DEVELOPMENT OF PILOT MODELING AND ITS APPLICATION TO MANUAL CONTROL TASKS

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Abstract

There are considered two models of pilot behavior in manual control tasks. One of them is the modification of structural model and the second is composite model based on neural network approach. The main steps in development of the last model are discussed in detail. The agreement between the composite model is given too.

The application of pilot modeling is considered for two manual control task: development of criteria for PIO and flyin g qualities prediction and display design.

Introduction

The improvement of accuracy in fulfillment of piloting task and flight safety are defined by the flight control system.

General methodology for their development is based on pilot-aircraft system consideration. It proposes the knowledge of pilot control response characteristics. Two approaches to mathematical modeling of pilot behavior are widely used. One of them is the structural approach [1] and the second is optimal control modeling of pilot behavior [2]. The both approaches demonstrated their potentiality to give good agreement with experimental results in crossover frequency range and to describe the main regularities of pilot behavior.

In current research there are considered some modifications of Hess model of pilot control response characteristics developed recently.

The goal to improve the predictive potentialities and accuracy of pilot modeling led to a search of new nontraditional approaches to description of pilot behavior. One of them is neural network approach. The potentiality of the pilot neural network model (NNM) to give characteristics adequate to characteristics estimated in ground-based simulation was shown in [3]. The modification of pilot NNM was called by the authors as composite pilot model.

The applications of the pilot-aircraft system approach are given below for the following manual control tasks:

- Development of criteria for flying qualities prediction;
- Display design.

The mathematical modeling of pilot behavior.

a. <u>Modified structural (Hess's) model</u>.

The experience of usage of Hess model and comparison of its frequency response characteristics with experimental results demonstrated its several limitations:

- the resonant peak of modeled closed loop pilot-aircraft system is lower considerably in high frequency range;
- the adjustment rules for the choice of parameters are based on consideration that crossover frequency (ω_c) is constant for any dynamics configuration (W_c). The experiments [4] demonstrated that ω_c is differed considerably for the different W_c.
- too simplified model describes the visual block (gain coefficient).

Modifications of the Hess model shown on fig. 1 are the following;

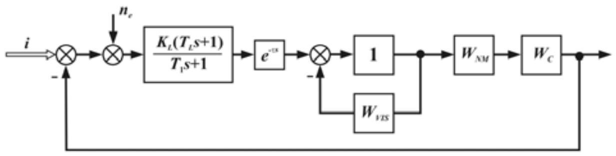

Fig. 1 Modified Hess model

- more complicated model of visual block ($K_L \dfrac{T_L s+1}{T_I s+1}$);
- change of the inner loop;
- taking into account the pilot's remnant;
- change of adjustment rules.

It was offered to choose the model parameters by the minimization of variance of error σ_e^2.

$$\sigma_e^2 = \sigma_{e_i}^2 \left[1 + \frac{1 + T_L^2 \dfrac{\sigma_{\dot{e}_i}^2}{\sigma_{e_i}^2}}{\dfrac{1}{K_{ne}} - \int\limits_0^\infty |W_{CL}|^2 d\omega} \int\limits_0^\infty \frac{|W_{CL}|^2 d\omega}{1 + T_L^2 \omega^2} d\omega \right],$$

where

$$\sigma_{e_i}^2 = \frac{1}{2\pi} \int\limits_{-\infty}^{\infty} \left| \frac{1}{1 + W_{OL}} \right|^2 S_{ii} d\omega;$$

$$\sigma_{\dot{e}_i}^2 = \frac{1}{2\pi} \int\limits_{-\infty}^{\infty} \omega^2 \left| \frac{1}{1 + W_{OL}} \right|^2 S_{ii} d\omega;$$

T_L – pilot-lead time constant;

W_{OL} – open-loop pilot aircraft system frequency response characteristic;

W_{CL} – closed loop pilot aircraft system frequency response characteristic;

K_{ne} – level of remnant spectral density

$$K_{ne} = \frac{0{,}01}{1 - \Delta f},$$

Δf – fraction of attention paid to other (except manual control) task.

