodness-of-fit indices and the χ^2 values indicate that the SEM model fits the empirically derived data quite good.

Second, the results of the validation experiments demonstrate that the modeling could still be improved by adding further participants to the sample, which is also expected to enhance the results regarding the validation experiments. This issue is especially crucial as the sample size of N = 322 was derived by collecting data on 23 participants in 14 course sections, by standardizing the wheelchair control variables and the joystick inputs and by treating each section as if it came from an independent participant. From a methodological point of view, this procedure can be criticized in two aspects: First, the predictive validity of the different sections might differ, so that the overall model is biased. Second, data on only 23 participants was at hand regarding the psychomotor abilities. This procedure could have worsened the results. It was, however, necessary in order to be able to develop the introduced models, as analyzing the sections separately would lead to model underfitting.

Despite these problems, the results are quite promising: They show that BN can be applied for automatically assessing the users' fine motor abilities, as they outperform the traditional SEM approach, so that they can be implemented in technical systems, which operation requires its user to have good psychomotor abilities. One such example is the operation of a wheelchair system. Hence, on the basis of BN, an adaptive wheelchair system can be envisioned, which changes its LOA depending on the results of the BN and herewith, significantly reduce the time it takes persons with severe disabilities to use the assistive device efficiently and - even more important - in a safe and dependable manner. This is the case, as the wheelchair system can – on the basis of the BN – classify its user's level of current psychomotor abilities and change the LOA, such that – on the one hand- the wheelchair system can use a highly intelligent level and provides the user with a high level of autonomy (e.g., by autonomously driving the user safely to a, from the user, designated goal position), if the user's abilities does not allow a safe navigation. On the other hand, the wheelchair system can use a less intelligent mode when the motor abilities of the user are good, so that the user navigates the wheelchair and the wheelchair assistance system "only" avoids collisions. Such an adaptive wheelchair system is expected to significantly reduce the time it will take persons in need to learn to apply a wheelchair; it is expected to increase the number of those who can actually benefit from a wheelchair system as it reduces the motor demands put on the person in need, and it is also expected to increase the satisfaction and usability of the wheelchair users with their assistive device by still giving the users the opportunity to train their remaining abilities.

Future work will aim (1) at collecting further data in order to improve the BN and the validation results, (2) at implementing the BN in an assistance system for powered wheelchair control, which can be applied on different LOAs, such that the activation of the LOAs depends on the outcomes of the BN and (3) at evaluating the resulting overall system with regard to user acceptance, satisfaction, and usability. Additionally, dynamic BN can be applied in order to tackle problems such as skill acquisition, which changes the predictive validity of the wheelchair control behavior over time.

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