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MODELLING AND SIMULATION OF INTERACTION IN DRIVER/VEHICLE DYNAMICS

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Abstract. Future requirements of vehicle control dynamics especially cars, requires to consider ability of driver systematically. This research is needed in recent information and automation technologies, which have the potential to change vehicle control towards a new quality that shall be called "decision making in human/vehicle system". This paper describes conceptual model for driver's behaviour, control levels in the intelligent control system driver/vehicle/traffic situation and conceptual simulator model for generation and measuring of dynamics in this system. To study this, mathematical (cybernetic) and simulation models which represent (in the first research steps) dynamics between driver's eye-hand/legs will be needed. In the paper there is detailed description of experiments for obtaining operator's/driver's responses (eye/hand, eye/leg channels) and also identification procedures for obtaining parameters in their models. Particular results of simulation experiments, which have been made with linear models (constant and changeable parameters), are finally given at the end of the paper. Simulation experiments made until now show that key parameter which described operator dynamics behaviour acts as their "dead time," or "delay". It was supposed as constant in simulation experiment but in real driver behaviour it varies in large scale and fundamentally represents driver dynamics. First experiments with changeable dead time were made, but research of more accurate drivers models needs to continue.

1 Introduction

Research on the manual control of dynamic systems has its origin in the servomechanism theories of the 1940's. In subsequent years, several models of the human as a controller in closed-loop feedback control systems [1] have been advanced [4]. On model structure supposed in [1] for eye-hand channel, the paper [5] describes real time simulation experiments and parameter identification in this channel, for second order linear model with constant parameters. Simulation experiments were realized as tracking of input signals (unit step, sinusoidal and pseudorandom) by operator and operator's model. Simulation experiments documented in this paper showed that linear models with constant parameters are not able to characterize operator behaviour, whose dynamics is variable. Identification algorithm, which is more suitable for systems with variable parameters and also some identification experiments with linear model with variable parameters for operator's eye-hand channel were described in paper [6]. In this paper there is also comparison of the operator responses with responses on both linear models: model with constant and model with variable parameters. In the model with variable parameters the operators' "dead time" (delay) were supposed as constant during identification, because method, which would be able to identify variable dead time was not available. Simulation experiments documented in paper [6] showed that models with variable parameters are able to characterise operator behaviour better then model with constant parameters, but wide range in which the model parameters change, is a sort of disadvantage. Subsequently there arises a need to study two problems. First one is to find and verify such identification algorithm, which enables to detect variable dead time in operator's eye-hand channel. This is not needed for operator models, which are simple. Second one is studying of driver/vehicle control especially in the unavoidable (emergency) situations in which operators' time constants as well as variable operators dead time have to be taken into consideration.

Future requirements of vehicle control dynamics especially cars, requires to consider human operator needs as well as it's ability more systematically. Recent information and automation technologies including graphic display have the potential to change vehicle control towards a new quality, which shall be called "*decision making in human/vehicle system*". This needs such design approaches, which take into consideration and also utilize physical, psychological and intellectual human abilities. To measure these abilities and verify suitable models for their description, detailed and exact models of driver dynamics in the eye-hand and eye-leg channel are crucial. This paper describes conceptual model for the driver in the car behaviour, from which can be seen some relations between psychological, intellectual and physical driver abilities. In paper is also documented the first simulation experiment with model where driver delay is variable.

The paper is organized as follows: Conceptual model and driver in the car behaviour models are described in the next section. Experiments for obtaining operator responses and behaviour of the driver in the car are in section 3 and 4. Procedures for parameters identification in the driver dynamic model are described in section 5. Section 6 contains results of simulation experiments. The paper ends with section 7, conclusion and outlook.

2 Conceptual Model of Operator Behaviour

Main problem in this conceptual model is modelling the part of "problem solving and decision making" from human behaviour. This part of conceptual model has different levels and phases, which are shortly described, with acceptation of lit [3], [7] in Figure 1 and Figure 2 and as we know depends on physical, psychological and intellectual human abilities. When we are speaking about psychical abilities, we mean how the human affects do dynamic parameters change in critical situations and how do they depend on predispositions of a driver in a specific transport situation. Especially there is ability to pay attention instantly, time of this process and influence of weariness and exhausting stimuli on operator's dynamics. Intellectual abilities of driver mean ability to solve critical situations based on own models of traffic situations gained by experience or training. It relates with quality of internal model of outer world/situation, ability to solve problems and decide effectively.

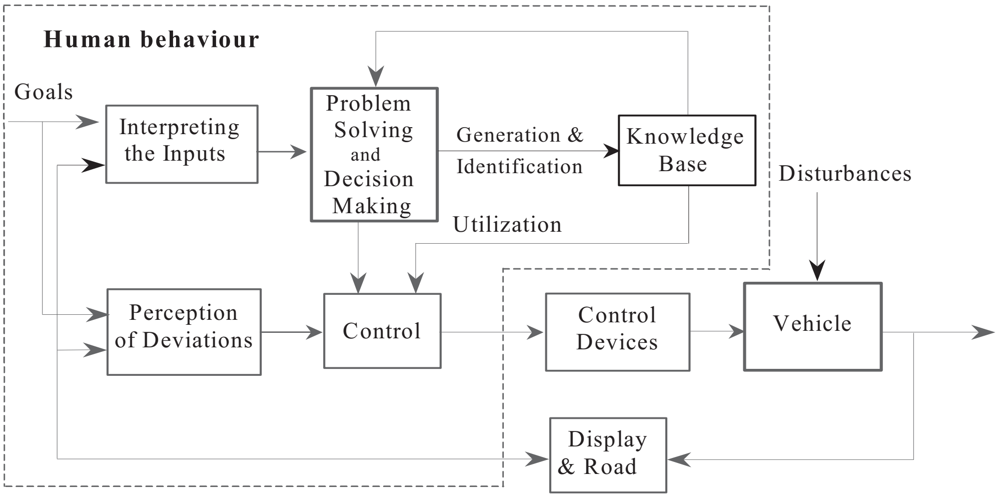

Figure 1. Conceptual model of behaviour by human/vehicle interaction

Modelling of behaviour in human as a driver of transport vehicle and its dynamics concerns following: operator responses by vehicle driving (control) measurement, correspondent models structure selection, dynamics and non-dynamics parameters of the model identification (transport delay, time constant, gain, knowledge base for problem solving) from measured responses and simulation experiments on PC. From this point of view human/operator can be characterised as the complex non-linear dynamical system with varying parameters and varying dead time.

