A SIMULATION-BASED STUDY ON NIGHT TRAIN OPERATOR’S TRACK INSPECTION PERFORMANCE BY USE OF COGNITIVE-PERCEPTUAL MODEL

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ABSTRACT

This study presents a simulation approach employing a cognitive-perceptual model to discuss a train operator’s performance of obstacle detection on the rails of a Japanese high-speed railway. As its application, we specifically focused on a “Track Inspection Task” which is operated after completion of daily track maintenance operations with a special purpose track maintenance train, i.e., so-called “Track Inspection Train”. This model described a train operator’s perceptual and cognitive process during track monitoring and inspection, and it allows us to simulate his behaviour as well as to track states during train operations. As input data to reproduce his visual function, the model required a train operator’s attention allocation patterns and eye-gaze distribution for each location, both of which were obtained by task observation in reality, as well as experimental data of the obstacle detection rates with eccentricity of visual field and its size. In the present paper, a great number of simulation runs were carried out to estimate the operator’s obstacle detection rates under various operating conditions, changing the size of an obstacle, its location on the track, driving speed, and so forth. Based on these simulation results, we discuss missing detection of obstacles that may cause a critical accident of the bullet train.

Keywords: track inspection, track maintenance train, eye tracking analysis, cognitive-perceptual model

INTRODUCTION

Human factors play a crucial role for railway safety as in other high-tech man-machine operations such as aviation, ship navigation and nuclear power plant control. It is well-known that human errors are the predominant cause of accidents and incidents in those areas (Margetts, 1976; Miller and Swain, 1987), and their rates are largely affected by an individual operator’s factors such as work experience, skills, knowledge, and workload and fatigue as well as working conditions. Train operations share many of these characteristics.

There are many types of trains operated in the railway: high-speed trains, commuter trains, subway trains, freight trains, track maintenance trains, and so forth. In this study, we focus on the track maintenance trains operated to maintain tracks and rails for the high-speed train (Shinkansen) in Japan. Track maintenance trains are operated by a team consisting of a supervisor and a driver both working in a driving cockpit under more changeable and more stressful conditions in comparison with those of normal passenger trains. For example, these trains have no traffic signals available when they are operated in operation interval break during the night time after the last evening train and before the first bullet train on the following morning. Thus, this requires the train crew to make go/stop decisions based only on their own perception and judgement. In this study, we have a special concern with “track inspection task” since the track monitoring – one of the most important activities comprised of this task – exhibits train operators’ activities common to all the types of track maintenance trains. The major purpose of this task is to ensure there are no obstacles on the track and the surrounding environment after completion of daily track maintenance constructions so that high-speed trains can be running safely on the rails. When the supervisor finds an obstacle during his monitoring process, he orders a driver to stop the train and picks it up from the track though there is actually very few occasions with something on the track. The choice of focus on this task was motivated not only by the above-mentioned difficulty of operating condition but also by the necessity of operation/task. This task is of critical importance since it serves as the final check for safety driving of bullet trains after daily track maintenance operations. In addition, the accident and incident rate of track maintenance trains is higher than that of passenger trains, though it is actually very low in terms of the absolute number and rate of accidents and incidents.
As can be easily understood from the above task description, the track inspection task is performed in skill-based manner (Rasmussen, 1986), and its quality and efficiency depend highly on the operator's visual perception and attention allocation on the track and its surroundings as well as on operational conditions. For tasks of man-machine operations having the above-mentioned characteristics, the eye-tracking technique has been employed in investigating operators' cognitive and perceptual performances with various ergonomics purposes, e.g., interface design (Itoh, 1998; Itoh et al., 2001b). Furthermore, operators' cognitive processes elicited by the eye-tracking analysis were modelled so that computer simulations could be performed for the purpose of safety assessment (e.g., Itoh et al, 1998; Itoh et al., 2001a). A cognitive simulation approach like in these studies may have suggested its potential abilities for large-scale risk analysis of man-machine operations due to its advantage of cost and time savings.

In the present paper, we apply the cognitive simulation approach to risk analysis for track inspection task, i.e., estimating risks of missing obstacles left on the tracks and its surroundings. A cognitive-perceptual model for the track inspection task was constructed based on the task analysis employing the eye-tracking analysis (Itoh et al., 2000). As for the input data to the model, we obtained a database of their visual perception functions through an experiment with ten train operators as subjects. To uncover derailing risks of bullet trains by an obstacle on the track, its detection rates were estimated by a number of simulation runs of the cognitive-perceptual model under various operating conditions, changing driving speed of track maintenance train, size of obstacle, its position on the track and so forth. Based on these results, we discuss risk factors for missing obstacles in the track inspection task.