The results of mathematical modeling of the modified model are shown on fig 2.

There is seen that this model has better agreement with experimental results then the original version especially at high frequency range.

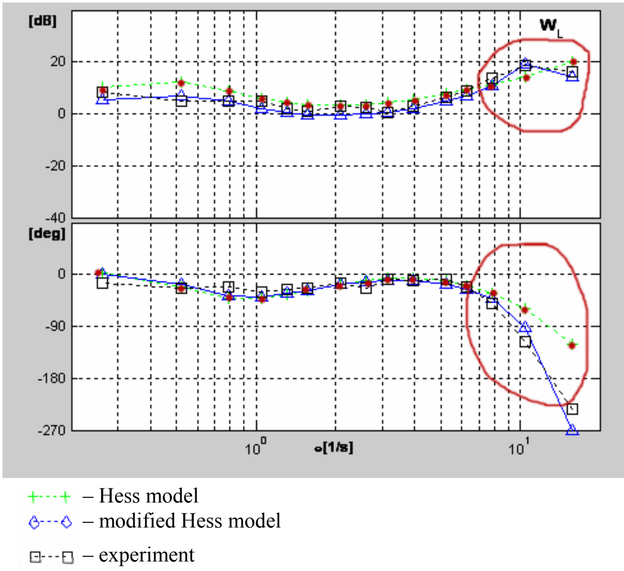

Fig. 2 Comparison of Hess modeling and experimental results

b. <u>Composite pilot model</u>.

The developed pilot composite model is based on consideration that pilot control response characteristics corresponding to the specific configuration are generated by use his experience to control the configurations with close dynamic characteristics.

The development of composite model is based on neural network approach and requires:

- to define a set of pilot neural network models (NNM), $W_{p_i}(j\omega)$. Each of them corresponds to the specific dynamic configuration $W_{C_i}(j\omega)$. The determination of $W_{p_i}(j\omega)$ is carried out from consideration of pilot-aircraft system (fig. 3);

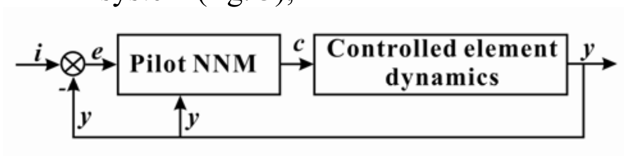

Fig. 3 Pilot–aircraft system

- to define the composite pilot model $W_{p_k}(j\omega)$ for prediction of pilot-aircraft characteristic in case of configuration $W_{C_K}(j\omega)$ which is not included in a set $\{W_{C_i}(j\omega)\}$.

The development of each NNM $W_{p_i}(j\omega)$ consists of the following stages:

1. Selection of technique and definition of criteria for pilot model training.
2. Definition of training set.
3. Definition of model structure.

Selection of technique and definition of criteria for pilot model training.

There were defined four criteria for definition of agreement between NNM and experimental data.

The first criteria is based on the set of values $c^*(t_i)$ (called below as $c^*(i)$) generated by pilot in experiment on simulator in pilot aircraft close-loop system. This criteria using for provision of model training process (fig. 4) is the following

$$mse(c)\_\text{training} = \frac{1}{N}\sum_{i=1}^{N}\left[c^*(t) - c^*_{\text{mod}}(i)\right]^2 .$$

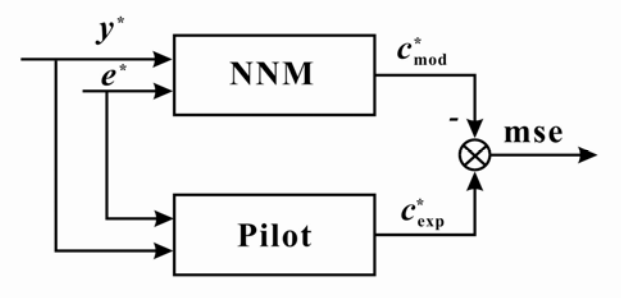

Fig. 4 Model training process

The second criteria $mse(c)\_\text{checking}$ is close to the first one:

$$mse(c)\_\text{checking} = \frac{1}{N}\sum_{i=1}^{N}\left[c_{\exp}(i) - c_{\text{mod}}(i)\right]^2$$

However the difference is in the set of values. This set (so-colled "test set") does not include no one value from the training set.