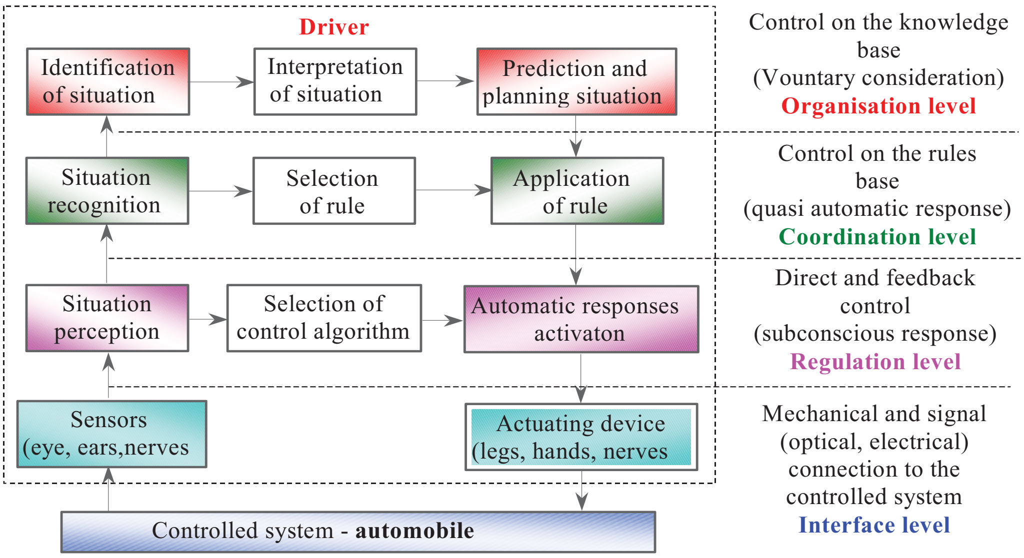

Figure 2. Control level in the intelligent control system “human/vehicle/traffic situation”

The models should include all control level shown in Figure 2, that means from dynamics of sense organs in the eye-hand channel and eye-leg channel (interface level), over psychometric dynamics (regulation level), up to dynamics of human decision making (coordination and organisation level). Vehicle dynamics is known and range of constant for biomechanics behaviour (time constant and dead time in eye-hand/leg channels) can be measured. If response in traffic situation are measured (see Figure 3) then it is possible to find part of dynamics responsible for decision-making.

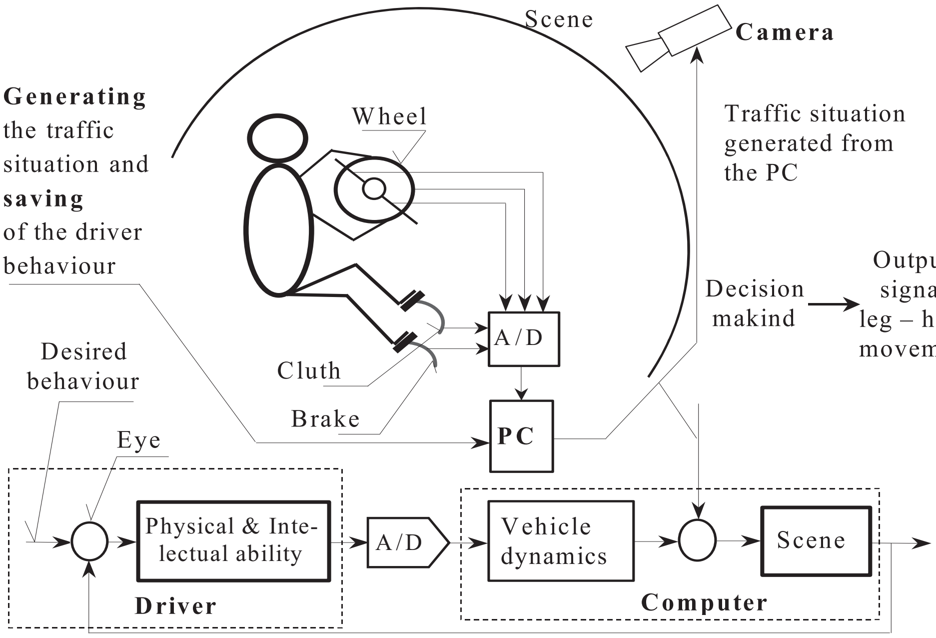

Figure 3. Conceptual model simulator on generation and measuring of dynamics at the system driver/vehicle/traffic situation

By measurement and modelling of operator/vehicle interactions we must take into account that operator/vehicle final dynamic includes position and speed of vehicle control and also includes cognitive element as decision making and hazard reception and acceptation. This decision is based on capacity and attributes of memory for past situations, past effective strategies of solving and ability to learn from past, reconsideration of how invasion of driver/operator affects development in outer traffic situation (planning future activity) as well as structure of local goals of behaviour and ability to create the global goal.

All of these are parts of "*artificial intelligence*" in models/systems. Because we speak about suggestion and verifying of model of driver it is useful to count on its own attributes as well.

3 Behaviour of the Driver in the Car

Time constants and delays, which characterise dynamics between eye and hands, eye and legs are very important for the modelling the driver/vehicle interaction in driver behaviour and are described on Fig. 4. The range of drivers “delays” in Figure 4 are informative, exact range can be obtain after response measurement.

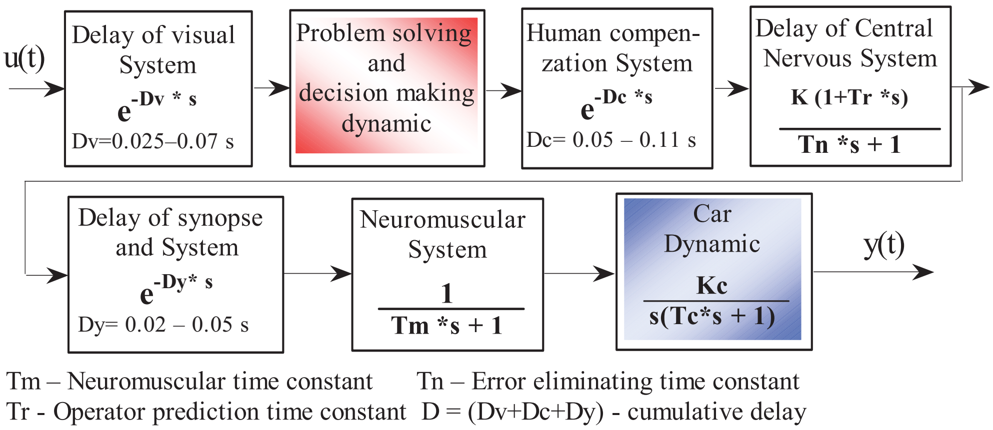

Figure 4. Block scheme of model for the human operator.

