EMPIRICAL VALIDATION OF MODEL FOR HUMAN DECISION MAKING

Fahad Mansoor
College of Information Technology
University of the Punjab
Lahore, Pakistan
fahadmansoorali@gmail.com

Muhammad Rohail
College of Information Technology
University of the Punjab
Lahore, Pakistan
bsef09m032@pucit.edu.pk

Syed Waqar Jaffry
College of Information Technology
University of the Punjab
Lahore, Pakistan
swjaffry@pucit.edu.pk

***Abstract*—In the current postmodern socio-technical world when machines are everywhere a harmonious relationship between man and machine is essential. The harmony of this relation and survival of this socio-technical world can only be guaranteed if machines can understand the human state of mind and can act accordingly. For this, several computational models of human cognition have been presented in the literature while very few efforts have been made to validate them. In the current paper a model of trust based human decision making in dynamic environment is taken from the literature and validated against the human decision traces generated through computer based experiments. The results of this experiment shows that model under study can be trusted as to be a computational representative of human decision making process with a satisfactory level.**

Keywords—trust; decision making; empirical; validation; computational modeling; cognitive model; simulated annealing.

I. INTRODUCTION

Humans interact with several machines every day and the rate of such interactions is increasing on a regular basis. Now machines are entering in the human personal space through which a huge impact on the human's social and psychological dynamics is being observed. To realize a harmonious man-machinerelationship and for the long term survival of postmodern socio-technical world, it is essential to make machines aware of human cognitive dynamics, so that machines can adapt their behaviors as per human needs. If it is achieved then these machines will become capable of understanding human's state of mind, forecast the human's future behavior and provide timely support as a true companion. In the existing literature several such models have been proposed which have claimed to be the representative of different human cognitive dynamics. Beside their design, verification and validation of these models is essential so that empirically validated models can be embedded into machines.

In this paper an existing model of human cognition is validated which deals with the human's decision making in dynamic environments based on trust [1]. In order to achieve this validation a computer game is designed which can generate a dynamic environment for a human player. Humans interact with this computer game and take different decisions. Game stores human behavior logs (i.e. decisions taken by the player throughout the game) so that it can learn human personality traits required to personalize proposed decision making model. After personalization, this game can compare the behavior of human players and the forecasted behavior by the proposed model in different game runs.

Primary research question for this study is to see that how far a designed computational model (under study) is a computational representative of the human behavior. Rest of the paper is divided into six sections. Section two briefly explains human cognitive model of trust based decision making, section three and four describe the design of the experiment and model personalization, in section five results of this study are presented and finally section six and seven provide conclusion and some future extensions in current work.

II. THE MODEL

Trust is generally believed as an important factor in human decision making. In literature different models of human trust dynamics has been proposed which can be used for modeling human decision making. Usually for trust based decision making, models in the literature select the most trusted option and hence assume that the rest of the options do not change their behavior over time (see e.g. [4], [5], [7], [8]). These models assume that the world is static and that it does not change often. But in a real world scenario this is not the case, the world is changing continuously. Hence, recently a trust based model of decision making in dynamic environments is proposed in [1] which deals with such situations. This model measures changes in the environments indirectly and hence tries less trusted options as well for exploration of better options in future.

Trust model proposed in [1] is taken from [6] which calculates the change in trust overtime using the equation 1.

$$\frac{dT_i}{dt} = \beta * \left(E_i(t) - T_i(t) + \tau_i(t)\right) - \gamma * T_i(t) \qquad (1)$$

In this model it is assumed that there are several trustees which may provide experience to trustor (if requested) furthermore trustor's trust on these trustees might be interdependent e.g. change in trustor's trust on one trustee may affect trustor's trust on other trustees indirectly due to trustor's perceived relationship between them. This notion is controlled with the concept of relative trust represented by τ in above equation. This model also has two more trustor's personality attributes namely rate of change of trust and autonomous decay of trust represented by parameters β and γ respectively. For further details about this trust model see [6].