The approach of this criteria to the zero means that the NNM is able to generate the processes which are not included in training process.

The third and forth criteria used for evaluation of trained NNM in closed-loop system are the following:

$$mse(y)\_\text{closeloop} = \frac{1}{N}\sum_{i=1}^{N}\left[y_{\exp}(i) - y_{\text{mod}}(i)\right]^2$$

$$J = \sum_{k=1}^{15}\left[A_p(\omega_k)\big|_{\exp} - A_p(\omega_k)\big|_{\text{mod}}\right]^2 + \frac{\pi}{180}\left[\varphi_{\exp}(\omega_k) - \varphi_{\text{mod}}(\omega_k)\right]^2,$$

where $A(\omega)$ and $\varphi(\omega)$ – amplitude and phase pilot frequency response characteristics.

All these criteria define the requirements and character of the model.

The development of the model and fulfillment of calculations was carried out with help of Mathlab Neural Network Package. The training of NNM was fulfilled by use of inverse distribution technique [5].

Definition of training.

The technique developed in [6] allows to define correlated $e_i(t)$, $c_i(t)$, $y_i(t)$ and uncorrelated $e_n(t)$, $c_n(t)$, $y_n(t)$ with input $i(t)$ components of the measured signal $e(t)$, $c(t)$ and $y(t)$, where: $e(t) = e_i(t) + e_n(t)$, $c(t) = c_i(t) + c_n(t)$, $y(t) = y_i(t) + y_n(t)$. The training set includes the definition of signal (for example, $c(t)$ or $c_i(t)$) used for the training process and definition of number of signal values in training set. The computer experiments fulfilled for case of linear controlled element dynamics allowed to select correlated with input components of signals in training process. In case of nonlinear controlled element dynamics it was selected the signals included noise component ($c(t)$, $e(t)$, $y(t)$). It was shown also that training set has to be equal to 2400 points.

Definition of NNM structure.

Definition of model structure includes:

- selection of architecture type of model;
- definition of model input and output;
- definition of layers, number of neurons, type of neuron actuation functions.

The time delay neural network (TDNN) type was selected for development of model.

The great number of experiments fulfilled in [5] allowed to define the optimal number of inputs, their type, parameters of time delay, number of neurons and type of actuation function. It was shown that the actuation function has to be linear for the linear controlled element dynamics and nonlinear controlled element dynamics.

The structure of the NNM for the linear dynamic configuration developed in [3] is demonstrated on fig. 5.

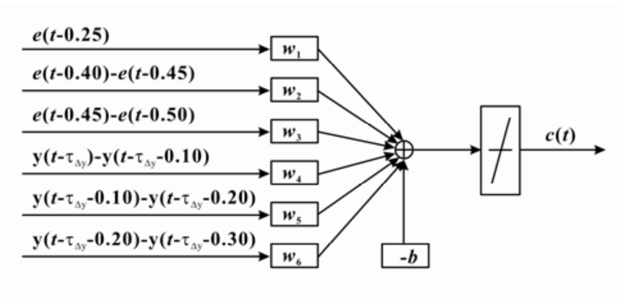

Fig. 5 Structure of NNM

The further application of model demonstrated that in case when pilot generates lag type of compensation the disagreement between experimental and modeling results was demonstrated. It was offered to avoid this shortcoming by installation of the filter $\frac{1}{T_y s+1}$ in the model.