OPERATOR'S PROCESS FOR TRACK INSPECTION

Observation of Track Inspection Task

We observed four track inspection sessions, each of which was carried out in the same driving area on a different day using a different scenario. In each session, a supervisor performed the track inspection task while the train was running approximately 40 km distance on the outbound track and the same distance on the return track at 3:00-5:20 am. Each scenario included a supervisor with or without geographic knowledge on the inspection area, eye-tracking recording time either on outbound or on return trip, and so forth. The supervisor's eye-tracking data was recorded for approximately one hour on either one way using an ASL 4000 eye-tracking system. In Session IV, in particular, four boxes (15x25x8.5cm) were put at different locations dispersed throughout the inspection area to observe the supervisor's actual monitoring process in detecting an obstacle.

Attention Allocation of Track Monitoring

A general pattern of a supervisor's track monitoring process is generated, aggregating eye-movement data from all three sessions involving the supervisor having the geographic knowledge (Itoh et al., 2000). Figure 1 indicates the transition network of the supervisor's attention allocation during the track inspection task. In this figure, the size of each circle represents the percentage of total gaze time at each location on the track and surrounding environment. The bigger a circle is, the more attention was paid to that location during the task. The thickness of the arrowed arc between two locations indicates the frequency of transition in terms of the relative percentage over the total number of eye-movements. The thickest lines in this figure, i.e., lines between the distant position on the running (own) track and the side of the running track, and between the distant position and the parallel track, represent 5-10% of transition over all the attention shift. The thinnest lines mean 0.5-1.0% of transition. No line is provided for a smaller percentage of transition than 0.5% in the network.

Figure 1 Transition pattern of train operator's attention during track monitoring

Figure 2 Operator's eye-movement in detecting an obstacle
The most frequently attended location was a distant region on the running track (approximately 200 metres ahead), on which a head light of the train focused. The supervisor gazed at this location for about 30% of time during the task. From this fact, this location seems to be the home-base of his attention for track monitoring. Besides this location, he also frequently looked at the side of the running track for about 20% of total duration. In this location, markers indicating distance from Tokyo and a telephone box were placed at regular intervals and shining dots sometimes appeared due to the reflection of the train's light. Therefore, it is natural to deduce that his fixation shifted automatically to this location, rather than that he paid critical attention to this region. His attention was also shifted frequently to the area between the two tracks (9.3%), the parallel track (8.9%) and a near-point (approximately 50 metres ahead) on his own running track (7.1%). Attention in the direction of the other parallel track was relatively infrequent, totalling less than 20%. Regarding gaze times at specific locations on the track - no figures are provided due to space limit - , their distributions were highly skewed and biased towards shorter duration. The mean gaze time was approximately one second for every location, and its standard deviation was about one second.

From these results, the supervisor's track inspection process can be conjectured to be a home-base monitoring strategy for inspecting the states on the tracks and surroundings. In this strategy, his home-base of attention is the distant region of the present running track approximately 200 metres ahead. He monitors the states on his tracks around his home-base by a short look-at each gazed location (taking less than a few seconds). That is, his attention shifts from the home-base to another location such as the side of his own track, the parallel track, etc. and then returns to the home-base of monitoring.

Obstacle Detection Process

Using eye-tracking data recorded in Session IV, the supervisor's actual detection process of an obstacle was analysed (Itok et al., 2000). Transition of fixation points is shown in Figure 2 for one of the four boxes left on the track. This was the case where a box was put at the most difficult place to detect, i.e., on the centre-pathway between two tracks (one metre below the track level).

Up until about 10 seconds before his report of the obstacle detection, the supervisor was inspecting the states in his track and its surroundings in a usual home-base monitoring as shown in Figure 1. About 5 seconds before the detection, he obtained a sense of something left on the centre-pathway when he attended to the parallel track. He later described this situation as follows: "When gazing the parallel track he got a visual image of its surrounding in his peripheral vision. He performed a pattern matching of his acquired visual image with the visual template stored in his memory as geographic knowledge. As a result of the pattern matching, he supposed there be a discrepancy between his visual acquisition and his geographic knowledge". Thus, at this moment, he might catch a hypothetical visual image of obstacle in his parafoveal or peripheral vision, i.e., a few to ten degrees in eccentricity. Then, he shifted his attention to the location where he sensed the discrepancy, i.e., on the centre-pathway, to test his hypothesis concerning the obstacle. After fixing properly at the box, he reported its detection approximately 150 metres before the obstacle. The other three boxes examined in Session IV were also detected by the same process.