Car dynamics depends on car mass, speed, focusing point distance (see figure 5 and equation 2) and driver delay plus time constant. In the equations, which describe cross and longitude car control (for car simulator), it is simpler to use only “cumulative delay” (Fig. 4) instead of neuromuscular, error eliminating and prediction time constant. Then equation (1) can describe driver error elimination and equation (2) can describe cross control (v – speed, D - driver dead time - delay). Variables that describe driver behaviour (by [8]) in this equation are illustrated on Fig. 5. More detailed models, which describe cross control of vehicle, are on Fig. 6. For better results in driver/vehicle control especially in the unavoidable (emergency) situations it is needed to take into consideration not only "delay but also all operators time constants. This is reason to solve problems with measurement and identification of driver dynamics.

$$\varphi(t) = K\,\varepsilon(t - D) \tag{1}$$

$$\delta(t) = \frac{K}{L} y_L\left(t + \frac{L}{v} - D\right) - \frac{K}{L}(y_0 - D) - K\varphi(t - D) \tag{2}$$

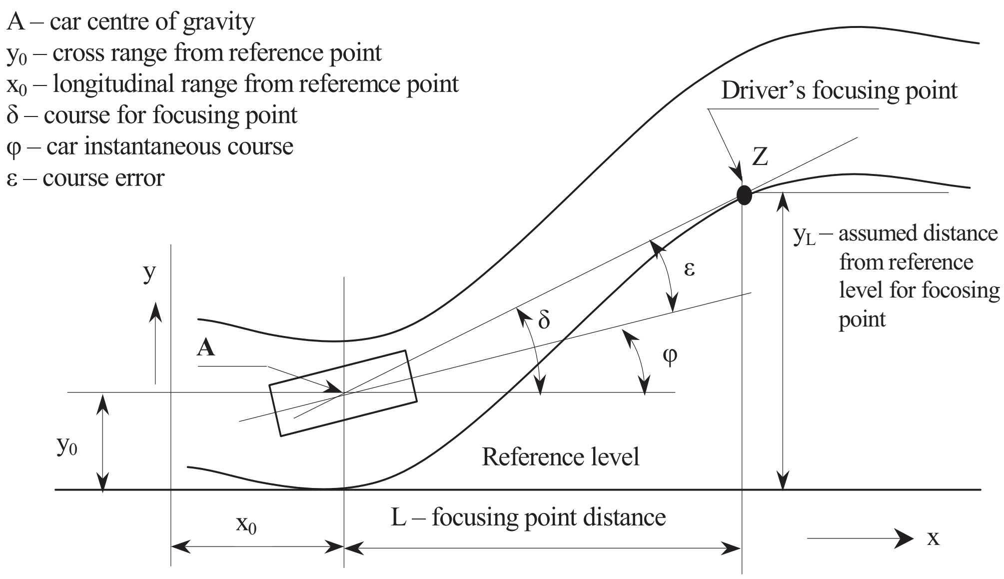

Figure 5. Variable, which describe in cross control of vehicle by driver

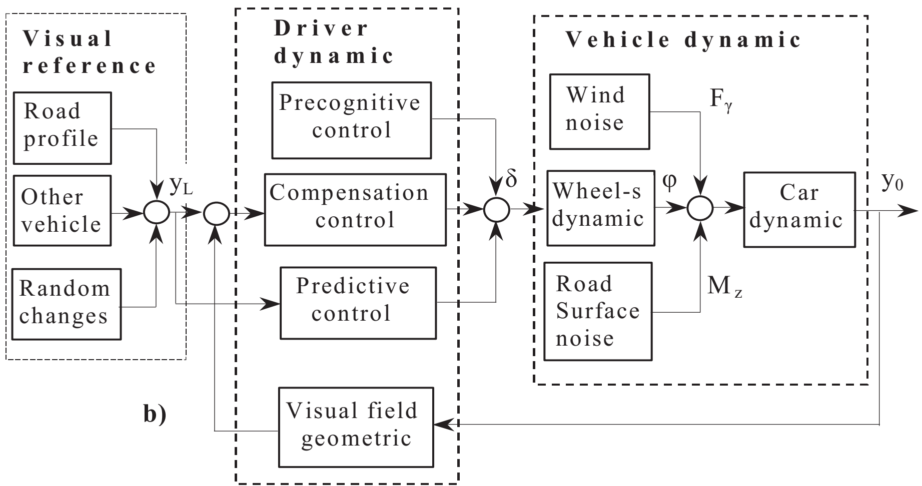

Figure 6. Cross control model by Mc Ruer

As can be seen from Figure 5 and equation (2), driver dead time "D" can be eliminate if focusing point distance "L" is "distant enough" and car speed "v" is not "too big". In this case tracking the route line (also in soft curve) is "programmable control" problem, because "desired value" is forwardly known. In such case the operator response "time constant" is not so important, this behaviour can be described by first order transfer function and small dead time. For "critical traffic situation" we can suppose, that focusing point distance approach to zero. In this case operator response substantially depends on time constant and dead time, and such behaviour can be described by more complex models (3) to (5), which will be verified by simulation experiments.

4 Experiments for Obtaining Operator Responses

During the simulation experiment the operator is tracking the target movement signal "**u(t)**" generated from PC and by moving the lever or wheel he generates signal "**y(t)**" (the reaction of the operator), which corresponds to his tracking the signal "u(t)". Moving the lever in the range 0-60 [deg] is generated voltage signal 0-4 [V]. The operator starts the experiment. He generates logic signal by pressing the button on the lever. Block scheme of the system of human dynamics measurement and identification is depicted in Fig. 3. Laboratory environment for responses measurement are on Figure 7. Typical operator step responses and data for off –line identification are shown in the Figure 8.

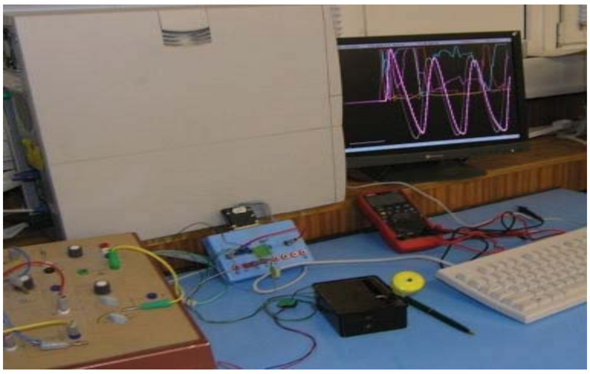

Figure 7. Laboratory environment for measurement of the operator responses.

Subsequent change of signal from zero level to desired value we need to track is randomised in the first third of the scale. The signals were generated in form: unit step, harmonic signal and pseudo-random signal. After the measurement finishes, the identification is done from measured data in off-line mode. Figure 8 shows a random start of input target movement signal and differences in transport delay and responses between two operators.