The model which describes the trust based decision making in dynamic environment is presented in [1] as mentioned above this model detects change in environment C(t) by calculating the disparity between the short term trust ST(t) and the long term trust LT(t) on all trustees using the equation 2.

$$C(t) = \frac{\sum_{i=1}^{n} |LT_i(t) - ST_i(t)|}{n} \tag{2}$$

This trustor's perceived change in the environment at a time point *t*, C(t) is used to calculate trustor's extent of environment exploration E(t) as described in equation 3 and 4 respectively.

$$dE(t)/dt = Pos\big(\alpha * C(t) - \rho * E(t)\big) * \big(1 - E(t)\big) - Pos\big(-\alpha * C(t) + \rho * E(t)\big) * E(t) \tag{3}$$

Here, the function *Pos(V)* is defined by:

$$Pos(V) = V if V > 0$$
$$Pos(V) = 0 \qquad if V \leq 0 \tag{4}$$

In this model to update *extent of exploration* two aspects are considered. The first aspect in equation 3 specifies that the *extent of exploration* would be increased with a factor α. The second aspect in the equationdenotes that there is an autonomous decay of *exploration* by a factor ρ. Here it can be noted that whenever the change in the environment *C(t)*approaches *0*, the value of *exploration* will also approach to *0*, which would signify that the trustor is very exploitative.

For the selection of a trustee, the model assigns a request probability $RP_i(t)$ by using the $E(t)$ the *exploration extent* to each trustee. Using equations 5 and 6 the request probability is calculated.

$$RP_i(t) = \big(1 - E(t)\big) * \left(E(t) * \frac{T_i(t)}{\sum_{j=1}^{n} T_j(t)}\right) + E(t) * \left(\frac{E(t)}{n}\right) \tag{5}$$

$$RP_i(t) = \left(1 - \sum_{j \neq i} RP_j(t)\right) \tag{6}$$

Equations 5 and 6 show that in case the *exploration factor* $E(t)$ is 0 the request probability will also be zero. In case the exploration factor $E(t)$ is 1 the request probability will be equal for all trustees and will have the probability of $\left(\frac{1}{n}\right)$, where n is the total number of trustees. When the *exploration factor* resides in the interval [0, 1] a combination of values including the relative trust to all other trustees and a fraction of an equal request probability is taken in to account. In equation (6) the request probability of the most trusted trustee is calculated. When the exploration factor is 0 the value of request probability is 1 and it is $\left(\frac{1}{n}\right)$, in case the exploration factor is 1. Here n is the total number of trustees. For further details see [1].

III. THE EXPERIMENT

To validate decision making model proposed in [1]. A computer based experiment in the form of a computer game is designed. This game produces a dynamic environment as described in the following sections.

A. Mechanics

In this computer based game experiment player's objective is to reach the goal destination (a hospital) within the minimum time while making the best possible decision in the travelling environment provided.

The game primarily consisted of a vehicle and three navigation systems, these navigation systems periodically update their plan to show paths towards the goal. The results of these navigation systems are dynamic and rapidly changing that is, not all of the systems show the correct path at a time instant but at least any one of the systems always shows the correct path. User follows one of these navigation systems at a time. A label on the top left corner of the screen shows the distance to the destination. If user follows a navigation system and distance to destination at screen start increasing then the user receives a negative experience which affects user's next decision about the selection of the navigation system. The behavior of navigation systems depended upon certain configuration files. Fig. 1 shows a screen shot of the game.

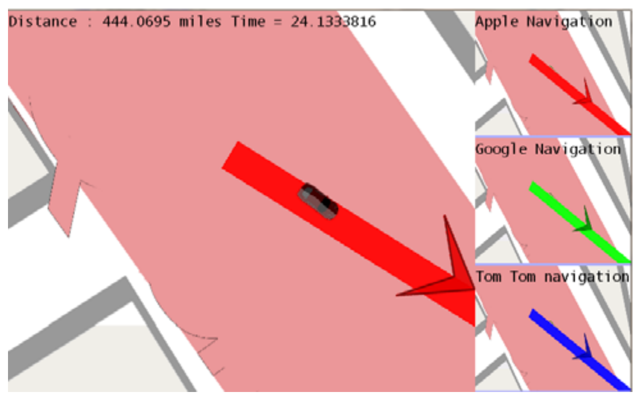

Figure 1: Computer based game designed for experiment

As the user plays the game logs of user's decisions is saved which contains, the time point, the decision made (navigation system selected), and the position of the user. The user plays this game two times with different configurations files. These logs are later used for parameter estimation and decision prediction.