COGNITIVE-PERCEPTUAL MODEL

Modelled Process of Obstacle Detection

In this section, we build a model of track maintenance train operator's cognitive-perceptual process in detecting an obstacle mentioned in the last section. The obstacle detection is modelled straightforward as a relation between cleanness of its visual image and his visual acuity. The image cleanness depends on the location and size of an obstacle, and viewing distance from the operator. Thus, it can be defined by a combination of visual angle of the obstacle and the place of its visual image on retina, i.e., the eccentricity from his fixation point. Regarding the human visual acuity, it is well-known to be reduced rapidly with the eccentricity from fovea, and therefore it can be represented as a function of these two variables. When the visual acuity clear enough to percept a particular obstacle, the operator can detect it. According to this activity modelling of obstacle detection, the image cleanness of a particular obstacle is changing time to time because of changes in viewing distance and eccentricity of the obstacle's image from the fixation point by his eye-movement while the train is running.

The process of obstacle detection is modelled stochastically using random digits to reproduce the operator's attention allocation during track monitoring and to determine whether he can detect an obstacle and where he does. The train operator's fixation point during track monitoring is generated from time to time by a random
digit following the attention allocation pattern. Fixation duration at any particular location is also determined based on its distribution. Process of his “hypothesis generation” on an obstacle is modelled to be initiated according to the clearness of its visual image, depending on its size, viewing distance from the operator and his fixation point, i.e., its visual angle and eccentricity from fovea. A clearness index can be calculated based on these variables as well as his visual acuity at the eccentricity from the fovea. A index value exceeding its lower limit activates to generate a hypothesis on an obstacle. The hypothetical obstacle is tested by comparing the index value with a random number uniquely distributed ranging between 0 and 1. If the random number is less than the clearness index, the hypothesis is supported and thus the operator’s attention shifts to the obstacle. Then, the visual clearness is tested again while he gazes the obstacle in his foveal vision. If its index value exceeds a random number selected at the new fixation point, the model decides to detect the obstacle. In case of selecting a larger random number than the clearness index in the hypothesis testing of the obstacle, the next eye fixation is generated following the attention allocation pattern, and the operator continues to perform usual track monitoring process.

Databases of Visual Detection

As mentioned above, the cognitive-perceptual model requires the train operator’s attention allocation pattern during track monitoring and distribution of gaze duration for each location in order to simulate the operator’s behaviour during track inspection task. The both data input to the model were obtained in the above-mentioned experimental sessions by use of eye-tracking recordings (Itoh et al., 2000). Particularly, the operator’s attention allocation pattern was shown in Figure 1.

In addition to these data, a database on the operator’s visual performance, i.e., detection rates for different-sized obstacles with several levels of eccentricity of visual field are required to input to the model. In order to obtain these data, an experiment was carried out with ten track maintenance train operators as subjects. In the experiment, each subject identified objects from driving cockpit of a track maintenance train in the dark at an identical luminance level to the actual driving condition on the track. All the visual objects were rectangular shaped and covered with fluorescent paint on their surfaces similar to that attached on tools used for usual track maintenance operations. Four different sized objects were presented at five different locations 100 metres ahead from the subject, i.e., 0, 2, 4, 6 and 8 degrees in eccentricity from the fixation point, randomly in order with five repetitions. Each subject was asked to report whether he could identify an object or not, while he fixated at a mark attached on another track maintenance train parked also about 100 metres straight ahead.

As a result of the experiment, detection rates are shown in Figure 3 for each combination of object size and its location. As can be seen in this figure, the detection rate was reduced with increase of eccentricity and with decrease of its size, but not linearly for the both factors, although there were also individual differences in the detection rate. To generate input data to the model, the detection rate was approximated as a function of the eccentricity from the fixation point and the visual angle of an object (in degrees), as shown in Figure 4 for several example conditions. A detection rate for any combination of size and location was obtained by this function in a simulation run.

SIMULATED OBSTACLE DETECTION

Simulation studies were conducted, applying the cognitive-perceptual model presented in this paper to various operational scenarios, changing driving speed, size of obstacle and its location on the track, and so forth. One

![Figure 3](image3.png) Detection rates obtained in the experiment  
![Figure 4](image4.png) Approximated obstacle detection rates
thousand simulation runs were performed using a different seed of random digit for each scenario. An obstacle detection rate for each operational condition was derived from simulated performance obtained by these 1,000 trials. As an example result of simulation studies, Figure 5 indicates a distribution of train’s position, i.e., distance between the train and the obstacle, at the moment of obstacle detection as well as a missing rate of detection for different sized obstacles. In the case shown in this figure, the obstacle was left in the centre of the running (own) rails while the train is running at the maximum speed limit, i.e., 60 km/h. As can be seen in this figure, the detection rate for a not-very-small obstacle put at the operator’s home-base of attention, i.e., in the centre of the own rails is estimated 100% in driving at the speed of 60 km/h. For the smaller obstacles examined in this study, there were not many cases of missing detection, i.e., 21% and 3.5% for 5x5x5 and 10x10x10 cm boxes, respectively. However, the size of obstacle is found to critically affect the detection timing when the operator can detect it even if it is left at his home-base of attention. For example, the operator was expected to detect a 40x40x40 cm obstacle more than 200 metres ahead in about 90% of cases. This means that the train can stop enough before the obstacle anytime. In contrast, for the smallest, 5x5x5 cm box, the simulated operator detected an obstacle at the distance shorter than 50 metres in all the detecting cases, and less than 100 metres in about 90% cases for a 10x10x10 cm box. In these cases, it is impossible for the operator to stop the train before the obstacle.

