IDENTIFICATION METHODS OF MATLAB SYSTEM IDENTIFICATION TOOLBOX USING FOR MODELLING HUMAN BEHAVIOR

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Abstract: The paper is deal with modelling of human behavior using toolbox of MATLAB® called System Identification Toolbox. The paper describes identification methods included in System Identification Toolbox. The measurement of several pilots was held in cooperation in University of Defence in Brno where a flight simulator is placed. The experiment consisted in measurement of pilot´s response to step change of altitude. The measured data were identified by the various identification methods and compared with each other.

Keywords: Man-Machine System, human behavior model, System Identification Toolbox

1 INTRODUCTION

The technical equipment surround the human population and form an integral part of human life. Systems which human interact with technical equipment called Man-Machine Systems (MMS). The article focuses on modeling pilot´s behavior, who controls one of the most complex systems – the aircraft. The pilot performs the function of regulator. There are several mathematical models describing the behavior of the pilot which are described in detail in [1], [2], [3].

2 IDENTIFICATION METHODS USED BY SYSTEM IDENTIFICATION TOOLBOX

The toolbox of MATLAB® called System Identification Toolbox (SIT) offers identification of parametres for dynamic systems. SIT can find optimum parameters of a known transfer function. SIT performs a calculation based on input and output original data and the sampling frequency. The original flight altitude forms the input data and the output data are performed by elevator deflection. This toolbox offers to set fixed numbers of parametres for transfer function, if they are knowing. System identification toolbox offers setting of initial condition. SIT can compare original measured data with calculated model.The similarity level of the measured data and the model is given by parameter Best fit, which is mean quadratic deviation in percentage. [4]

The next advantage of SIT is that user can choose one of the five identification methods: Gauss-Newton method, Levenberg-Marquardt method, Steepest descent gradient algorithm, Trust-region reflective method and Adaptive Gauss-Newton method which is described in detail in [5].

2.1 GAUSS-NEWTON METHOD

The Gauss-Newton method is used for solving nonlinear least squares problem which is defined by equation (1)

$$\min_x \phi(x) = \frac{1}{2}\|f(x)\|_2^2 \tag{1}$$

, where x is n-dimensional vector and f is m-dimensional vector function of x. The advantage of Gauss-Newton method compared to Newton method consists in the fact that Gauss-Newton algorithm does not require the evaluation of the second-order derivation. [6], [7]

The gradient equation (2) is used to finding the stationary points of the function $\phi(x)$

$$\nabla\phi(x) = J^T(x)f(x) = 0 \tag{2}$$

, where $\nabla\phi(x)$ is gradient of function $\phi(x)$ and $J(x)$ represents the Jacobian of the function $f(x)$. This problem can be solving by Gauss-Newton algorithm which comprising the following steps.

Step 1: selection of an initial estimate $x_0 \in R^n$

Step 2: repeation until convergence

Step 2.1: solving the equation $J(x_k)^T J(x_k)s_k = -J^T(x_k)f(x_k)$

Step 2.2: $x_{k+1} = x_k + s_k$

2.2 STEEPEST DESCENT GRADIENT METHOD

The steepest descent gradient method is used for the finding of local minimum or local maximum of a function. After determining the initial guess of solution x_0 the gradient of function in this point $\nabla f(x_0)$ is evaluated. The minimum of function $f(x)$ is approached by a sequence of steps s in the negative gradient direction by equation (3). Algorithm converges when the gradient is equal to zero. The algorithm find the local maximum when there is the positive gradient direction. [8]

$$x_{k+1} = x_k - s\nabla f(x_k) \tag{3}$$

2.3 LEVENBERG-MARQUARDT ALGORITHM

Levenberg-Marquardt algorithm is iterative method for finding the local minimum of a function. This method is a combination of the Gauss-Newton method and the Steepest descent gradient method. If the current solution is far from the result, the algorithm uses the method similar to Gradient method. On the other hand if the current solution is close to the result, the algorithm uses the Gauss-Newton method. [9]

2.4 TRUST-REGION REFLECTIVE METHOD

The Trust-Region method represents one of the most effective optimization method. Consider the function $f(x)$, where x is a vector and the resulting value is a scalar. The function $f(x)$ is aproximated by a simpler function $q(x)$ in the region N of the point x. The region N is called trust region. The quadratic approximation of the function $q(x)$ is defined by the Taylor expansion. The first step s is determined from the equation (7).

