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Improvement and Parameters Optimization of Washout Algorithm in Motion Simulator

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Abstract

The purpose of this paper is to improve the low amplitude signal and get optimal washout algorithm parameters that can accurately provide vehicle motion sensation at high fidelity, within motion platform's limitations for a motion simulator. To achieve the first goal, an improvement based on the fuzzy strategy is made to enhance its ability to simulate the low amplitude signals. To get the optimal parameters of the washout algorithm, a fitness function is proposed based on the human perception and its correlation coefficients, perception error and displacement of the platform. To ensure the stability of the whole algorithm, the Hurwitz criterion is applied to restrict parameters. To get the optimal solution of the fitness function, the fireworks algorithm is used and can efficiently avoid local extremum. The proposed algorithm is proposed in Matlab/Simulink. The results of Fireworks algorithm show that it is an excellent multi-objective optimization algorithm and can get optimal results. With the results of the improvement algorithm and optimal parameters, we can prove that the method provides better performance in human perception, reference shape tracking and exploiting the platform more efficiently within motion limitation.

Key words

Stewart platform, motion simulator, washout algorithm, fireworks algorithm, parameters optimization

1. Introduction

The Stewart platform has been used in various motion simulators as motion sensation generating source within its limited movement space, such as flight and drive simulators [1].

Washout algorithm is one of the key factors that affect human sensations, which reproduces real feelings for the operators of the simulator. Its inputs are specific force [2] and angular velocity of the real vehicle. For now, classical washout algorithm, adaptive washout algorithm [3], optimal washout algorithm [4] and nonlinear washout algorithm [5] are four commonly used washout algorithm. Among them, the most widely used is the classical washout algorithm. Its structure is so simple that easy to implement [6]. According to the previous studies, the classical washout algorithm exists two usual problems: (1) The simulation result of low amplitude signal is not very obvious; (2) Parameters are hard to determine and improper parameters may lead to large distortion easily, even cause the instability of the simulator.

There are two methods to determine washout algorithm parameters in the previous. The first one is filed adjustment based on the experiences of engineers. This way is highly subjective and easily affected by the experience of debuggers, besides, the debugging process is complex for the large number of parameters. The other is the exhaustive search method according to the washout filter's time domain response [7], this method in order to ensure the safety of the motion platform that adjustment of the parameters if more conservative, for the consideration of extreme driving condition.

In this paper, Firstly we improve the structure of classical washout algorithm to better reproduce the low amplitude signal; then according to the factors of simulator such as stability and simulation fidelity and platform movement performance conditions, washout algorithm parameters are optimized using the firework algorithm; lastly, a simulation analysis is made to the above algorithm to verify the superiority of its performance.

2. Motion simulation technology

The motion simulator consists of the Stewart platform, operation module, visual system, dynamical system and washout algorithm. The basic function of washout algorithm is generating specific forces and rotations at driver's perception in the simulator to those they would experience like in a real vehicle [8]. The well known classical washout algorithm mainly consists of translation channel, tilt-coordinate channel and rotational channel. The basic structure of classical washout algorithm is shown in Fig. 1.

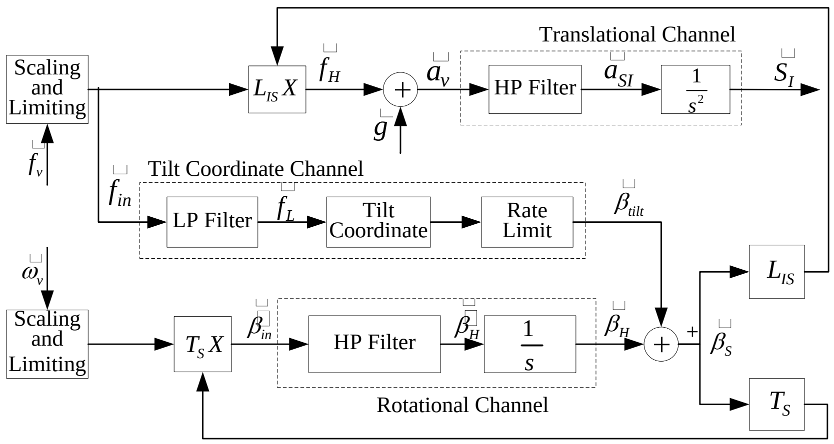


Fig.1. Structure of Classical Washout algorithm

For the low-frequency component of acceleration and angular velocity will lead to the movement of the platform beyond its limit. The high-pass filter is used in the translational and rotational channel to eliminate it and ensure the platform return to its original point timely. High-pass filters of translational and rotational channel are shown in equation (1) and (2).