The frequency $\frac{1}{T_y}$ is selected as the value equal to the frequency of controlled element transfer function when the slope of its amplitude frequency response characteristic starts equal to zero. The final structure of the pilot NNM is shown on fig. 6.

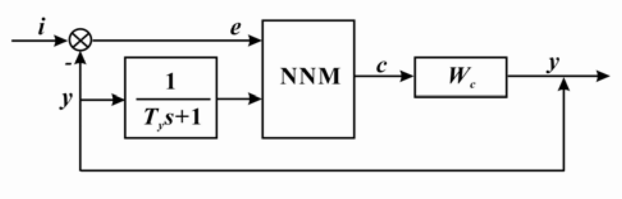

Fig. 6 Final version of pilot NNM

The investigations demonstrate the influence of controlled element dynamics on selection of $\Delta\tau_y$. The increase of dynamics delay required the increase of $\Delta\tau_y$.It was shown that value of $\Delta\tau_y$ is the function of frequency ω_{-135}. The last one is a frequency at which phase frequency response of $W_c(j\omega)\cdot\frac{1}{T_y j\omega+1}$ is equal to 135 deg:

- $\omega_{-135} > 2$ 1/sec for $\Delta\tau_y = 0.35$ sec;
- $1.12 < \omega_{-135} \le 2$ 1/sec for $\Delta\tau_y = 0.4$ sec;
- $0.65 < \omega_{-135} < 1.12$ 1/sec for $\Delta\tau_y = 0.7$ sec;
- $\omega_{-135} \le 0/65$ 1/sec for $\Delta\tau_y = 1.0$ sec.

The potentiality of the NNM to give adequate frequency response characteristics to the experimental results is demonstrated on fig. 7. There are given here frequency response characteristics corresponding to optimal and structure model calculated for the same dynamic configuration and input signal.

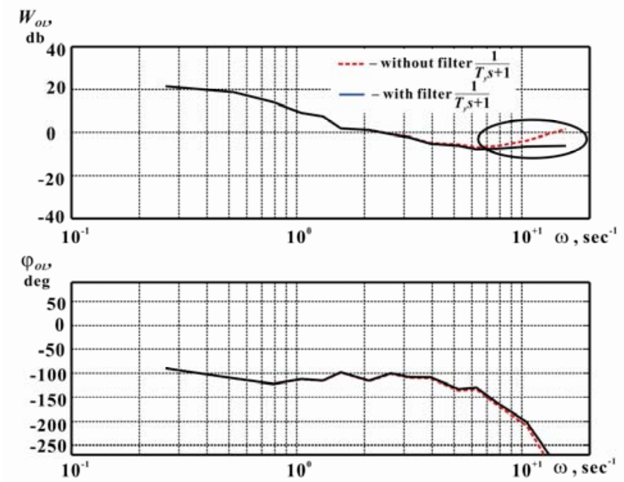

Fig. 7 Comparison of NNM and experimental results

<u>Development of composite model</u>.

Each mathematical model has to correspond to the requirements of adequacy and prediction. The last one is the potentiality to predict the behavior of any object for conditions differed from conditions for which the model was developed. As for the pilot model prediction means the potentiality to select control response characteristic corresponding to the specific set of task variables (controlled element dynamics, input signal, etc) differed from the a set investigated before.

Determination of pilot composite model corresponding to a configuration $W_c(j\omega)$ requires the knowledge of pilot frequency response characteristics of the NNM models calculated before and corresponding to the dynamic configurations $W_{c_k}(j\omega)$ and $W_{c_m}(j\omega)$ close to $W_c(j\omega)$.