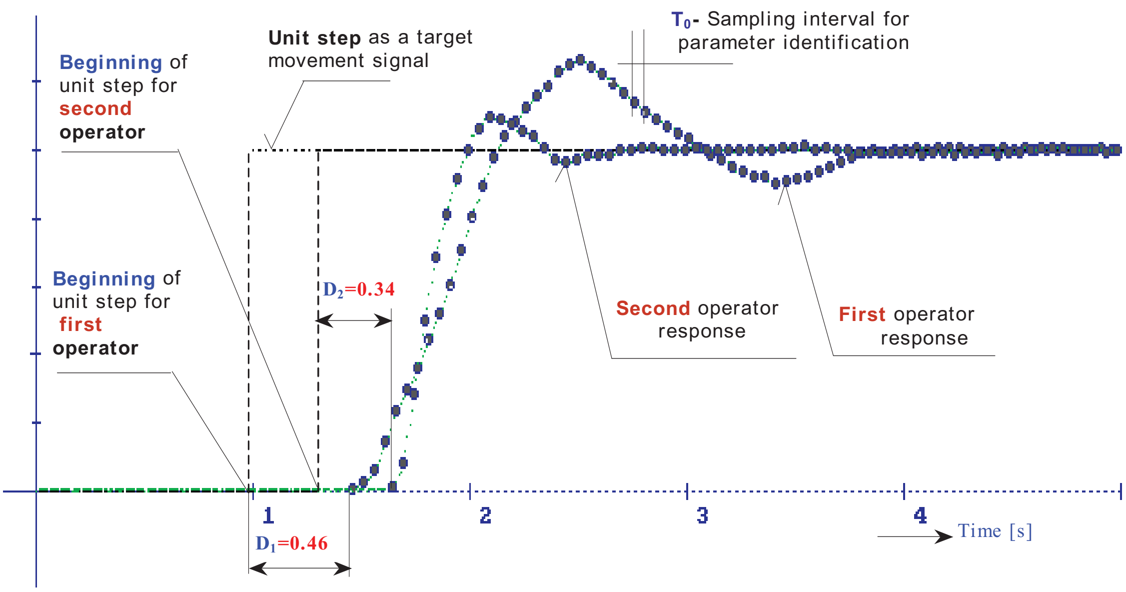

Figure 8. Real time measurement of the operator responses on unit step target movement signal

Both responses on Figure 8, which are with overshoot, look like unit step response from second order transfer function with relative damping "a < 1", which can be described by (3). It is certain, that driver which drive carefully generate response without overshoot, where relative damping is "a > 1", which can be described by transfer function (4).

$$S(s) = \frac{K * e^{-D*s}}{T^2 * s^2 + 2aT * s + 1}\ ; \quad a < 1 \tag{3}$$

$$S(s) = \frac{K * e^{-D*s}}{(T_1 * s + 1)(T_2 * s + 1)}\ ; \quad a \geq 1; \tag{4}$$

If driver drives curves or solves traffic situation, which is known from previous rides, he is able to predict development in traffic situation and suitability own behaviour. Then appropriate model for operator behaviour is transfer function with “predictive time constant” *Tr* described by (5).

$$S(s)=\frac{K\left(Tr*s+1\right)*e^{-D*s}}{T^2*s^2+2aT*s+1}\ ;\quad a<1\ or\ a\geq 1 \tag{5}$$

$$S(z)=\frac{b_0+b_1*z^{-1}+b_2*z^{-2}}{1+a_1*z^{-1}+a_2*z^{-2}}*z^{-d_0};\quad D_0=\mathrm{int}(D/T_0) \tag{6}$$

Transfer function (5), (6) and (7) which describe continuous models of driver behaviour have four different structures, which depend on overshoot and predictive or non-predictive driver behaviour. After identification of sampled input/output data, which represent driver behaviour, we can obtain one structure (6) only, which characterize driver behaviour in the discrete domain.

5 Identification Procedures

For parameter identification of the linear model for operator, two types of identification algorithms were used. In simpler case, it was a classical analysis of the transient function. This analysis is described in [5]. In the second case, there are recursive least square identification methods, namely the algorithms LDFIL, LDINT and REDIC. These are necessary to apply for identification response on periodical and pseudo-random target movement signal. First problem is that if the model of operator (3) or (4) or (5) is assumed then after the identification it has the same form (6) in Z-transformation. Relations for the recalculation of the parameters from discrete second order model (6) into parameters of continuous models (4) or (5) were described in [5] and [6].

Value “D” [s], in the models (3) to (6) is operator’s „dead time“ and „T_0“ [s] in (6) means “sampling interval” for which is parameters in (6) computed from parameters of (3) to (5). Value of "Tr"- operator predictive time constant, depends on "situation". In some situation operator's behaviour has "Tr=0"and can be described with models (3) or (4). If “Tr” is not zero cannot be calculated only from parameters of denominator in (6), but also from numerator of (5) and parameters of (4) or (5).

Author deduced calculation of parameter "Tr" as follows. The transient responses for transfer function (5) are (7) and (9) and after recalculation denominator parameter (5) from (6) it can be calculate operator's predictive time constant “Tr” from (8) or (10).

$$y(t)=K\left(1-\frac{1}{\cos(\varphi)}*\exp[-\lambda(t-D)]*\sin[\omega(t-D)+\varphi]\right);\qquad \varphi=arctg\left[\frac{\omega T^2}{T_r-T^2\lambda}\right];\qquad \text{for } a<1 \tag{7}$$

$$T_r=\lambda T^2+\frac{\left[(a_2-b_2/K)/e^{\lambda T_0}-\cos(\omega T_0)\right]}{\sin(\omega T_0)}*\omega T^2 \tag{8}$$

$$y(t)=K\{1-c*\exp\left[-(1/T_1)*(t-D)\right]+d*\exp\left[-(1/T_2)*(t-D)\right]\};\ c=\frac{T_1-T_r}{T_1-T_2};\ d=\frac{T_2-T_r}{T_1-T_2}\ ;\ \text{for a}>1; \tag{9}$$

$$T_r=\frac{(T_1-T_2)/K*b_1-z_2T_2+z_1T_1+T_2-T_1}{z_2-z_1} \tag{10}$$

As it is shown in the simulation experiment result, that for linear with constant parameters cases of operator behaviour, model (3) and (4) (without "Tr") can be applied. The best results were obtained with model (5) when varying parameters were applied.

Identification algorithm LDFIL is the version of the recursive least square algorithm with forgetting. In the LDFIL algorithm forgetting factor is constant (around 0.995 for slowly varying parameters) and cannot vary on identification error evolution during identification procedure. After several identification experiments with different forgetting factors it is possible to find forgetting factor, which is suitable. For identification of varying parameters, it is better to use algorithms REDIC (Recursive Identification with Directional Forgetting) first described in [2]. REDIC working with directional forgetting and forgetting factor "φ"; it can be also “adaptive”. Directional forgetting technique in comparison with exponential forgetting has advantages, especially using in continuous estimation of normal regression model with time varying parameters. Differences between LDFIL and REDIG are in the computation of matrix (13) using (14) and (15).