$$HP_{trans} = \frac{s^2}{s^2 + 2\varsigma\omega_n + \omega_n^2} \tag{1}$$

$$HP_{rot} = \frac{s}{s + \omega_b} \tag{2}$$

The low-frequency component of acceleration is obtained by the low-pass filter in the tilt coordinate channel, which can be called the sustained component. This part is simulated by tilting the platform below the human perception threshold. The components of gravity work as a deceptive sustained component. The low-pass filter is shown in equation (3).

$$LP_{tilt} = \frac{\omega_n^2}{s^2 + 2\varsigma\omega_n + \omega_n^2} \tag{3}$$

In the above three equations, ω is cutoff frequency and ς is damping ratio. The commonly used parameters of classical washout algorithm are shown in table 1 that is from UTIAS simulator [9].

Table.1. Commonly used Washout Algorithm's Parameters

Model name	Order	ω_n / (rad/s)	ζ
Translational HP filter for the x direction	2	2.5	1.0
Translational HP filter for the y and z directions	2	4.0	1.0
Translational LP filter for the x direction	2	5.0	1.0
Translational LP filter in the y direction	2	8.0	1.0
HP filter for rotational channel	1	1.0	--

Human perceives the movement of the simulator by the vestibular system located in the inner ear. According to the human perception model provided by Young and Meiry[10], the human perception can be obtained after the washout algorithm.

3. Improvement of the Washout Algorithm

The classical washout algorithm consists of high-pass filter, low-pass filter and tilt-coordinate module [8]. In general, the translation and rotation channels are second-order high pass filter, and the tilt-coordinate channel is the first-order low pass filter. For improving the defects that the simulation result of low amplitude signal is not very obvious discussed in section1, we need to make a fuzzy adaptive transformation for the low amplitude input signals, which are below 1.5m/s2 for acceleration. The fuzzy controller is SISO mode. Input is U (equation 4). The proportional coefficient for the output is k. The lower amplitude input acceleration is transformed as equation 5. The basic structure is shown in Fig. 2.

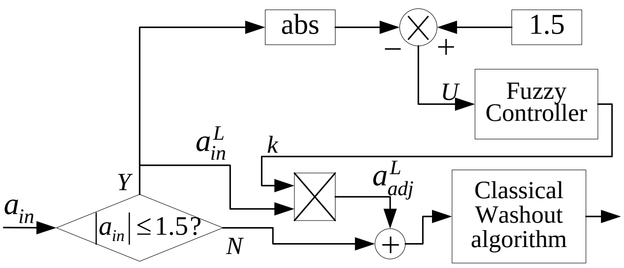


Fig.2. Sketch diagram of fuzzy adaptive transformation of input acceleration

$$U = 1.5 - abs\left(a_{in}^L\right) \tag{4}$$

$$a_{adj}^L = k a_{in}^L \tag{5}$$

The greater the U is, the smaller the input acceleration amplitude is, so the larger scale factor is needed, and vice versa. Fuzzy subsets of u and K are defined as{ NB (negative big), NS (negative small), ZO (zero), PS (positive small), PB (positive big) }. To make the platform return to median timely after a motion simulation, we need to change the form of washout filters, namely: change the high-pass translation channel from the second order to the third order and the high-pass angular channel from the first order to the second order [11].

4. Parameter Optimization Based on Fireworks Algorithm

4.1 Methods to Determine the Objective Function

According to requirements for the motion simulators, Fitness function of washout algorithm optimal parameters should be considered in the following four principles:

1) Human perception error of occupant between the real vehicle (hereinafter referred to as the reference sensation) and the motion of the simulator system (hereinafter referred to as the simulation sensation) is less.

2) The fluctuation of the sensory error is small, so that it can reduce the fluctuation of the signal caused by the change of the signal.

3) The correlation coefficient between the reference sense and the simulated perception is small in order to make the two shapes are similar.

4) The overall posture variation of the platform is small. That is, the angle and the displacement are small.