The procedure for definition of composite model is the following:

a. Definition of configurations $W_{c_k}(j\omega)$ and $W_{c_m}(j\omega)$ from a set $\{W_{c_i}(j\omega)\}$ investigated before which are close to

$W_c(j\omega)$. This procedure is carried out by minimization of criteria

$$J = \sum_{j=1}^{n} \left[\left| A_{c_i}(\omega_j) \right| - \left| A_c(\omega_j) \right| \right]^2 + \frac{\pi}{180} \left[\varphi_{c_i}(\omega_j) - \varphi_c(\omega_j) \right]^2,$$

where A_c and φ_c – amplitude and phase frequency response characteristics of new dynamic configuration $W_c(j\omega)$ for which the pilot frequency response has to be defined, A_{c_i} and φ_{c_i} – amplitude and phase frequency response characteristics of dynamic configuration $W_{c_i}(j\omega)$ from the data base.

The result of this procedure are two configurations W_{c_1} and W_{c_2} characterizing by the lowest values of J_1 and J_2.

b. Calculation of composite pilot model $W_p(j\omega)$ corresponding to $W_c(j\omega)$.

The pilot frequency response characteristics $W_p(j\omega)$ are calculated by linear interpolation of pilot describing functions $W_{p_1}(j\omega)$ and $W_{p_2}(j\omega)$ corresponding to two controlled element dynamics which are the closest to the $W_c(j\omega)$.

The values of amplitudes $A_p(\omega_i)$ and phases $\varphi_p(\omega_i)$ are defined from the following equations

$$A_p(\omega_i) = A_{p_1}(\omega_i) - \frac{A_{p_1}(\omega_i) - A_{p_2}(\omega_i)}{I_{A_1}(\omega_i) - I_{A_2}(\omega_i)} \cdot I_{A-1}(\omega_i)$$

$$\varphi_p(\omega_i) = \varphi_{p_1}(\omega_i) - \frac{\varphi_{p_1}(\omega_i) - \varphi_{p_2}(\omega_i)}{I_{\varphi_1}(\omega_i) - I_{\varphi_2}(\omega_i)} \cdot I_{\varphi-1}(\omega_i),$$

here $A_{p_1}(\omega_i)$, $A_{p_2}(\omega_i)$ and $\varphi_{p_1}(\omega_i)$, $\varphi_{p_2}(\omega_i)$ – amplitudes and phases of $W_{p_1}(j\omega)$ and $W_{p_2}(j\omega)$ corresponding to the dynamic configurations $W_{c_1}(j\omega)$ and $W_{c_2}(j\omega)$;

I_{A_1}, I_{A_2}, I_{φ_1}, I_{φ_2} – are differences between dynamic configurations $W_{c_1}(j\omega)$ or $W_{c_2}(j\omega)$;

$I_{A_m}(\omega_i) = \left| A_{c_m}(\omega_i) - A_c(\omega_i) \right|$, where $m = 1, 2$.

c. Development of NNM of pilot composite model $W_p(j\omega)$.

The developed composite model has to be trained in time domain to get NNM. In case when input signal is $i(t) = \sum_k A \sin \omega_k t$ it can be done by the following equation:

$$c_i(t)\big|_{W_c} = \sum_k \left| \frac{W_{CL}}{W_c} \right| A_k \sin(\omega_k t + \varphi^*)$$

$$y_i(t)\big|_{W_c} = \sum_k \left| W_{CL} \right| A_k \sin(\omega_k t + \varphi^{**}_{\Phi_{CL}})$$

$$e_i(t)\big|_{W_c} = \sum_k \left| \frac{W_{CL}}{W_{OL}} \right| A_k \sin(\omega_k t + \varphi^O),$$

These signals were used for development of pilot NNM corresponding to $W_c(j\omega)$.

The developed technique was tested for prediction of $W_p(j\omega)$ corresponding to the different configurations. One of them is shown on fig. 8.

