A Computational Agent Model of Automaticity for Driver’s Training

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Abstract. Driver’s training is essential in order to assess and provide the driver with sufficient skills to handle vehicles in complex and dynamic environment. These skills are related to the cognitive factors that will influence the automaticity of the driver to make effective decision. To illustrate these skills, simulation scenarios based on driver’s training has been conducted. It has pointed out that the simulation results are related to the existing concepts that can be found in literatures.

1 Introduction

Driving is an activity that requires human cognition where the driver continuously encounters tasks in need of solutions. The ability to master these tasks will depend on the knowledge, the skills the person has, and the person’s intellectual abilities. Furthermore, it aims to remove the barrier between knowledge and the skills required to drive safely and efficiently when commencing training where these skills must be known, for the training to be appropriate [1]. Moreover, the objective of training for critical decision making is to provide the learner with experiences, and instruction on cues, patterns, mental models, and actions that could efficiently establish a collection of well-learned concepts which enable the operator to perform mainly at the skill-based level of processing, while providing adequate knowledge-based foundation to perform well in new situations [2]. Thus, training is needed in recognizing situations, in communicating situation assessment, and in acquiring the experience to conduct mental simulation of options through the act of human cognitive unconscious decision making, or automaticity [3], [4]. Having analyzed this ability, it will provide a good perspective towards driving assisting systems.

To address this issue, this paper proposes a computational agent model of automaticity, which integrates related dynamic factors based on cognitive and psychology theories to describe basic training process that enhances the automaticity required by a driver to make fast decision in a driving domain.

The organization of the remaining part of this paper is as follows. The underlying concepts and a computational agent model of automaticity are discussed in Section 2. The study scenario and
simulation results are described in Section 3. Finally, Section 4 concludes this paper with a review of the contribution of this research and recommendation for future work.

2 Computational Agent model of Automaticity

2.1 Underlying Concepts of Automaticity
One of the theoretical concepts in automaticity is overlearning information or operations to the point where they can be used or recall with little mental effort is known as automaticity in simple term. “Automaticity” denotes limited conscious awareness, attention, and control of one’s actions, intentions, or psychological processes [5]. It explores the effect of basic practice, basic skills, sensory ability, operator’s goal, potential hazardous information, exposure on task complexity and intention on the driver’s practice, experience, knowledge, risk perception and experienced automaticity for effective decision-making. Automaticity needs a learned or conditioned response to stimuli; learning and conditioning, in turn, require rehearsal [6]. Though frequency is a vital standard for the development of automatic behaviour, it is not enough by most theoretical accounts. Whereas frequency is equal to the performance of behaviour itself, automaticity is a cognitive process essential for certain behaviours of individuals.

Automaticity is developed due to experience and high level of learning (training). At that point automatic processing tends to be fast, autonomous, effortless and unavailable to conscious awareness in that it can occur with no attention. Having advantage of automatic processing, that is providing good performance with little attention allocation thus, allowing people to achieve situation awareness (SA).

2.2 Computational Representation of Automaticity
This section describes the details of the model in mathematical specifications. Varieties of interactions occur between the driver and a dynamic situation in a real-world driving environment. This model is presented in Figure 1. In this figure it can be seen that the model consist of several interrelated nodes. After the structural relationships in the model have been determined, the models can be formalized. In the formalization, all the nodes are designed in a way to have value ranging from 0 (poor) to 1 (good).

The proposed model consists of several external, instantaneous and five temporal factors that are related. The external factors determine the outcome of the whole processes and the relationship is explained in details below. Equations (1) to (15) are representing the instantaneous equations because they give the resultant process that led to the temporal equation. The weight functions in the equations are divided mostly into two $w_1$ and $w_2$. The value 0.5 was assigned to each weight parameter.
**Instantaneous Relationships:**

Basic practice ($Bp$) of the driver increased with practice ($Pc$). Drivers practice ($Pc$) is influenced by Basic practice ($Bp$) and driver’s knowledge ($Dk$). Rehearsed Experience ($Re$) of the driver is influenced by driver’s practice ($Pc$) and ability ($Da$) by saying “with continuous practice any knowledge or skill is retained in short term memory and later transfer to long term memory otherwise it will decay”. Driver’s experience ($De$) is influenced by rehearsed experience ($Re$) and driver’s knowledge ($Dk$).