$$\min_s\{q(s), s \in N\} \tag{7}$$

If $f(x+s)<f(x)$ the actual point is changed to $x+s$. If the inequality does not apply, then the actual point does not change, the trust region N is reduced and the step is determined again. [4]

3 PILOT BEHAVIOUR MODELS

Tustin-McRuer model is one of the most widely used model of pilot´s behavior currently. This model is based on physiological and neurological description of the man. Tustin-McRuer model is described by transfer function (8). The model is described in detail in [1], [3].

$$F_{(p)} = K\frac{(T_3p+1)}{(T_1p+1)(T_2p+1)}\exp(-\tau p) \tag{8}$$

, where K is a human gain [-], T_1 is a neuromuscular time constant [s], T_2 is a lag time constant [s], T_3 is a lead time constant [s] and τ is a reaction delay [s].

It was used another model for approximation of pilot´s behavior. This extended model is described by equation (9) and contains next pole in the denominator. The time constants and other parametres are the same as in the previous model (8),T_4 is the lag time constant [s]. [10]

$$F_{(p)} = K\frac{(T_3p+1)}{(T_1p+1)(T_2p+1)(T_4p+1)}\exp(-\tau p) \qquad (9)$$

4 EXPERIMENT DESCRIPTION

The experiment was held in cooperation in University of Defence in Brno. It was used fixed-based flight simulator with software which can record elevator deflection, fligth altitude and other data. The experiment consisted in measurement of pilot´s response to visual perception which was a step change of flight altitude during longitudinal movement of the airplane. It was the altitude drop of 300 meters. Pilot was trying to return to its original flight level in the shortest period of time. The pilot controled the aircraft using only the elevator, so the aircraft engine thrust was constant.

5 IDENTIFICATION OF PARAMETRES FOR PILOT MODEL

The System Identification Toolbox was used to parameter identification of pilot behavior model. The measured data was identified by all five identification methods and there were used two pilot behavior models – Tustin-McRuer model defined by equation (8) and extended model described in (9). The same pilot is used for the approximation by both models. The initial condition were set to zero. The transport delay was determined manually from the measured data and it was set as fixed parameter in SIT before the start of identification.

Figure 1**:** shows the resulting responses of the pilot approximated by Tustin-McRuer model (8). This is a comparison of original data of elevator deflection with the approximation by models evaluated by five identification methods. It is clearly visible from the graph that the best approximation was achieved by Trust-Region identification method with Best fit parameter of 69.74%. Approximation by Gauss-Newton method was very similar with Best fit parameter of 68.01%. The model identified by Adaptive Gauss-Newton method reached good result. On the other hand, the Levenberg-Marquardt algorithm and Gradient method were not appropriate for approximation by Tustin-McRuer model of pilot. Parameter Best fit of these two methods is less than 10%.

Table 1 shows the parameters of Tustin-McRuer pilot behavior model (8). Model identified by Gradient method contains a very large time constant T_2 and large gain K which confirmes that this model achieved bad results. The similar situation occured with the model identified by Levenberg-Marquardt method which contains very small time constants T_1 and T_2.

method	K [-]	T_1 [s]	T_2 [s]	T_3 [s]	τ [s]	Best Fit [%]
Gauss-Newton	-0.117	0.70964	0.70985	14.122	0.680	68.013
Adaptive Gauss-Newton	-0.086	0.00001	1.49784	19.648	0.680	53.208
Levenberg-Marquardt	-0.220	0.00002	0.00001	13.734	0.680	8.641
Gradient	-98.547	0.04591	10000	18.575	0.680	2.596
Trust-region	-0.116	0.68195	0.66962	14.211	0.680	69.739

Table 1: Parameters of the Tustin-McRuer pilot behavior model (8)

Approximation by Tustin-McRuer model using Gradient method achieved bad results for all pilots, the Levenberg-Marquardt algorithm and Trust-Region method achieved bad results in several cases.