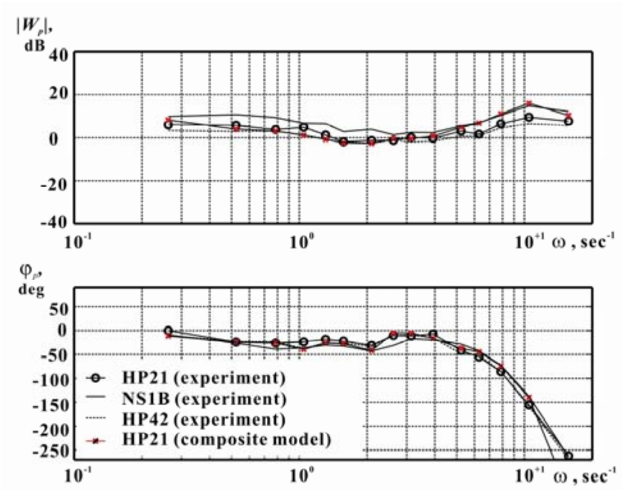

Fig. 8 Comparison of composite model and experimental results

Here $W_p(j\omega)$ is composite model corresponding to configurationHP21. The other two pilot describing functions are the pilot frequency response characteristics corresponding to configurations HP42 from HAVE PIO data base and NS1B from Neal Smith data base which are the closest to HP21. The shown results demonstrates good agreement of the predicted pilot described function with $W_{p_{\exp}}$ identified then in experiment on simulator.

The application of pilot–aircraft system modeling.

There are given below two applications of pilot modeling. One of them is the development of flying qualities where the composite pilot model was used. The second application is the display and flight control system design where modified Hess's model was used for that purpose.

<u>The criteria for prediction of flying qualities and PIO tendency level</u>.

The criteria for prediction of flying qualities and PIO tendency was developed in [6] where the parameters are resonant peak of closed loop system (r) and pilot workload parameter $\Delta\varphi(t)$ were measured in experiments fulfilled with more then 80 HAVE PIO, Neal Smith and LAHOS configurations.

On the basis of the measurements and comparison of the results with pilot rating there were obtained the boundaries of the first and the second levels of flying qualities and PIO tendency. The same parameters were calculated by modeling of pilot-aircraft system, where composite pilot model was used. The results of the modeling demonstrated the necessity to change the boundary. The modified criteria is shown fig. 9.

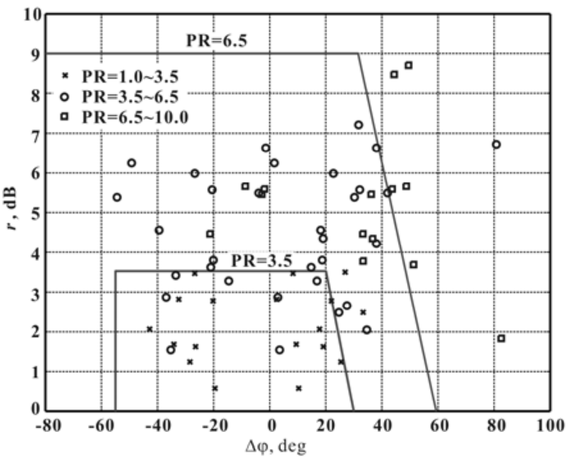

Fig. 9 Modified criteria for flying qualities and PIO prediction

The comparison of predicted levels of ratings with pilot rating level from data base for the same configurations demonstrated that criteria allowed to predict the first level with probability 0.8, the second, 0.75 and the third 0.65.

The other criteria for prediction of flying qualities is based on direct calculation of pilot subjective rating (PR). Such criteria requires the knowledge of relationship between pilot rating and calculated pilot-aircraft system parameters. Two parameters were selected for definition of this relationship. One of them is the mean square error correlated with input signal σ_{e_i}. The values of σ_{e_i} were calculated by mathematical modeling of pilot aircraft system where pilot neural network model corresponding to the investigated configuration was used. The correlation between pilot rating and σ_{e_i} is given on fig. 10.