$$Bp(t) = \beta_{bp} . Bp_{basic} (t) + (1 - \beta_{bp} ) . Pc (t)$$ (1)

$$Pc(t) = \omega_{pc} . Bp(t) + (1 - \omega_{pc} ) . Dk(t)$$ (2)

$$Re(t) = \gamma_{re} . Pc(t) + (1 - \gamma_{re} ) . Da(t)$$ (3)

$$De(t) = \lambda_{de} . Re(t) + (1 - \lambda_{de} ) . Dk(t)$$ (4)

The Basic skills ($Bs$) of the driver increased as more skills are acquired. The acquired skills ($As$) is influenced by basic skills of the driver, his goals ($Dg$) and his knowledge ($Dk$). Driver ability ($Da$) is influenced by the skills acquired ($As$) and experiences of the driver ($De$) in training. Priming is influenced by three main factors namely; Driver’s experience ($De$), ability ($Da$) and intention ($In$). Perception about hazard ($Hp$) is determined by driver’s sensory ability ($Sa$), potential hazardous information ($Hi$) and perception about task ($Tp$). Attention ($An$) is influenced by rehearsed experience ($Re$) and perception about the risk ($Rp$) by the driver. Perception about task ($Tp$) is influenced by Exposure on task complexity ($Tc$) and driver ability ($Da$). Exposure on Task Complexity ($Tc$) decreased as knowledge increased. Habitual-directed action ($Hd$) is influenced by driver’s knowledge ($Dk$) and priming ($Pg$). Goal-directed action ($Gd$) is influenced by priming ($Pg$) and attention ($An$). Acquired Automaticity ($Aa$) is influenced by involuntary ($Iv$) and voluntary ($Vy$).

$$Bs(t) = \beta_{bns}. Bs(t) + (1 - \beta_{bns} ). As(t)$$ (5)

$$As(t) = \beta_{as}. [W_{d1}. Bs(t) + W_{d2}. Dg(t)] + (1 - \beta_{as} ). Dk(t)$$ (6)

$$Da(t) = W_{d1}. De(t) + W_{d2}. As(t)$$ (7)

$$Pg(t) = [\xi_{pg}. Da(t) + (1 - \xi_{pg} ). De(t)] . In(t)$$ (8)

$$Hp(t) = [W_{hp1}. Sa(t) + W_{hp2}. Tp(t)] . Hi(t)$$ (9)
\[ A_n(t) = [\xi_{an}.R_p(t) + (1-\xi_{an}).R_e(t)] \]  
\[ T_p(t) = [\eta_{tp}.D_a(t) + (1-\eta_{tp}).T_c(t)] \]  
\[ T_c(t) = \beta_{tc}.T_{c\text{ basic}}(t) + (1-\beta_{tc}).D_k(t) \]  
\[ H_d(t) = W_{hw1}.P_g(t) + W_{hw2}.D_k(t) \]  
\[ G_d(t) = W_{gd1}.A_n(t) + W_{gd2}.P_g(t) \]  
\[ A_a(t) = W_{aa1}.I_v(t)+W_{aa2}.V_y(t) \]  

Temporal Relationship:

Driver’s knowledge \((D_k)\) primarily contributed to the accumulation of rehearsed experience \((R_e)\) and driver’s experience \((D_e)\). Perception of the driver about risk \((R_p)\) is influenced by perception of the driver about the hazard \((H_p)\) and driver’s ability to handle vehicle \((D_a)\). Involuntary \((I_v)\) is influenced by habitual-directed action \((H_d)\). Voluntary \((V_y)\) is influenced by goal-directed action \((G_d)\).

\[ D_k(t+\Delta t) = D_k(t) + \gamma_{dk}.\left(\text{Pos}((W_{dk1}.R_e(t) + W_{dk2}.D_e(t)) - D_k(t)).(1-D_k(t))) - \lambda_{dk}\right).D_k(t) \cdot \Delta t \]  
\[ R_p(t+\Delta t) = R_p(t) + \gamma_{rp}.\left(\text{Pos}((W_{rp1}.H_p(t) + W_{rp2}.D_a(t)) - R_p(t)).(1-R_p(t))) - \lambda_{rp}\right).R_p(t) \cdot \Delta t \]  
\[ I_v(t+\Delta t) = I_v(t)+\beta_{iv}.\left[\text{Pos}(H_d(t)-I_v(t)).(1-I_v(t))-\text{Pos}(-(H_d(t)-I_v(t)).I_v(t))\right].\Delta t \]  
\[ V_y(t+\Delta t) = I_v(t)+\beta_{vy}.\left[\text{Pos}(G_d(t)-V_y(t)).(1-V_y(t))-\text{Pos}(-(G_d(t)-V_y(t)).V_y(t))\right].\Delta t \]  
\[ E_a(t+\Delta t) = E_a(t)+\beta_{ea}.\left[\text{Pos}(A_a(t)-E_a(t)).(1-E_a(t))-\text{Pos}(-(A_a(t)-E_a(t)).E_a(t))\right].\Delta t \]  

