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STUDY ON PERFORMANCE SHAPING FACTORS FOR MANUAL RENDEZVOUS AND DOCKING

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Abstract. *Based on the artificial neural network (ANN) model, this paper analyzed the performance shaping factors (PSFs) for manual rendezvous and docking (MRVD). Firstly, using the analytic hierarchy and the linear weighting method, some performance indicators were integrated to establish a performance evaluation model for MRVD. Then, five important factors (system delay, docking direction, initial deviation, operator type, and skill recession) were identified under the PSF analytic framework. Finally, training data of more than 2000 MRVD in China spacecraft simulators were acquired and the radial basis function (RBF) neural network model was conducted to analyze the impact of each PSF on performance using a two-hidden-layer neural network. In this network, the five factors were input variables and performance score was output variable. The result showed that system delay had the maximal impact on operational performance (33%), followed by docking direction (26%), initial deviation (24%), operator type (11%) and skill recession (6%) in turn. Furthermore, how PSFs impact performance was also discussed in this paper. The results have been applied to the astronaut's ground training with significant outcomes.*
Keywords: Manual rendezvous and docking (MRVD), Performance evaluation, Performance shaping factors (PSFs), Neural network

1. **Introduction.** Spatial rendezvous and docking (RVD) refers to the process in which two spacecrafts meet at the preset position and time on the orbit in a certain height, and connect mechanically into one whole [1]. It can be controlled automatically or manually. Both control technologies of RVD were validated through two manned spaceflight missions which are named Shenzhou 9 and 10. Although astronauts have performed well in space practices and not been seriously affected by the extreme environment present in spaceflight, they have perceived that, from ground training and space practices, many factors affect the accuracy and reliability of Manual RVD (MRVD) operation. These factors involve many aspects, such as personal characteristics, system performance, task characteristics, and external environment. They are called Performance Shaping Factors (PSFs) which can be used to describe how individuals, systems, tasks and environment affect personal performance [2].

PSFs analysis is an important basis of human reliability analysis (HRA), which is a key part of safety analysis and management of a complex system and can be used to analyze, predict and prevent human error. Some researchers already paid attention to PSFs analysis of RVD. Du et al. found that two performance shaping factors (operator skill level and automation level) have significant effect on the performance of astronauts during MRVD [4]. Zhou et al. investigated the effect of time delay on remote RVD operations through 900 groups performing experiments based on one semi physical simulation system [5]. Overall, a very small body of research addressed PSFs analysis of MRVD, and systematic and quantitative methods or models were lacking.

Meanwhile, some researches showed that context changes should be considered as a PSF since it is obvious that operators' task performance will be influenced by the context changes. Therefore, it is necessary to put forward a systematic approach which can conduct PSFs analysis while taking the context changes into consideration [3]. However, such kinds of approach for PSFs analysis of MRVD is lacking currently.

Thus, this study tried to explore the impact and the impact pattern of various PSFs on astronaut performance during MRVD. With considering various PSFs, it is helpful for the training design to get a higher efficiency in ground training and thus make spaceflight missions more reliable and safer [6].

To be specific, this paper investigated some PSFs of MRVD. First, the performance evaluation model of MRVD and possible PSFs were introduced. Then, data of astronaut training was analyzed on the basis of ANN model, and the order of impact level of PSFs for various tasks was obtained. Meanwhile, the impact patterns of various PSFs were analyzed and discussed. Finally, conclusion was drawn and future research focus was determined.

2. Performance Evaluation and PSFs for MRVD.

2.1. Performance evaluation model.

MRVD usually takes the control of tracing spacecraft when the distance between two spacecrafts is within 120m [7]. In terms of manual control, the astronaut on the tracing spacecraft observes relative positions and attitudes of two spacecrafts using on-board devices such as TV cameras, operates two control handles (translation and attitude) to make the spacecraft satisfy the required docking conditions such as position, speed, attitude and angular speed, and finally makes two spacecrafts rendezvous and docking together [1,7]. MRVD is a continuous task execution process; operation performance of astronauts during MRVD cannot be represented by one or a few performance indicators. Therefore, an overall performance evaluation model is developed in this paper.