It is possible to prove [2] that incoming data [u(t), y(t)] modify only the conditional probability density (c-p-d) of model parameter **d**(t) and variance e(t) in equation (11). However, the exponential forgetting, (indicates the confidence rate, at which posterior c-p-d is able to correctly describe model's parameter also in next sampling interval) represses all model's parameter information accumulated up to now (up to time "t=k*T_0"). If the vector of incoming data [u(t),y(t)], observed in time interval which is long enough does not excite "well" controlled plant, than it results in permanent forgetting of accumulated information part, which is not compensated with new information acquisition. For all that, it was necessary to limit exponential forgetting only for alternative c-p-d.

$$\begin{aligned} &y(k) = \mathbf{d}^T(k) * \mathbf{p}(k) + e(k) \\ &\mathbf{d}^T = \left| y(k), y(k-1), y(k-2), -u(k), -u(k-1), -u(k-2) \right| \\ &\mathbf{p}^T = \left| a_1, a_2, b_0, b_1, b_2 \right| \end{aligned} \tag{11}$$

$$\begin{aligned} &e(k)[\mathbf{p}] = y(k) - \hat{y}(k) = \mathbf{d}^T(k) * \begin{vmatrix} 1 \\ \mathbf{p} \end{vmatrix} \\ &y(k) - \text{measurement value of the operator output} \\ &\qquad \text{in time } \mathrm{t} = \mathrm{k} * \mathrm{T}_0, \text{ or step "k"} \\ &\hat{y}(k) - \text{estimated value of the operator output} \\ &\varphi - \text{parameter of the exponential forgetting} \, (0.1 - 1) \\ &\mathbf{d}(k) - \text{measurement data vector in the step "k"} \\ &\mathbf{p} - \text{estimated parameter vector} \end{aligned} \tag{12}$$

Application of alternative c-p-d is the same as increasing uncertainty of the model parameter only in their projection into "vector of data **d**(k) direction". Application of this idea into algorithm afterwards provides preventing from permanent growing of some equation root in the covariant matrix **P**(k) which would otherwise cause numerical breakdown of estimation. This application also remarkably limits (but does not remove, if sampled data store little information) long-run deflection of model's parameter point estimation. Directional forgetting enables to obtain high numerical reliability of identification process. This identification algorithm enables also application of relatively small value of forgetting factor (φ or $\varphi_A > 0.05$), and sets algorithm adaptability depending on variable velocity of individual model parameters time variation.

$$\begin{aligned} &\mathbf{P}(k+1/k) = \mathbf{P}(k/k-1) - \frac{\mathbf{P}(k-1)\mathbf{d}^T(k)\mathbf{P}(k-1)}{\varepsilon^{-1}(k/k-1) + \xi(k/k-1)} \\ &\xi(k-1) = \xi(k/k-1) = \mathbf{d}^T(k)\mathbf{P}(k/k-1)\mathbf{d}(k) \end{aligned} \tag{13}$$

$$\begin{aligned} &\text{where } \ \varepsilon(k/k-1) = \varphi(k) - (1-\varphi(k)\xi^{-1}(k/k-1) \\ &\text{for slowly varying parameters } \varphi(\mathrm{k}) \text{ is computed from} \\ &\varphi(\mathrm{k})^{-1} \approx 1 + (1+\rho)\left(\xi(1+\xi)^{-1}(\gamma+1)\eta(1+\xi+\eta)\right) \end{aligned} \tag{14}$$

$$\begin{aligned} &\text{for rapidly varying parameters } \varphi(\mathrm{k}) \text{ is computed from} \\ &\varphi(\mathrm{k})^{-1} \approx 1 + (1+\rho)\left(\ln(1+\xi) - \xi(1+\xi)^{-1} + \xi(1+\xi)^{-1}(\gamma+1)\eta(1+\xi+\eta)\right) \end{aligned} \tag{15}$$

$$\begin{aligned} &\left.\begin{matrix} \varphi_A(k) \ge \varphi_A(k)_{\min}; & \varphi_A(k) = (1 + k_1 * \rho)^{-1} \\ k_1 = 1 \ \text{ for } \ (14) & \text{and} \quad k_1 = 2 \ \text{ for } \ (15) \end{matrix}\right\rangle \\ &\text{Mode: } \ 1) \text{ Constant forgetting} - \text{then set } \ \varphi(\mathrm{k}) \\ &\qquad\qquad 2) \text{ Adaptive forgetting - then set } \ \varphi_A(k)_{\min} \end{aligned} \tag{16}$$

Algorithm works with constant or adaptive forgetting factor. By using adaptable forgetting factor it is needed to order regime (slowly or rapidly varying parameters) and adaptive forgetting factor is computed from (14), (15), (16). It is possible to use rather equation for adaptive forgetting factor computation. After several identification experiments with different adaptive forgetting factors it is possible to find adaptive forgetting factor, which is suitable for huge range, in which driver time constant are vary.

6 Results of Simulation Experiments with Operator

For evaluation of experimental results of dynamics "eye-hand" of human operator, the following parameters were compared: the dead time of the operator response, time constants of the transfer function, integral of absolute value of an error (IAE) between operator and model response and structure of the model as the result of parametrical identification.

Typical example of single sinusoidal target tracking is shown in Figure 9 by LDFIL identification algorithm and forgetting factor φ= 0.985 application. During tracking the sinusoidal signal dead time of operator is changeable however, "constant" parameters in model of the operator are able to represent only constant dead time. This is clearly shown in Figure 9, in time interval between 5 and 7 [s], where values of delay D_1, D_2 are drawn out of the time line. That is why we cannot distinguish between parameter and dead time changes in the three identified parameters of the model in Figure 9

The same input signal as in Figure 9 is shown also in Figure 10 for identification algorithm REDIC but with varying parameters of the operator's model. Although model in Figure 10 has constant dead time (Dm=0,16 < D=0.275), application of other varying parameters (K, Tr, T^2, 2aT) makes model response much more close to operator's response. This fact is seen in comparison of Figure 9 and Figure 10 especially from 5[s] to the end.

To find appropriate model with varying parameters, it is needed to carry out more simulation and identification experiments to search for applicable model delay -Dm different from real delay of operator –D, which is changeable. Model delay -Dm is namely constant in used model with varying parameters. Response of the best operator's model by sinusoidal tracking is drawn in Figure 11. This can be seen in relation to IAE, which is much smaller in simulation experiment oh Figure 11 than in experiment from Figure 10. It means, that change of model parameters on Figure 11 better represented human behaviour. Disadvantage of much smaller IAE in Figure 11is that value of identified parameters vary in large scale.