Note that the change process is measured in a time interval between \(t\) and \(t+\Delta t\). Moreover, the rate of change for all temporal specifications is determined by flexibility rates \(\gamma_{dk}, \gamma_{rp}, \beta_{iv}, \beta_{vy}\) and \(\beta_{ea}\). The temporal specifications are those that are time-bound and evolve with respect to changes in time and all the temporal specifications \((\text{factors})\) have 0.1 as the initial value in the simulation environment. A simulator was developed using all defined formulas for experiment purposes; precisely to explore interesting patterns and traces that explains the behavior of driver agent model related automaticity.

### Simulation Results

This section illustrates the mechanism of the proposed model whereby three scenarios were simulated using fictional driver’s conditions as shown in Table 1. All the simulations conditions are based on the input values of the seven input factors \((\text{basic practice}, \text{basic skills}, \text{sensory ability}, \text{driver’s goal}, \text{potential hazardous information}, \text{exposure on task complexity} \text{and} \text{intention})\). In this simulation, we used the following settings: \((0\leq t \leq 500)\) with \(t_{max} = 500\) (to represent training activity of the driver up to 8 months), each time step denotes the time range for the training, where 1 time step represents 5 hours of training, \(\Delta t = 0.1\), \(\alpha, \beta, \gamma, \xi, \omega, \eta, \phi\) are all assigned to 0.8 each and \(\lambda = 0.01\). These settings were obtained from a number of experiments to determine the most appropriate parameter values for the model. The simulation results for three scenarios are shown in Figure 2, Figure 3 and Figure 4.

| Scenarios | Conditions | Description |
|-----------|------------|-------------|
| #1        | 1111111    | Skilled driver who has potential hazard information and exposed to task complexity, having an intention to achieve a specified goal. |
| #2        | 1110000    | Skilled driver who has no potential hazard information and exposure to task complexity |
Scenario #1: Skilful-Cautious Driver

In scenario 1, Fig (2a) showed that the driver’s level of experience proportionally increased higher with higher increased in practice [7][8]. Fig (2b) showed that the driver’s perception about risk increased higher with higher proportional increased in driver’s knowledge. Fig (2c) showed that the voluntary level increased higher with higher proportional increased in involuntary level due to increase in the level of attention of the driver [9], [10]. Fig (2d) showed the automaticity level of the driver increased higher with higher increased in practice and experience [8].

Scenario #2: Skilful-Risk Taking Driver

In scenario 2, Fig (3a) showed that the driver’s level of experience proportionally increased higher with higher increased in practice [7][8]. Fig (3b) showed that the driver’s level of perception about risk increased with proportional increased in driver’s knowledge but the driver’s knowledge is higher compared to the driver’s level of perception about risk due to the effect of drivers ability and his perception about in the traffic environment [11], [12]. Fig (3c) showed that involuntary level increased with decreased in the voluntary level due to increase in the driver’s knowledge [13], [10]. Fig (3d) showed that the automaticity level of the driver decreased with decreased in practice and experience [8].
Figure 3: Simulation Conditions Result (for scenario 2)

Scenario #3: Unskilful – Cautious Driver
In scenario 3, Fig (4a) showed that the driver’s level of experience proportionally decreased with proportional decreased in practice ([7][8]. (4b) showed that the driver’s level of perception about risk decreased with proportional decreased in the level of knowledge of the driver [11], [12]. (4c) showed voluntary level proportionally decreased with decreased in the involuntary level due to increase in the level of attention of the driver [9], [10]. (4d) showed that the automaticity level of the driver decreased drastically low with decreased in practice and experience [8].

Figure 4: Simulation Conditions Result (for scenario 3)
4 Conclusions
This paper proposed a computational agent training model to train drivers in order to enhance their automaticity to make effective decision. The model was formalized and simulated based on scenarios. Scenarios to evaluate the applicability of the model in real life domain have been conducted. It has shown for the given scenarios that the external factors have effect particularly on the automaticity of the driver to make effective decision. Our next step is to integrate the training model with the awareness model which will evaluate the performance of action of the driver in making primed decision.

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