B. Participants

In this experiment total thirty one (31) participants (29 male, 2 female) participated which were mostly university students. The average age of the participants was 21 years. The participants who took part in this study were given refreshment and a special gift was given to the person completing the experiment in the shortest time.

C. Procedure

The participants were first briefed about the significance of the experiment and its mechanics. When they had thoroughly understood the main objective of the game they participated in a practice session. The practice session lasted for 10-15 minutes, it was held to make the participants familiar with the controls of the game. After they were confident of their ability of playing the game then they were exposed to play on the experiment configuration files. They played the game in two independent sessions with different game configurations. As they played the game their playing logs were generated and saved which were later used for parameter tuning.

IV. PARAMETER TUNING

Decision making model presented in [1] is subjective in nature. There are a few parameters which represent human personality characteristics. Hence to make this model representative of a particular person these parameters should be tuned using some parameter tuning technique. These parameters are presented in table 1.

Table 1. Model parameters

Parameter Name	**Symbol**
Rate of change of trust	β
Options relativeness	η
Autonomous decay of short term trust	γ_s
Autonomous decay of long term trust	γ_l
Autonomous decay of exploration	ρ
Initial exploration	E(0)
Rate of change of exploration	α

A. Simulated Annealing

In this study parameters are estimated using Simulated Annealing. Simulated annealing technique as described in [2] was used to tune the parameters so that the personalized model becomes as close to the human as possible. In this technique, the algorithm searched for the best available parameters for the model. Equation 7 is used to calculate parameter estimation error. A fixed amount of computational budget was set at the start of each tuning process.

This technique generates a random parameter vector of fixed length (seven in this case). After that in each successive iteration a displacement is calculated for all parameters, which is randomly added to or subtracted from the parameters. If the parameters generated are better than the current best estimated parameters then this new parameter set is saved and labeled as the best known parameters. The tuning process is terminated either when the computational budget has been exhausted or the error calculated for the estimated parameters is zero or reached to a desired threshold. The pseudo code for the parameter estimation module using Simulated Annealing is given below:

Estimate_SimulatedAnnealing (theta, ActualDecisions, budget)

```
1. BestEstimate = theta
2. ErrorBestEstimated =1
3. TotalBudget = budget
4. Until budget > 0 OR ErrorBestEstimated=0 do 5-13
5.    Temperature =ErrorBestEstimated * (budget / TotalBudget)
6.    NewTheta=DisplaceTheta(temperature, BestEstimate)
7.    AgentDecisions = RunSimulation(NewTheta)
8.    NewError=CalculateError(AgentDecisions, ActualDecisions)
9.       if ( NewError<= ErrorBestEstimated)
10.          ErrorBestEstimated = NewError
11.          BestEstimatee = NewTheta
12.      endif
13    budget =budget -1
14. returnBestEstimate
```

The error for a specific set of parameters is calculated using the following equation:

$$Error\ (X,Y) = \frac{(\sum_i^n CompareDecisions(Xi,Yi))}{n} \tag{7}$$

Here *CompareDecisions* is a simple function as defined in the equation 8 and X_i and Y_i are the decisions taken by the human subject and the tuned model respectively.

$$CompareDecisions(Xi,Yi) = \begin{Bmatrix} 0 & if\ Xi == Yi \\ 1 & if\ Xi\ != Yi \end{Bmatrix} \tag{8}$$

V. RESULTS

The results of the validation experiments are presented here. First the parameters are tuned against the first play of the subject and then, tuned models are used for prediction of human behavior against second play of the subject.

A. Parameter Tuning and Prediciton Results

As described earlier that the Simulated Annealing technique is used for parameter tuning on the data collected from the 31 subjects. The algorithm is run multiple times with different values of the computational budget. Once the most proximate parameters of model representing subject's personality traits are found then these parameter are used by the model to forecast subject's behavior in the second play. The prediction is done by setting the environment's configuration to the configuration used in the second play of experiments, and executing the prediction module with the estimated parameters. The results are shown in the table 2.