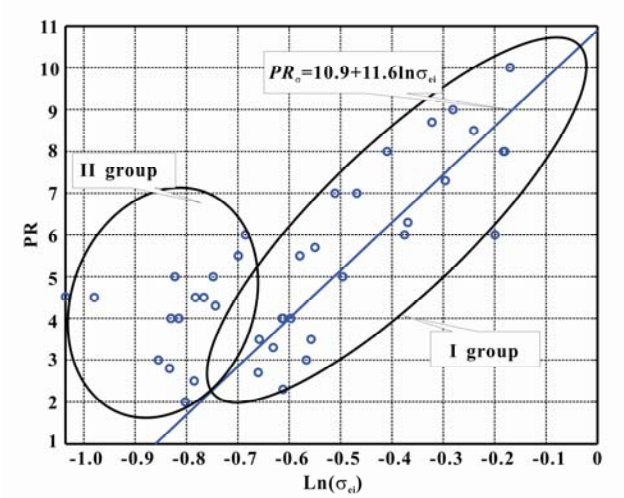

Fig. 10 Agreement between pilot ratings and accuracy of tracking

There is seen that all configuration can be divided on two groups. One of them is characterized by good correlation of PR and σ_{e_i} which can be described by Weber-Fechner law

$$PR = A + B\ln\sigma_{e_i} = 10.9 + 11.6\ln\sigma_{e_i}\,.$$

The other group of dynamic configuration is characterized by the other parameter correlating with PR. It is pilot lag-lead phase parameter $\Delta\varphi_p^-$. The value of this parameter is the maximum negative difference between $\varphi_p(\omega)$ and $\varphi_p^{opt}(\omega)$ (where $\varphi_p(\omega)$ – describing function phase corresponding to investigated W_c, $\varphi_p^{opt}(\omega)$ – pilot describing function corresponding to dynamic configuration which does not require pilot any lag or lead compensation. The parameter $\Delta\varphi_p^-$ has to be defined on all frequency range. It was obtained the following relationship between PR_φ and parameter $\Delta\varphi_p^-$:

$$PR_\varphi = -0.075\Delta\varphi_p^- + 0.75 .$$

The final value of pilot rating is calculated according to the following equation

$$PR = \max(PR_\sigma, PR_\varphi) .$$

The agreement between calculated pilot rating given by pilot in the flight for the same dynamic configuration is good enough (fig. 11). Only three configurations from 40 Neal Smith and HAVE PIO data base, are out of the limits $\Delta PR = \pm 1.5$.

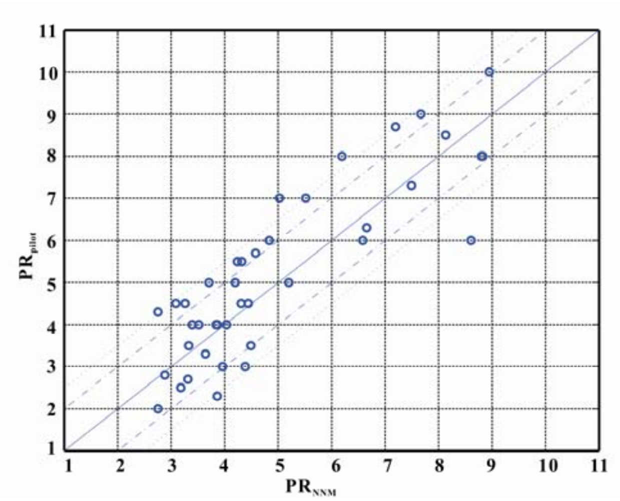

Fig. 11 Experimental (PR_{pilot}) and calculate (PR_{NNM}) pilot retings

<u>The display and flight control system design</u>.

One of the more difficult piloting task is the path control. The terrain following and landing (including spot landing) piloting tasks are related here. In all of them the controlled element dynamics has high order of pole. For example in longitudinal channel pilot has to carry out altitude control. Which is characterized by the transfer function, $W_c = \dfrac{H(s)}{\delta_e(s)} \cong \dfrac{K_c}{s^2(s^2 + 2\xi\omega_{sp}s + \omega_{sp}^2)}$. Such dynamics causes considerable workload and decrease of variance $\sigma_{\Delta H}^2$. Except it the spot landing is accompanied by additional problem – speed instability, requiring constant pilot's actions in speed channel.