In this model, performance indicators for MRVD are divided into two layers. Performance indicators at the first layer include three types of indicators named docking result, docking accuracy and docking process respectively [8]. Each type includes various kinds of sub-indicators which are identified in the sense of engineering and shown as the second layer. For the indicators at each layer, an analytic hierarchy process (AHP) with expert scoring is used to determine the relative weight of each indicator. 10 MRVD experts from China Astronaut Research and Training Center participated in the survey of scoring. The weight of each indicator from the analytic hierarchy processes was finally confirmed by the astronauts of Shenzhou 9 who execute the MRVD task. Then, the linear weighting model was used to integrate indicators to establish an MRVD performance evaluation model with the equation shown below:

$$S = 0.61 * Dr + 0.28 * Da + 0.11 * Dp \tag{1}$$

where Dr represents docking result: 1 if docking succeeds; 0 if docking fails; Da represents docking accuracy; Dp represents docking process.

$$Da = 0.88 * (0.25dt + 0.25ax + 0.25ay + 0.25az) + 0.12 * vt \tag{2}$$

where dt is the translation deviation, ax is the deviation of the roll angle, ay is the deviation of the pitching angle, az is the deviation of the yaw angle and vt is the relative speed of two approaching spacecrafts.

$$Dp = 0.32 * T + 0.34 * F + 0.10 * RRA + 0.11 * CD + 0.13 * V \tag{3}$$

where T is the control time, F is fuel, RRA is the retention rate of relative alignment, CD is the control deviation and V is the speed.

2.2. **Performance shaping factors (PSFs).** Swain, who built the human error prediction method, proposed the concept of PSFs [9] to represent the situational environment that influences human behaviors (performances). The concept was generally accepted by researchers [2]. It is known from the concept that various situational environmental factors constitute the connotation of PSFs. Kim and Jung summed up PSFs involved in various data and information and concluded that PSFs came from four aspects: human, system, task and environment [10]. The paper used this classification method to analyze PSFs which possibly affect the performance of MRVD.

- Human (individual characteristics)

In the space, astronauts are under great physical and mental pressure in an attempt to complete high-precision MRVD operations within the required time and fuel [11]. To mitigate effect of various stresses on astronaut performance, they have to undergo highly intensive training on ground. In addition, operator's cognitive characteristics, experience level, etc., also affect their task performance.

- System Performance

System performance is one of important aspects affecting human-machine interaction and the identified PSF related to this includes the times of human-computer interaction per unit time, activity space, equipment capabilities, etc [12]. For such dynamical human-computer interaction as MRVD, system delay is considered as an important PSF.

- Task Characteristics

Task characteristics could represent the difficulty in judging and executing tasks and are related with operator's cognition and physiological need. The difficulty of a task depends on the variability, uncertainty and the degree of interaction between the task elements [12]. The task characteristics of MRVD include factors such as initial position and attitude deviation (initial deviation), docking direction (forward/backward flight) of two spacecrafts.

- External Environment

External environment cannot be controlled or changed. Environmental factors include temperature, humidity, noise, light conditions etc. External environment may possibly affect performance of both human and the system/equipment [13]. Though many factors of the space environment are mitigated by the separation with the spaceship's module, the light condition is hard to change and astronauts have to be adapted to it.

Putting above analysis together and considering the controllable conditions for astronaut ground training, 5 important PSFs were identified from the four categories of PSFs (human, system, task and environment). They are operator type, skill recession, system delay, docking direction and initial deviation. The description of 5 PSFs were described in Table 1.

3. Method.

3.1. **ANN model.** The artificial neural network (ANN) is a calculative model that simulates the structure and functions of neural network of living beings [14]. ANN is a practical method of learning from examples and often used to model on complex relations between input and output. ANN is useful to analyze problems such as fault diagnosis, characteristic extraction and prediction of the mechanism which is unclear or cannot be expressed with a general mathematical model. One of ANNs, the radial-basis-function (RBF) artificial neural network (ANN) have been widely applied to many fields [15,16] and was adopted in this paper. It can deal with regularities hard to be solved within a system, has good ability in generalization and a fast rate of learning convergence.