For the 1st principle, we take the Integral of Squared Error (ISE) as the evaluation index. The smaller the value is, the better the simulation result. That is:

$$J_{d,\mathrm{err}} = \int \left(k_{err,f} \vec{e}_f^{\,2} + k_{err,\omega} \vec{e}_\omega^{\,2} \right) dt \tag{6}$$

Where, $J_{d,err}$ is the fitness value of human perception error, $k_{err,f}$ and $k_{err,\omega}$ represent the penalty factors, $\vec{e}_f$ and $\vec{e}_\omega$ represent specific force and angular velocity sensation error respectively and shown in Equation 3.

$$\begin{cases} \vec{e}_f = \vec{f}_v - \vec{f}_s \\ \vec{e}_\omega = \vec{\omega}_v - \vec{\omega}_s \end{cases} \tag{7}$$

Where $\vec{f}_v$ and $\vec{\omega}_v$ represent the reference sensation of specific force and angular velocity, $\vec{f}_s$ and $\vec{\omega}_s$ represent the simulation ones.

For the 2nd principle, although some feasible solution may reduce the sense error during the optimization process, there may be some sensible oscillations. These solutions are not the optimal solution. So we take the differential of human perception's error as the evaluation index, and the smaller the value, the better the simulation. That is:

$$J_{d,err\_der} = \int \left(k_{\dot{e},f} \dot{\vec{e}}_f^{\,2} + k_{\dot{e},\omega} \dot{\vec{e}}_\omega^{\,2} \right) dt$$

(8)

Where J_{d,err_der} is the fitness value of the differential of human perception error, $\dot{\vec{e}}_f$ and $\dot{\vec{e}}_\omega$ are the differential of specific force and angular velocity, $k_{\dot{e},f}$ and $k_{\dot{e},\omega}$ are their penalty factors.

For the 3rd principle, we use the correlation coefficient to measure the simulation and reference signal's consistency, the larger the correlation coefficient, the more similar the shape of the two signals, and better simulation results. Therefore, fitness function of correlation coefficient is:

$$J_{d,cor} = k_{cor,f}(1-cor(\vec{f}_v,\vec{f}_s))^2 + k_{cor,\omega}(1-cor(\vec{\omega}_v,\vec{\omega}_s))^2$$

(9)

Where $J_{d,cor}$ represent the fitness value of this principle, $cor(x_1,x_2)$ means the correlation coefficient of x_1 and x_2, $k_{cor,f}$ and $k_{cor,\omega}$ represent the penalty factor for the correlation coefficients of specific force and angular velocity.

For the 4th principle, it is required to achieve a certain balance in the platform motion and simulation effects, that is, to achieve the best simulation results with less motion cost. Therefore, the fitness value function of this part is:

$$J_{d,dis} = \int k_{S_I}\vec{S}_I^2 dt + \int k_{\beta_S}\vec{\beta}_S^2 dt \qquad (10)$$

Where, $J_{d,dis}$ is fitness value of motion cost, $\vec{S}_I$ and $\vec{\beta}_S$ are displacement and Euler angle of motion platform, k_{S_I} and k_{β_S} are their penalty factor respectively.

According to the analyses above, we can get the whole fitness value that is equation 8. The main structure of calculation of fitness value and adjustment of optimal parameters for the washout algorithm is shown in Fig. 3.

$$\min\left(J\left(\vec{x}_d\right)\right) = \min\left(J_{d,err} + J_{d,err\_der} + J_{d,cor} + J_{d,dis}\right) \qquad (11)$$

Where, $\vec{x}_d = (x_1, x_2, \ldots x_n)$ is the vector to be solved, which is consists of parameters to be optimized. So the optimal solutions of fitness function are the optimal parameters.