The improvement of path control might be achieved by transfer from variable – $H(t)$ to its predicted value $H^*(t) = H(t) + \dot{H}T = A + VT\theta^*$.

This variable can be changed on $\gamma = \dfrac{H}{L} + \theta^*$, where $L = TV$.

There is possible to show that predicted variable $\theta^* = \theta + \dot{\theta}\dfrac{T}{2}$.

In that case the controlled element dynamic is the following

$$W_c = \frac{\varepsilon_\gamma(s)}{\delta_e(s)} = \frac{K_c\left(Ts^2 + 2s + \dfrac{2}{T}\right)}{2s^2(s^2 + 2\xi\omega_{sp}s + \omega_{sp}^2)} . \qquad (1)$$

The increase of T leads to improvement of controlled element dynamics. For example, when $T >> 1$

$$W_c \cong \frac{Ts + 1}{2s(s^2 + 2\xi\omega s + \omega^2)} .$$

Except it parameter T influences on transfer function

$$W_c = \frac{H}{\varepsilon_\gamma} = \frac{T}{\dfrac{T^2}{2}s^2 + Ts + 1}$$

and variance of altitude $\sigma_{\Delta H}^2$ too. The optimization of parameter T (or L) provided minimum variance $\sigma_{\Delta H}^2 = f(T)$ was carried out by mathematical modeling and in ground–based simulation.

The mathematical modeling includes the following steps:

- selection of pilot aircraft system parameters for controlled element dynamics (1) and modified Hess model (fig. 1). The parameters were defined by minimization of variance $\sigma_{\varepsilon_\gamma}^2$. It was shown that increase of time T leads to decrease of variance $\sigma_{\varepsilon_\gamma}^2$;
- definition of T_{opt} . This step was fulfilled by calculation, of variance $\sigma_{\Delta H}^2 = f(T)$. For the pilot's parameters defined at the previous step.

According to fig. 12 the optimum value T corresponds to $0.7 \div 0.8$ sec.

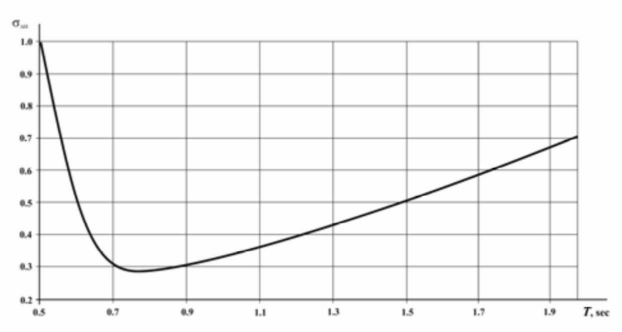

Fig. 12 Influence of T on mean square error $\sigma_{\Delta H}$

The ground–based simulation was fulfilled on MAI fixed–based simulator with wide angle of view computer–generated visual system. This system demonstrated the scenario and HUD on the screen (fig. 13).

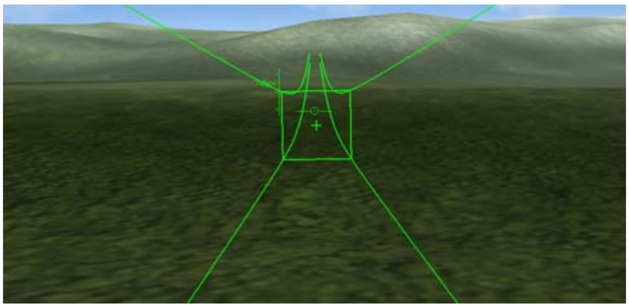

Fig. 13 HUD display

The last one imaged the tunnel with sliding window where the projection of velocity vector (ε_γ) was shown. The tunnel allowed to estimate the current error of altitude. The experiment fulfilled for terrain–following task and landing for the different parameter T gave its optimum minimum value ($T = 0.7 \div 0.8$ sec) corresponding to result of mathematical modeling.

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