Table 1. Description of PSFs

PSFs Category	PSFs	Detailed description
Individual characteristics	Operator type	Novice and expert astronaut.
Individual characteristics	Skill recession	Excessively long interval between two times of trainings will cause skill recession.
System performance	System delay	Time delay refers to the interval between handling operation controllers to system response shown on screen timely.
Task characteristics	Docking direction	Docking direction refers to the direction of the spacecraft relative to the moving direction of target orbit, including forward flight and backward flight.
Task characteristics	Initial deviation	Initial deviation refers to the relative deviation of position and attitude between two spacecrafts at the beginning of MRVD.

RBF is a three-layer feed-forward local approximation neural network and approximates any continuous function in any accuracy. Its working principle is as follows. The input layer, via the RBF, maps signals in nonlinear way to the hidden layer which responds locally to signals and then maps them in a linear way to the output layer [12].

The basic algorithm of RBF is:

$$f(X) = \sum_{i=1}^{M} W_i \alpha_i(X) \tag{4}$$

where $\alpha_i(X)$ satisfies the conditions for activation.

The activation function for the hidden layer is a hyperbolic tangent function:

$$\left(\gamma(c) = \tanh(c) = \frac{e^c - e^{-c}}{e^c + e^{-c}}\right) \tag{5}$$

The activation function for the output layer is an identity function ($\gamma(c) = c$), where M is the number of units in each layer [13].

3.2. **Selection of input and output variables.** In this paper, performance factors were used as input variables of the RBF model including five PSFs of four categories, namely system delay, docking direction, initial deviation, operator type and skill recession. There are four system delays: 0.0s, 0.8s, 1.0s and 1.2s; two initial deviations: small and big; two directions: forward flight and backward flight; two operator types: novice and expert; two levels of skill recession: recession and no recession.

The output variable is the total performance of each MRVD operation calculated from the performance evaluation model.

3.3. **Analysis of impact of performance factors.** Trainings data of more than 2000 MRVD of astronauts in two missions from the training simulator were acquired, RBF model was applied and MATLAB tool kit was used to explore the impact of PSFs on total performance.

According to literature review, no optimal method to calculate the number of units in the hidden layer was found. Thus, the ergodic method was used and the network-based minimum mean square error principle was adopted to get the optimal number of units in the two hidden layers which were 5 and 4 respectively and delivered the best prediction result.

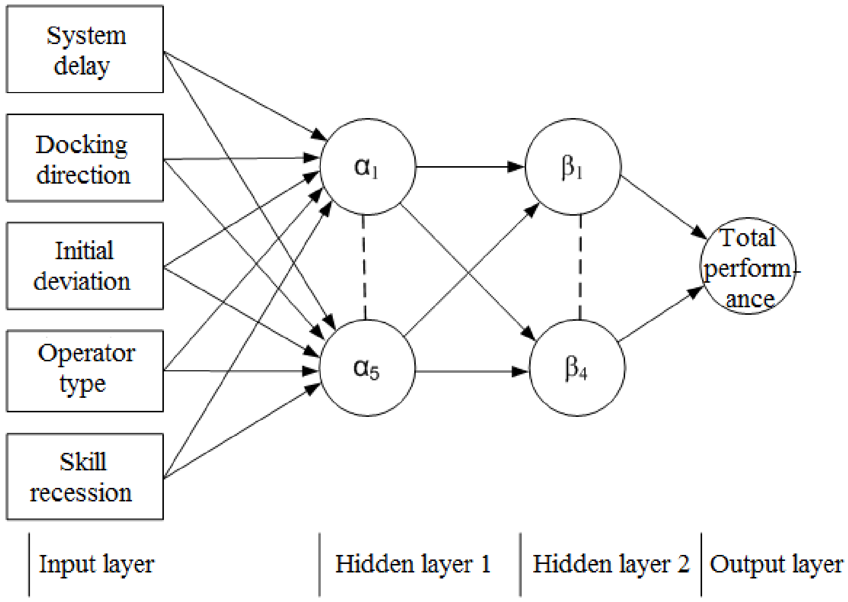

Figure 1. Sketch of RBF ANN model

As shown in Figure 1, the model includes five PSFs in the input layer, 5 units in the hidden layer 1 and 4 units in the hidden layer 2, and the total performance in the output layer.