Table 2. Results of parameter tuning and prediction when play 1 is used for tuning and play 2 is used for prediction

Exp. No.	**Total Runs**	**Computation Budget**	**Average Tuning Accuracy**	**Average Prediction Accuracy**	**Standard Deviation Tuning**	**Standard Deviation Prediction**
1	10	1000	64%	44%	10%	16%
2	100	100	60%	48%	13%	14%
3	100	1000	60%	47%	13%	14%

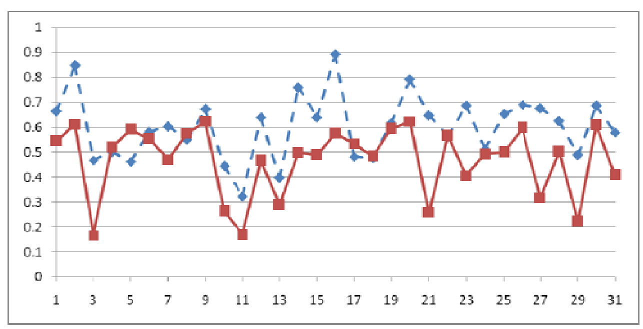

Figure 2. Average tuning (dotted line) and prediction (solid line) accuracies (y-axis) of model for different subjects (x-axis) when first play is use for tuning and second for prediction

The graphs generated from the above runs are shown in fig. 2. In fig. 2 dotted line represents parameter tuning accuracies for different subject while solid line represents model prediction accuracies. Here on x-axis subjects are presented while y-axis represents the accuracies.

Results in fig. 2 show that for the majority of subjects prediction accuracy is above 47%. In these experiments first play of the subject is used for parameter tuning and then tuned model is used to predict the subject's decisions in the second play. These results might give a slight tuning and prediction bias on the ordering of first and second play. In order to avoid this bias another experiment is performed in which model is tuned against data collected from subject's second play and the prediction is made on the subject's first play.

The results obtained for cross validation are very interesting which show that the tuning error is slightly increased while the prediction error is decreased significantly. The results of cross validation are shown in table 3 and fig. 3.

Table 2. Results of parameter tuning and prediction when play 1 is used for tuning and play 2 is used for prediction

Exp. No.	Total Runs	Computation Budget	Average Tuning Accuracy	Average Prediction Accuracy	Standard Deviation Tuning	Standard Deviation Prediction
1	100	100	55%	56%	13.3	14.6
2	10	10000	57%	55%	13.1	15.1

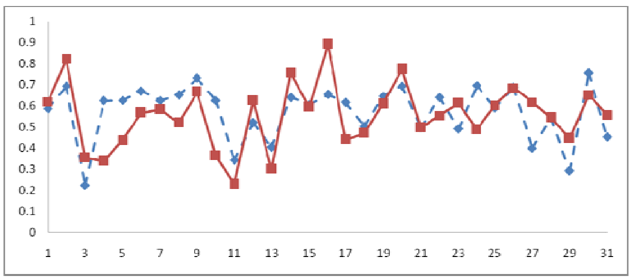

Figure 3. Average tuning (dotted line) and prediction (solid line) accuracies of model for different subjects during cross validation

VI. CONCLUSION

With the human evaluation and progress of the civilization involvement of machines in human's daily life is increased. For machines to be truly productive and helpful to humans they should be able to predict what the human might do in the time to come. The machines should be able to make the decisions on the behalf of humans so as to facilitate them further. The results of this study are an important step towards such man-machine relationship. These results show that the human decision making model as proposed in [1] is able to predict the decisions made by the human in a dynamic environment to a good extent. Furthermore it has been noted that in case of some subjects the accuracy is significantly high.

Another implication of this study is that when a computational agent is able to detect what we humans are thinking then this leads them one step further towards being truly autonomous. Hence in near future we might envision agents which are working autonomously serving humanity.

VII. FUTURE WORK

Experiment results can further be improved if an exhaustive search technique [9] is used with sufficient granularity. In current study it was not feasible due to the computational complexity of exhaustive search. In future this technique could be used for parameter tuning which might improve overall results. For this parallel programming could be used to parallelize the estimation process which could make the exhaustive search possible. Also advance sensors input might be used such as the Microsoft®Kinect to collect the subject's experience which can improve the validation experiment as a whole.

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