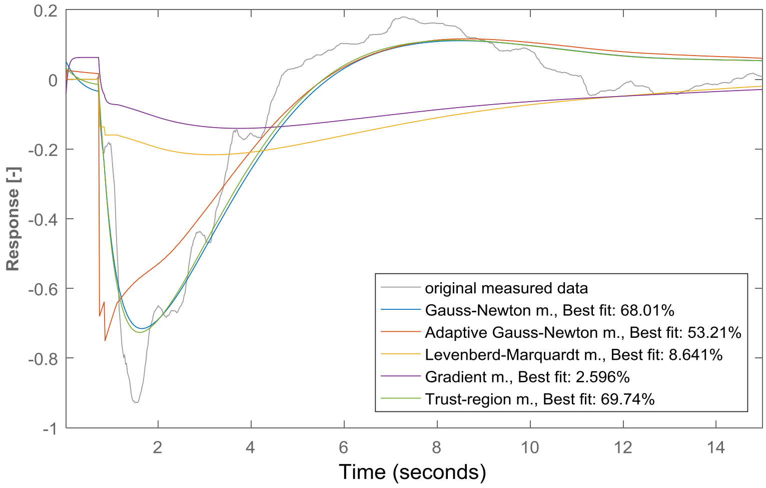

Figure 1: Comparison of acquired pilot response with approximation by Tustin-McRuer model (8)

Figure 2 shows the acquired responses of the pilot approximated by extended model (9). It is visible that the best accuracy was achieved by Gauss-Newton, Adaptive Gauss-Newton and Levenberg-Marquardt method. Parameter Best fit of these three methods is greater than 80%. Identification by Trust-Region method reached good result with parameter Best fit of 77.97%. It is clearly visible that Gradient method is not appropriate for approximation by extended model of pilot. The time constants T_2, T_4 and gain K are very large of model identified by gradient method which is shown in Table 2.

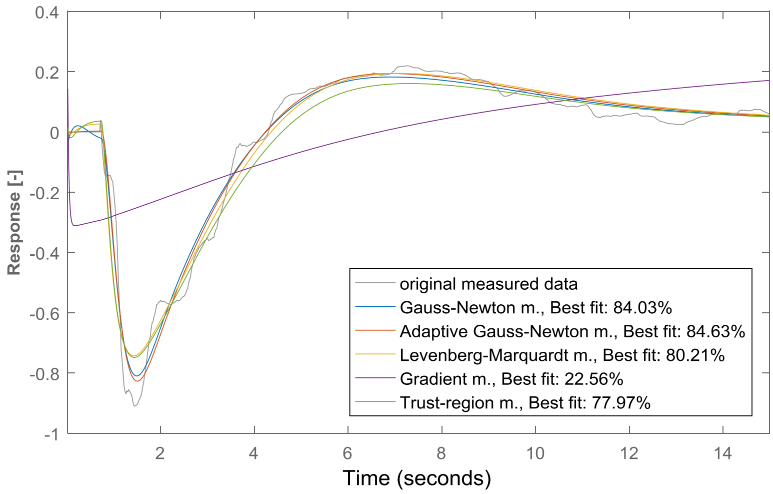

Figure 2: Comparison of pilot response with approximation by extended model (9)

method	K [-]	T_1 [s]	T_2 [s]	T_3 [s]	T_4 [s]	τ [s]	Best Fit [%]
Gauss-Newton	0.007	0.284	0.284	-207.880	0.532	0.700	84.028
Adaptive Gauss-Newton	0.009	0.532	0.263	-160.366	0.307	0.700	84.635
Levenberg-Marquardt	0.004	0.025	0.571	-348.658	0.561	0.700	80.208
Gradient	-70.853	0.025	162.223	-9.853	162.223	0.700	22.562
Trust-region	-0.040	0.033	0.554	38.077	0.553	0.700	77.969

Table 2: Parameters of the extended pilot behavior model (9)

The approximation models of other pilots were similar to pilot who is described here. The measured data were good approximate by extended models identified by all methods except for Gradient method which reached bad results and was not appropriate for approximation by extended model.

6 CONCLUSION

The paper deals with modelling of human pilot behavior using different identification methods of SIT. The paper focus on two approximation models – Tustin-McRuer model and extended model. The Gauss-Newton method, Adaptive-Gauss Newton algorithm and in several cases the Trust-region method or Levenberg-Marquardt method are appropriate for approximation by Tustin-McRuer model. All identification methods except for Gradient method are appropriate for approximation by extended model of pilot. Approximation by the extended model achieved best results than approximation by the Tustin-McRuer model. The goal of modelling of pilot behavior is to determine the status of their training and skills. Analysis of the pilot model should serve to recognize the pilot´s fatique or stress which could prevent the failure of human operator.

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