4. **Results.** The results showed that these five PSFs can explain 15.5% of all training data. Combining the descriptive statistics of the impact of the five PSFs (see Figure 2), the following results can be obtained.

1) System delay is a factor having the maximal impact on performance (33%). When there is no system delay, the mean performance is the best and the uncertainty is the smallest. When system delay is 0.8s, the mean performance is the worst and the uncertainty is the largest. Overall, with the system delay increasing, the performance declines and the uncertainty increases gradually.

2) The impact of docking direction on performance is 26%. The mean performance at backward flight is higher than that at forward flight and the uncertainty is smaller at backward flight than that at forward flight.

3) The impact of initial deviation on performance is 24%. The mean performance is better at the big deviation than that at the small deviation and the uncertainty is smaller at the big deviation than that at the small deviation.

4) The impact of operator type on performance is 11%. The mean performance of experts is better than that of novices but the uncertainty is poorer than that of novice, i.e., expert's performance varies greatly.

5) The impact of skill recession on performance is 6%. The mean performance at no recession is better than that at recession but their uncertainty is poorer than at recession, i.e., performance at no recession varies greatly.

5. **Discussion.** Based on the neural network, this paper calculated and analyzed the effects of five PSFs on the performance of MRVD. The five PSFs are system delay, docking direction, initial deviation, operator type and skill recession. The results showed that each factor had its impact on performance, but in different degrees and patterns.

System delay influences performance at the largest degree and the pattern is not that the performance gets poorer with the delay increasing but that at a certain delay the performance declines significantly and rises to some extent when the delay increases gradually. This may be explained with two reasons. (1) When the system delay changes from