By application Dm=D can it possible to find out forgetting parameter "φ" with minimal IAE and the best tracking of operator's response. Advantage of REDIC algorithm is not only directional forgetting but also adaptation of forgetting factor. Identification starts with "φ_s" and finishes with "φ_e", and following experiment starts with "φ_e". After 3-4 experiments we come into situation where " φ_s=φ_e" and also tracking of operator response with model response is the best one. However, the varying parameters of the model vary in wide range (compare Figure 10 and Figure 10-12).

Influence of starting parameters in identification algorithm REDIC namely forgetting factor "φ" and identification mode (φ = const. or φ = adaptive and adaptive φ for slowly or high - speed varying parameters) can be seen by comparison Figure 10 to Figure 12. Model parameters in Figure 10 and Figure 11 are identified in the mode "adaptive forgetting for high – speed varying parameters".

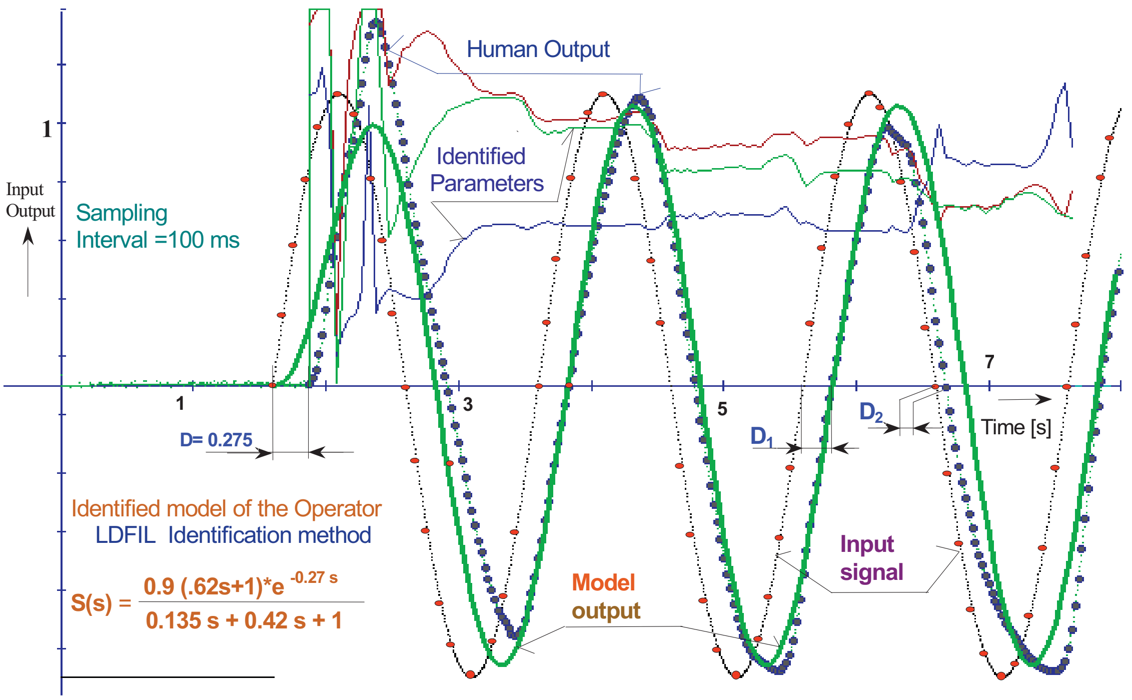

Figure 9. Model performance compared to Human by tracking sinusoidal target movement

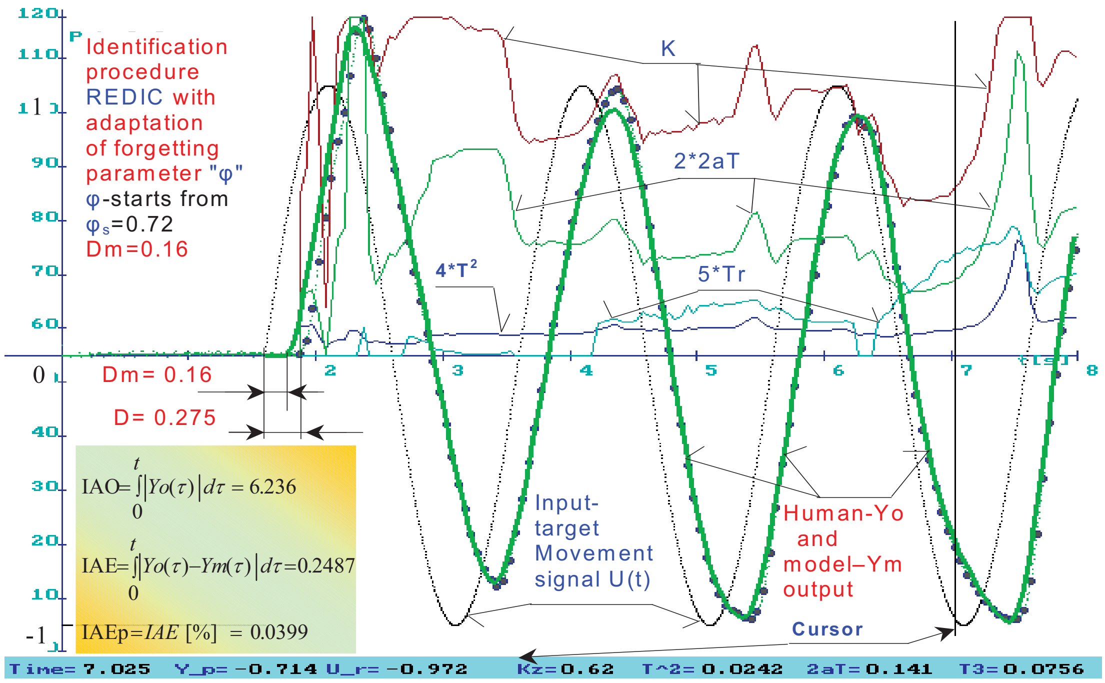

Figure 10. Model to Human compared performance by model with varying parameters

Model parameters in Figure 12 are identified in mode "adaptive forgetting for slowly varying parameters". The best results were acquired by using mode "adaptive forgetting with high – speed varying parameters. Best results, are achieved when operator performance and model performance are "the same" than integral of absolute value of an error (IAE) between operator response and model response is minimal. From all figured simulation experiments this is the case on Figure 11.

Further be needed take a note, that for correct output from identification process is needed several sampling interval (depends on model order, quantisation error, speed of parameter varying – minimum in ideal situation is number of identified parameters, in this discrete model this is five parameters). From all simulation experiments it can be seen, that in first 10 to 15 sampling interval identified parameters jumps in wide interval. This is due to identification procedure starting and adjusting and not from model parameters varies.