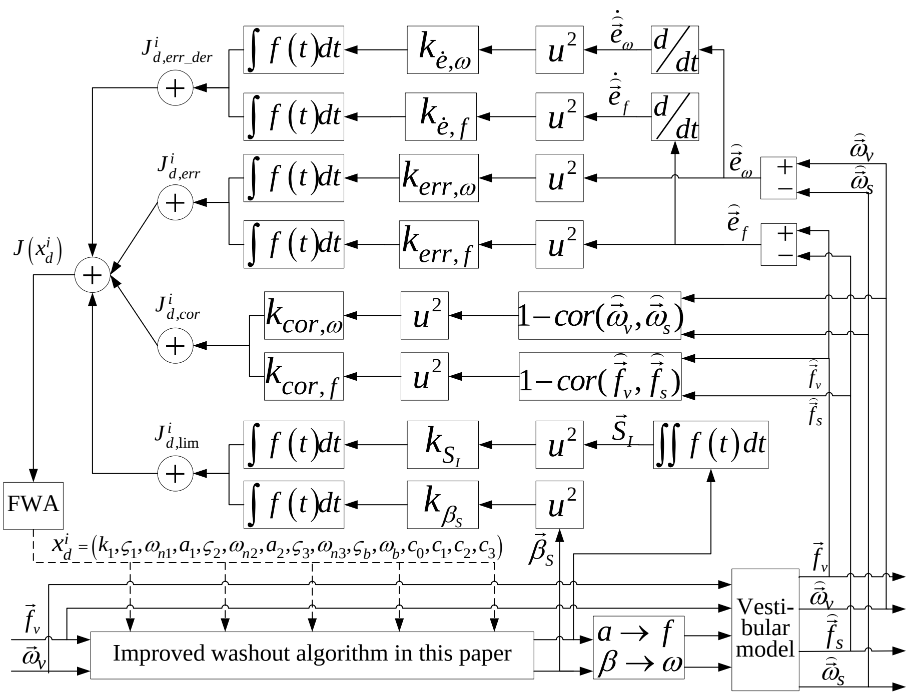


Fig.3. Flow chart of washout algorithm parameters adjustment and fitness calculation

4.2 Determination of the Constraint Conditions

The stability of motion simulator is closely linked to the washout algorithm's parameters. If chose not probable, it is easy to cause instability oscillation, and even damage the platform. So the parameters must ensure the system's stability firstly. Previous washout algorithm parameters selection rarely considers the stability constraint, in this paper; we introduce the Hurwitz criterion to constrain the washout filter's parameters to ensure the stability of the simulator.

The characteristic equation of the linear acceleration channel is 3rd order, that is,

$$s^3 + (2\varsigma_1\omega_{n1} + \omega_{n2})s^2 + (\omega_{n1}^2 + 2\varsigma_1\omega_{n1}\omega_{n2})s + \omega_{n1}^2\omega_{n2} = 0 \tag{12}$$

So its Hurwitz criterion is:

$$S.t.1 \begin{cases} 2\varsigma_1\omega_{n1} + \omega_{n2} > 0 \\ \omega_{n1} + 2\varsigma_1\omega_{n2} > 0 \\ \omega_{n1}^2 + 2\varsigma_1\omega_{n1}\omega_{n2} + \omega_{n2}^2 > 0 \end{cases} \tag{13}$$

The characteristic equation of tilt-coordinate channel is 2nd order. That is $s^2 + 2\varsigma_2\omega_{n3}s + \omega_{n3}^2 = 0$. Its Hurwitz criterion is:

$$S.t.2 \begin{cases} \varsigma_2\omega_{n3} > 0 \\ \omega_{n3}^2 > 0 \end{cases} \tag{14}$$

The characteristic equation of high-pass angular channel is 1st order. That is $s+\omega_{b1}=0$. Its Hurwitz criterion is:

$$S.t.3\ \omega_{b1}>0 \qquad (15)$$

In addition to stability constraints, it is necessary to consider the constraints of the platform motion capacity, that is:

S.t.4 The movement of the platform is within its limitation.

S.t.5 The acceleration and angular velocity of the platform are within the maximum of the platform movement capacity.

4.3 Optimization with Fireworks Algorithm

Based on the discussion above, Optimization parameters for the washout algorithm are a typical multi-objective problem, which can be solved by the swarm intelligence algorithm. Fireworks algorithm (FWA) is a kind of swarm intelligence algorithm proposed by Y Tan in 2010. It has been widely used in many fields, and has demonstrated good performance in solving complex optimization problems [12-14]. Through simulation of fireworks' explosion in the air, FWA establish its mathematical model and by introducing random factors and selection strategy, it becomes an explosive parallel search method. FWA mainly consists of four parts: the explosion operator, variation explosion, mapping rules and selection strategies. Compared with genetic algorithm (GA), particle swarm optimization algorithm (PSO), FWA with the idea of immune density chooses fireworks, and with its distributed information sharing mechanism, can effectively avoid the premature convergence, enhancing the effectiveness of the algorithm, so the FWA can be used to the washout algorithm parameters optimization process. According to the optimal parameters fitness function of the washout algorithm, we use the FWA search for the optimal solutions from the constrained probable space. Fig. 4 is the flow chart that uses fireworks algorithm search for optimal parameters.