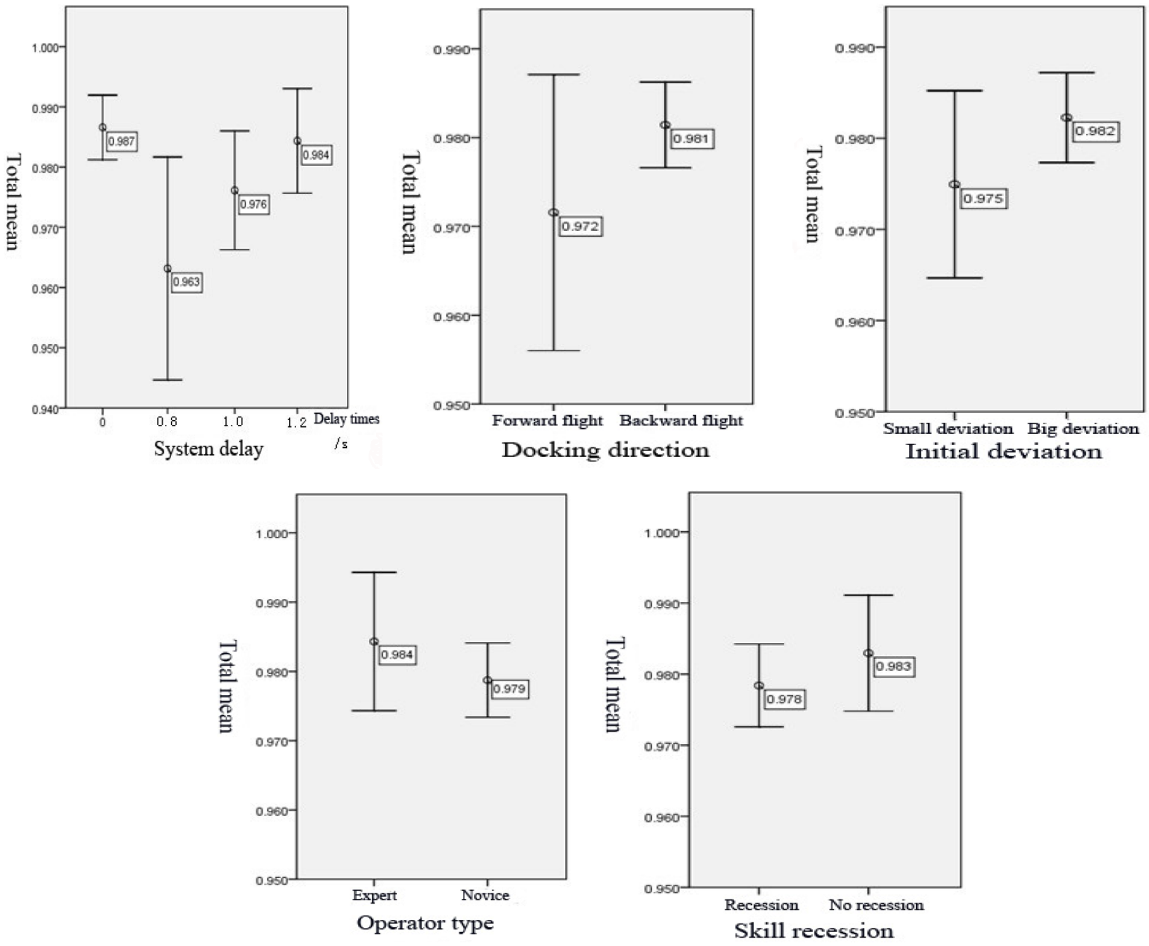

FIGURE 2. Descriptive statistics about impact of five PSFs

0 to 0.8s, the astronaut has to change the previously developed perception-operation rule and resultantly is unable to predict accurately the spacecraft's condition and motion trend thus resulting in lower performance. (2) When the system delay reaches to a certain level, the continuous operation becomes nearly discrete operation and making operation change less dynamic and as a result the performance rises to some level.

Both docking direction (forward/backward flight) and initial deviation describe the condition of MRVD task. In terms of task complexity, tasks at small deviation and at forward light are less complex while tasks at big deviation and at backward flight are more complex. In this paper, it is not found that the performance gets poorer with task complexity rising. This may be possible because when the initial condition is complex, the operator may make more efforts on MRVD thus performing better. In addition, in the condition of forward flight, the orbit height reaches a higher level after acceleration, thus the orbit height must be declined continually and this will consume more fuel, leading to lowering the total performance to some degrees.

Operator type and skill recession have weak impact on performance. Though the mean performance of experts is better than that of novices, their uncertainty is poorer than novices'. It is understandable that performance undulates more easily when the performance reaches to a certain high level. Though astronauts are divided into two levels in terms of their training levels – expert and novice – the impact of training level is not obvious since both groups are in pretty high learning ability and cognitive level. For the same reason, skill recession impacts the performance in a similar pattern.

Since there are plenty of PSFs, at present the ANN model built with these five PSFs can only explain 15.5% of all data. There are some reasons for this. On one hand, the variability of some factors are so big to impact the accurate form of the model. The variability of the factors may be from system error and individual difference which cannot be controlled in real astronaut training. In the future the impact may be reduced by eliminating abnormal value and adding more data. On the other hand, the performance of MRVD is affected by other PSFs which we did not identify and only 5 factors were considered in the ANN model. As described in Section 2, PSFs come from many aspects in practice and cannot be all considered in the paper.

6. **Conclusions.** In this paper, five PSFs including system delay, docking direction, initial deviation, operator type and skill recession were identified from four categories. Because of the outstanding self-adaptability and learning ability, the RBF ANN model was applied to analyze the impact of five PSFs on the performance of MRVD. Driven by more than 2000 MRVD data from astronaut training, one two-layer model was obtained and showed the different degree and pattern of the impact of five PSFs on the performance. The result also proposed a performance prediction method for astronaut training. Based on these results, training methods were designed to mitigate the impact of these PSFs and achieved great outcomes in the astronaut's ground training. In the future, some controlled trainings or experiments will be designed to include more PSFs to the model. And, based on PSFs analysis, more HRA research of MRVD can be conducted to predict and prevent astronaut operation error.

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