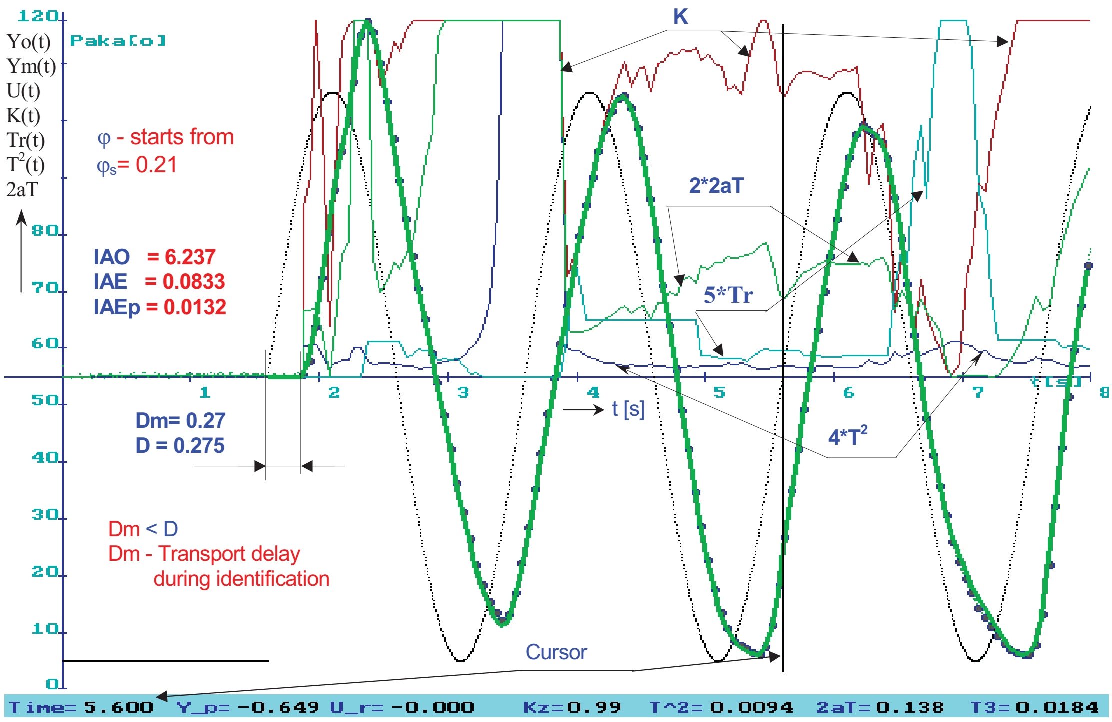

Figure 11. Model to Human performance compared by the best model with varying parameters

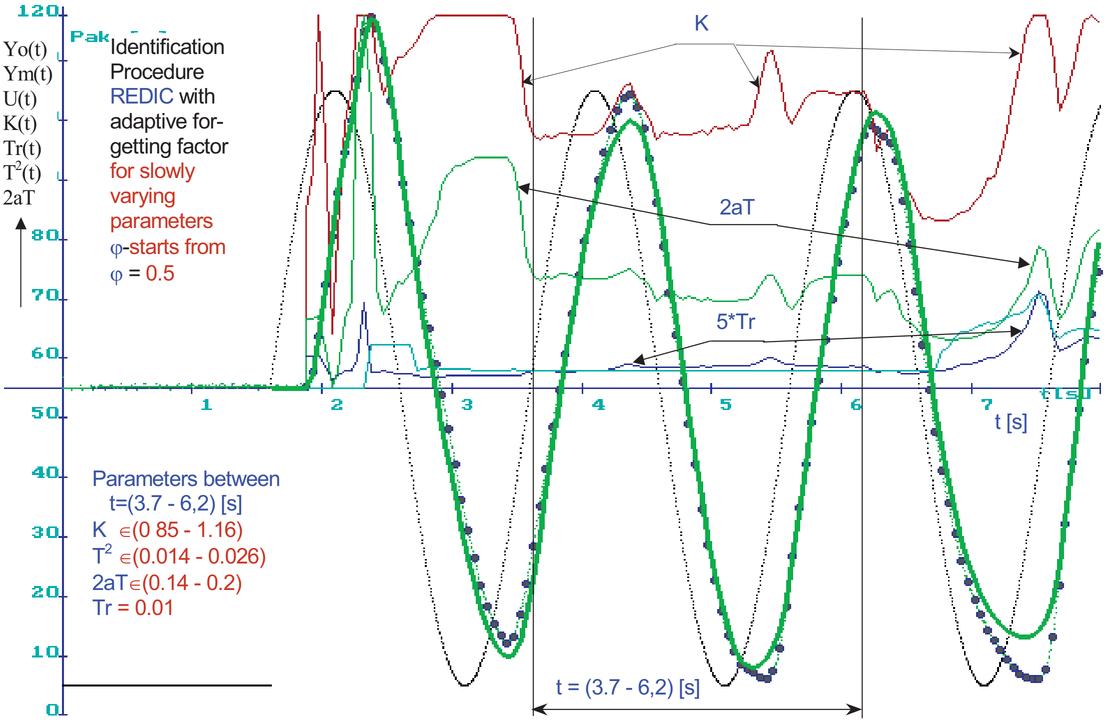

Figure 12. Model performance by model with slowly varying parameters

Comparison of simulation experiments on the Figure 10 to Figure 12 indicates that parameters changing between times 3.7 [s] – 6.2 [s] for all simulation experiments are approximately identical. In case operator delay varies, identified parameters vary in wide range in order to compensate delay variation because applied model for identification assumes constant operator delay and this is disadvantage of this method.

Tracking of pseudo-random target movement is shown in Figure 13. Pseudo-random signal consists of four superimposed sine waves with incommensurable frequencies of 0.11 Hz, 0.17 Hz, 0.21 Hz and 0.48 Hz with different phases, where the first one is randomised. Correct replacement of driver output by model output can be evidently seen from detail “A” in Figure 13.