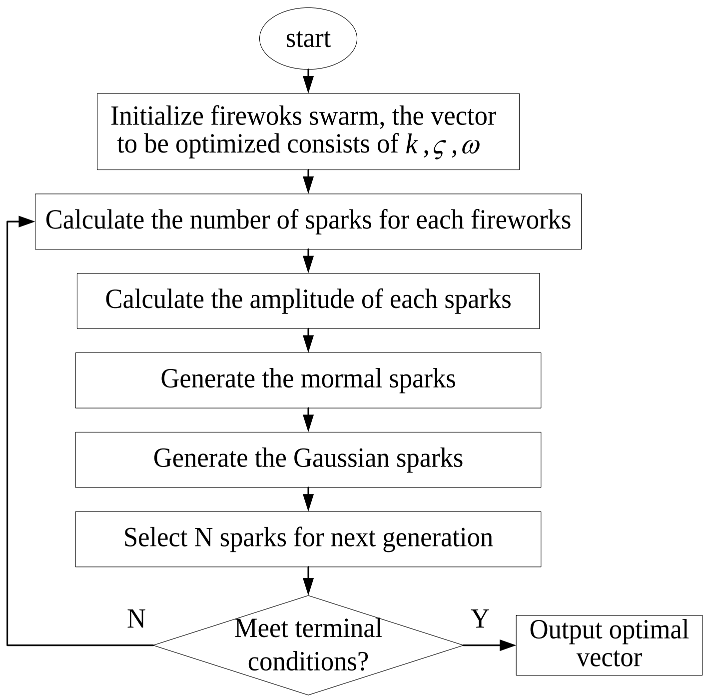


Fig.4. Flow chart of using FWA search for optimal washout parameters.

5. Results and Discussion

Multi-objective optimization problem generally exists a series of Pareto optimal solutions. The breadth and uniformity of the optimal solution distribution can effectively reflect the performance of the intelligent optimization algorithm when solving the multi-objective optimization problem [15]. In order to verify the performance of the fireworks algorithm in solving multi-objective optimization problems, we take the performance of FWA compare with that of GA and PSO in solving typical test functions. The two typical test functions are:

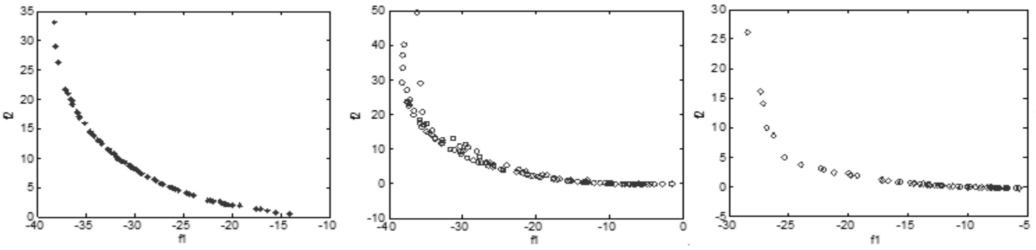
(1) 2-dimensional objective test function

$$\begin{aligned}&\min f_1 = x_1^4 - 10x_1^2 + x_1x_2 + x_2^4 - x_1^2x_2^2\\&\min f_2 = x_1^4 + x_1x_2 + x_2^4 - x_1^2x_2^2\\&\text{s.t.} -5 \le x_1, x_2 \le 5\end{aligned} \tag{16}$$