Changes in the detection rate with running speed are depicted in Figure 6 for several sized obstacles which are left in the centre of the own rails, assuming the operator’s attention allocation pattern is not changed with the speed. The smaller an obstacle left on the track, the larger the effect of train speed on the detection rate becomes. This figure also indicates that if an obstacle is big enough, i.e., no smaller than 20x20x20 cm, the detection rate is not decreased independent of speed increase up until 120 km/h. This means that there is no or little critical risk of derailing of bullet trains due to an obstacle on the track. That is, there exists no big obstacle close to the running rails after the track inspection task is completed, even if the speed limit of the “track inspection train” is increased to 100 or 120 km/h.

Figure 5 Distance from the train when detecting an obstacle (running speed: 60km/h)

Figure 6 Detection rates at different running speed

Figure 7 Detection rates of obstacles in various locations
To examine the effect of obstacle's location on the operator's inspection performance, Figure 7 illustrates detection rates for different sized obstacles which are left at different positions ranging from the side of the own track, i.e., 7.5 metres left from the centre of the own rails, to the parallel track, i.e., 10 metres right, when running at the speed of 60 km/h. For larger obstacles, i.e., no smaller than 20x20x20 cm box, the detection rate is not reduced greatly even for ones far from the own running rails. In contrast, for smaller obstacles, the detection rate is affected much more by its location on the track. For example, the simulated operator’s performance indicated to detect the smallest obstacle (5x5x5 cm) left in the centre of the own rails in about 80% cases while the detection rate was estimated to be decreased to about 20% for the same sized box left on the parallel track.

CONCLUSION

In this paper, we modelled the train operator's track monitoring and obstacle detection processes based on the task analysis applying the eye-tracking data (Itoh et al., 2000) as well as on experimental data collection of their visual functions. This model allows us to simulate the operator's perceptual behaviour during track inspection task while the track inspection train is running. Applying this model, obstacle detection rates were estimated under specific operational conditions to discuss derailing risks of the bullet train due to missing detection of an obstacle on the track. Major findings in this simulation study are as follows: There is no or very little derailing risk of the bullet train by an obstacle under the present operational condition of track inspection task, e.g., driving speed, etc., unless the vigilance level of track maintenance operator goes down greatly. The operator can detect a big obstacle, which may cause derailing of a train, at the position distant enough to stop the train before it. For an object small enough not to interfere with driving of the bullet train, 20% or higher probability of missing detection was suggested to exist, depending on its location on the track.

As we did not mention in this paper, we conducted additional simulation studies applying different databases of operator’s visual functions, which were also obtained in the former study (Itoh et al., 2000). For example, the attention allocation pattern of an operator having no geographic knowledge of the inspection area was found to be different from that of the knowledge-holding operator who was focused on in this paper. Thus, we performed a series of simulation runs by applying the same cognitive-perceptual model, only switching the database of attention allocation pattern to the operator’s having no geographic knowledge - although his cognitive process for obstacle detection might also be somewhat different from that of the knowledge-holding operator’s. As a result of these simulations, the detection rate of the knowledge-less operator was lower for obstacles left far from the own running rails than that of the knowledge-holding operator. With increase of the running speed, the knowledge-less operator’s detection rate was decreased more rapidly than that of the usual operator. Regarding an effect of running speed, it was found to have little difference in attention allocation between 40km/h and 60km/h in the former study (Itoh, et al., 2000), and therefore we used the same database which was obtained in sessions running at the speed from 40 to 60 km/h throughout all the simulation runs independent of the driving speed ranging from 40 to 120 km/h. However, it may be reasonable to exist a difference in attention allocation pattern between 60km/h and 120km/h or faster.

In a future study, further data collection is required to obtain more precise estimations of obstacle detection rates corresponding to specific operational conditions. In addition, the model should be improved in that appropriate cognitive process is built in according to individual human factors and operational conditions, as mentioned above. We believe it is possible to apply a simulation approach with a cognitive-perceptual model presented in this study to risk analysis of any type of man-machine operations which are routinely performed in normal situations. This is made possible by developing an appropriate model of a task under study based on the descriptive approach of cognitive task analysis (Vicente, 1999).

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