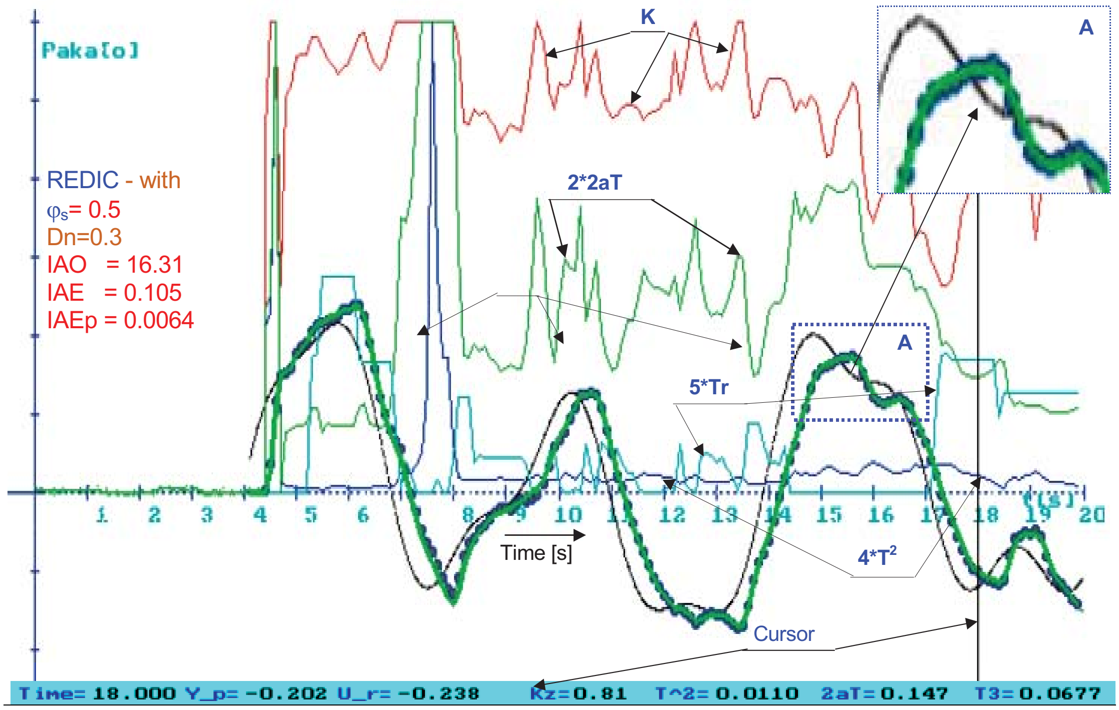

Figure 13. Model performance compared to Human by pseudo-random target movement.

Searching for "varying" operator model for pseudo-random target movement was the same as in case of sinusoidal input. In the Figure 13 there is shown wide range of the model parameter changes. Comparing the details in Figure 13, it is understood, that model with varying parameters describes the operator's behaviour more precisely than in constant parameters (see presentation). But there is also wide range of the model parameter changes, which is sort of disadvantage. The range of model parameter changing is bigger in pseudorandom target movement then for sinusoidal because speed of time change in input signal is also bigger in same parts of input signal.

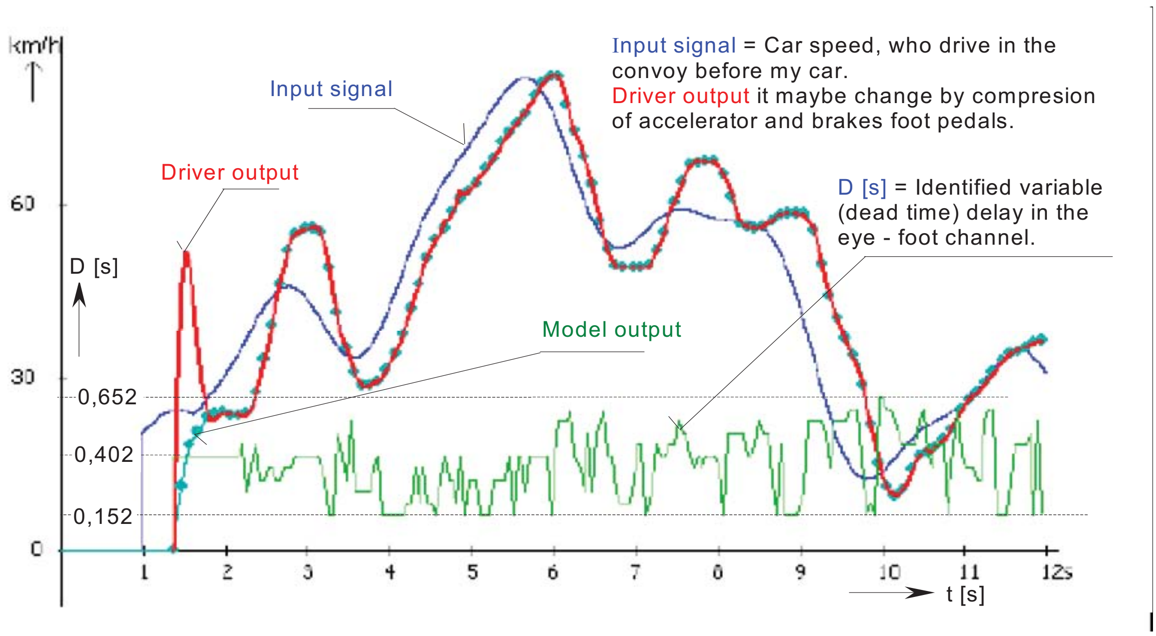

Figure 14. Pseudo-random target movement in channel eye-foot with variable transport delay.

First simulation and identification experiment with variable delay in the eye-foot channel can be seen on figure 14. Variable delay was computed by running more parallel identification procedures each started with different delay. Actual model parameters and delay were chosen by minimal identification error. In this simulation experiment 10 parallel algorithms were started. Applied sampling interval for input/output data was 0.005 [s] and sampling interval for identification procedure was 0.05 [s]. Identification procedure started with dead time 0.402 [s] and after initialisation process dead time start to change. Input signal in this experiment is previous car speed variation, its vary between 10 to 90 [km/h] as pseudorandom target movement signal. Output signal is realised by accelerator and break pedals compression. For eye-leg channel were realised smaller a number of simulation experiments than for eye-hand channel. Measurement method, identification algorithms for both channel are the same and from simulation experiments are alike qualitative results.

7 Conclusions and Outlook

Results showed that the eye-hand human dynamics models with constant parameters could be compared to human data qualitatively quite well only in case of tracking of unit step target movements. Description of human performance by sinusoidal and pseudo-random target movements tracking with the linear model is not very realistic [6]. This subscription is focused on conceptual model of behaviour by human/vehicle interaction and identification methods for constant dead time with previously used structure but with variable time constant. Models with varying parameters are able to characterise operator’s behaviour better but the wide range of the model parameter changes is a sort of disadvantage. For better study of driver/vehicle interaction especially in the unavoidable (emergency) situations it is needed taking into consideration not only drivers “dead time” but also all drivers’ time constants. This is reason to solve problems with measurement and identification of variable delays and time constant in driver dynamics.

In further research it is needed to focus on identification methods applicable for varying dead time and on realisation of context and structure oriented level of behaviour in human/vehicle interaction. Using parallel computation methods for continuous identification of varying parameters and varying dead time, it will be possible to carry out also on-line identification of operator behaviour. One example of this method is documented in this paper. Exact, certain and clear models for eye-hand, eye-leg channels are basic predisposition for building qualitative models of operators' decision making in particular situation, planning of future activities and impact of instant actions on development of future situations.

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