(2) MOP7 test function

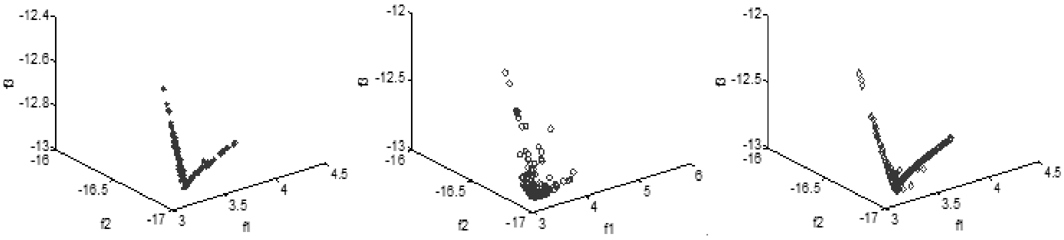
$$\min f_1 = \frac{(x_1-2)^2}{2} + \frac{(x_2+1)^2}{13} + 3$$
$$\min f_2 = \frac{(x_1+x_2-3)^2}{36} + \frac{(-x_1+x_2+2)^2}{8} - 17$$
$$\min f_3 = \frac{(x_1+2x_2-1)^2}{175} + \frac{(-x_1+2x_2)^2}{17} - 13$$
$$\text{s.t.} -4 \le x_1, x_2 \le 4$$

(17)



(a)FWA (b)GA (c)PSO

Fig. 5. Results of 2-dimensional



(a)FWA (b)GA (c)PSO

Fig. 6. Results of MOP7 test function

Fig. 5 is the result of 2-dimensional objective function, and fig. 6 is the result of MOP7 test function. In both of the two figures, graph (a) is the result of using FWA algorithm, graph (b) is the result of using GA algorithm, graph (c) is the result of using PSO algorithm. In figure 4, the horizontal and vertical axes represent the values of function f1 and f2 respectively. Experimental results show that, compared with GA and PSO algorithm, the FWA algorithm can maintain the optimal solution and the uniformity of the breadth of the distribution of the Pareto front are better. In figure 5, three axes represent the values of function f1~f3 respectively. Experimental results show that the Pareto front is convex, and compared with PSO and GA algorithm, FWA algorithm can better maintain the optimal solutions that with better distribution and broad. This is due to the explosion and mutation mechanism of FWA algorithm, which ensures the depth and breadth of searching. At the same time, the evolutionary and memory operation makes the algorithm low degradation probability, as well as keep the diversity of the searching population, while enhancing the algorithm's ability to self-regulate.

After verifying the performance of FWA, we apply it to calculate the optimal parameters of washout algorithm, and then compare the performance of optimization parameters with commonly used parameters through the experiment. Results are shown in Fig. 7 to fig. 9.

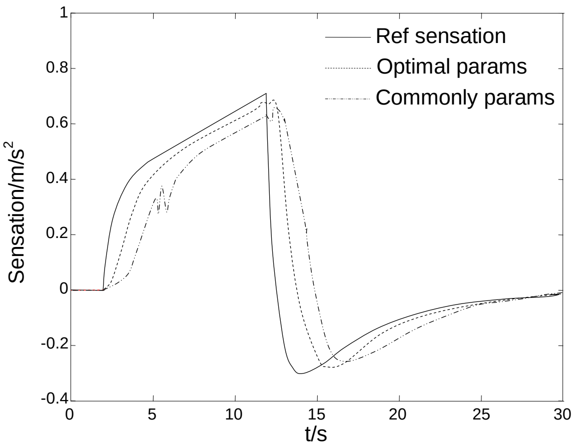


Fig.7. Contrast of the human perception

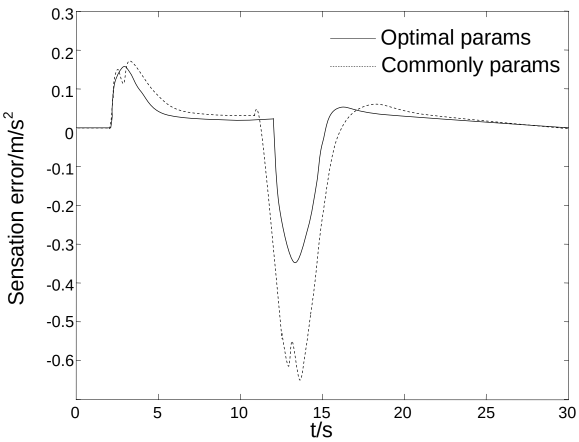


Fig.8. Contrast of the perception error

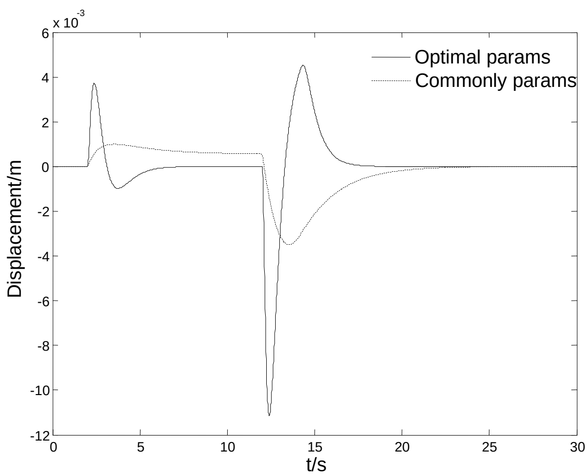


Fig.9. Contrast of platform's displacement

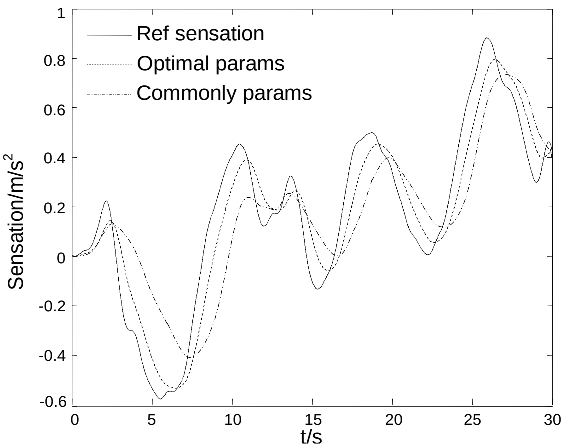


Fig.10. Contrast of the human perception

Fig.7 is the output perceptions of optimal and commonly used parameters. In this figure, the dashed line is the optimal parameters; the dash- dot- dot line is commonly used parameters; the solid line is the actual equipment (hereafter called the reference signal). It can be seen from the figure, compared to the commonly used parameters, the output of optimal parameters is basically the same with reference signal, the simulation for the low amplitude signal is more obvious and is closer to the reference signal; the output of commonly used parameters has a slight vibration when the signal mutate, which is an unstable phenomenon, while the optimal parameters with better stability. According to the statistical data, the correlation coefficient of the output of commonly used parameters and the reference signal is 85%, while the correlation coefficient of the output signal of the optimal parameters and reference signal is 97%. So the output of optimal parameters and the reference signal are higher consistency.

Fig. 8 is the comparison of human perception error between optimal parameters and commonly used parameters. The solid line represents the optimal parameters; the dashed line represents the commonly used parameters. From the figure, we can see that the maximum error of commonly used is 0.65m/s2. While the optimal parameter is 0.35m/s2, and the total error is also smaller.

Fig. 9 is the platform's displacement comparison. The meanings of line types are the same with Fig.7. It can be seen from the figure, that the optimal parameters can make more effective use of the platform's motion ability when comparing to the commonly used parameters. Also, the platform can return neutral timely after a motion simulation, so it can provide larger movement space for the next simulation.

In order to further verify the performance of optimal parameters' washout algorithm proposed in this paper, filtered white noise signal is introduced that includes acceleration, deceleration and other complex conditions as input signal for further simulation. The contrast diagram of human perception is shown in Fig. 10. The meanings of line types are the same with Fig.7. It can be seen from this figure that the optimal parameters' washout algorithm can effectively follow the reference sense with little time delay. While commonly used parameters classical washout algorithm has the output with a large time delay, and the overall simulation effect and the former is also an obvious gap.

6. Conclusion

In this paper, the structure of the classical washout algorithm has been improved by the fuzzy controller to enhance its ability to reproduce the perception with low amplitude. Then with the Hurwitz stability criterion and human perception error and other aspects, we propose an optimal algorithm parameters' adjustment method, and apply the fireworks algorithm to solve it. Specifically, for the following:

(1) Parameters of washout algorithm have great influence on the motion cueing effect, and different platforms need different parameters. In the past, parameter adjustment method was difficult to get optimal parameters. The main factors affect washout algorithm's parameters are platform's parameters and human perception characteristics. In order to ensure the stability of the system, the Hurwitz stability criterion is used to constrain the parameters.

(2) According to the platform pose, human perception error and its change rate, correlation coefficient, we formulate the washout algorithm optimal parameter fitness function, and use the firework algorithm for solving it. Simulation results show that compared with the commonly used

algorithm, this method gets higher fidelity and stability within platform’s limitation. This method can be used in aircraft, vehicles, ships and other types of motion simulators.

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