

ACCURACY AND QUICKNESS CRITERION-BASED DRIVING SKILL METRIC FOR HUMAN ADAPTIVE MECHATRONICS SYSTEM

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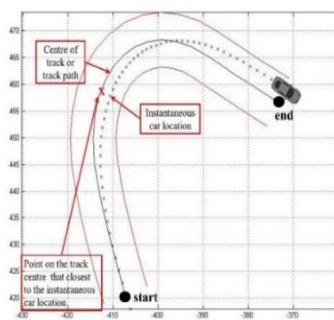
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Graphical abstract



Abstract

Previous studies on driving skill algorithm have combined tracking error and time related variables into algorithm formulation. This method however does not include a car orientation and lateral speed information as an integral part of the algorithm. Two new variables are introduced into the algorithm structure, namely, orientation angle and lateral speed. Nine participants were carefully recruited for a driving test to validate the algorithm. A simulated driving environment was specifically devised for this experiment. A driving track used in this experiment was segmented into five different severities for data analysis. Two fundamental goals have led to the collection and subsequent analysis of the data. The first is analysing the variables in relation to the driving task. The second involves data analysis being further extended into analysing the algorithm performance over estimating the driving skill index. The results reveal that the proposed variables are well correlated with the driving task, and improvement in algorithm performance is found to be almost double compared to the previous algorithm.

Keywords: Human adaptive mechatronics system; human factor; driver support system; driving skill quantification; driving skill algorithm

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1.0 INTRODUCTION

Almost half a million of Malaysian citizens are at risk of road accident every day [1]. 46.9% of all accidents are caused by human factor [2]. Thus, driving safety has become a tremendous problem since road accidents could jeopardize not only the driver, but also passengers and the vehicle's surroundings. Thus, this requires measures or driver support system that can help the driver to drive in a safe and practically efficient manner [3-5].

The driver support system needs first to understand and recognize the driver's competency level (i.e., driving skill) before it is able to provide the most suitable type of support to optimize overall system performance and better guide the driver in the learning process [6]. Hence, the system needs a

reliable and accurate skill estimation algorithm in order to provide suitable support and optimum enhancement. Previous study on analytical driving skill quantification method combines tracking error and time related driving criterion into driving skill metrics [7-9]. This method however did not include car's orientation angle and lateral speed control information as an integral part of the driving skill metric.

The aim of this study is to overcome such major drawbacks of current driving skill quantification methods. The first objective of this research is to define the car handling skill. Then, the parameters related to the car handling skill are chosen. The new driving skill metric incorporating those chosen driving parameters is developed. Lastly, a driving test was conducted to investigate and validate the viability of the chosen

parameter to represent driving skill as well as to validate the new metric performance improvement against previous studies.

2.0 HUMAN ADAPTIVE MECHATRONICS SYSTEM

In general, the greatest challenge of Human Machine System (HMS) is referred to as information asymmetry [10]. That is, human operator understands the computer's "way of thinking", but the computer does not understand the human operator due to the observability of the most critical signals of operator's psychological characteristics. Thus, the interaction between human and machine is not symmetrical in conventional HMS [11].

Human Adaptive Mechatronics System (HAM) is a new paradigm of intelligence mechanical system that has the capability to adapt and change its configuration to human skill and assist humans in improving their skill to achieve the objective of best system performance [11, 12]. Several important components that become the integral part of the HAM system are listed as follows [10, 13];

- i. Human control skill quantification
- ii. Human behaviour cognition by the machine
- iii. Non-intrusive human's support by the machine
- iv. Reconfiguration of machine function for total enhancement.

This paper only addresses issues in the area of quantification of human skill in the context of car driving applications.

3.0 SKILL METRIC DESIGN

Driving skill, seen from a controller's point of view, is defined as the ability of the driver to adjust the configuration of his/her control strategy according to the response of vehicle system. It is also suggested that the parameter of the driver model is dependent on the vehicle parameter [14, 15]. It can thus further be argued that any parameter from the car kinematics model can be used as the driving parameter to determine the driver's characteristics.

3.1 Path Coordinated Car Kinematics Modelling

From Figure 1, the kinematic model is then derived as [16, 17]

$$\begin{aligned} \dot{x}_c &= \vec{v} \cos \theta_c \\ \dot{y}_c &= \vec{v} \sin \theta_c \end{aligned} \quad (1)$$

The velocities, \dot{x} and \dot{y} cannot assume independent values; in particular Equation (1) must satisfy the constraint

$$[\sin \theta_c \quad -\cos \theta_c \quad 0] \begin{bmatrix} \dot{x}_c \\ \dot{y}_c \\ \dot{\theta} \end{bmatrix} = 0 \quad (2)$$

Entailing that the velocity of the wheel centre lies in the body plane of the wheel (zero lateral velocity i.e. no slipping) (See [16, 17] for detail).

An illustration in Figure 2 depicts how to model the vehicle in path coordinates. Point (x_s, y_s) is located at the track center, s is the closest to the car position (x_c, y_c) and the angle between the car and the tangent to the path is $\theta_p = \theta_c - \theta_s$ as illustrated in Figure 3. From Figure 2 the curvature along that path is defined as;

$$c(s) = \frac{d\theta_s}{ds}$$

Then;

$$\theta_s = c(s)\dot{s}$$

From (1), it is substantiated that;

$$\begin{aligned} \dot{s} &= \vec{v} \cos \theta_p + \dot{\theta}_s d \\ \dot{d} &= \vec{v} \sin \theta_p \end{aligned} \quad (3)$$

It is noted that the selection of driving parameter is chosen by assuming that they carry information and correlations against the driver's car handling skill. From the previous section of car kinematic formulation, four driving parameters of x are chosen, which are;

$$x = \{\theta_p, d, \dot{d}, \dot{s}\} \quad (4)$$

Those parameters are meant to measure a driver's car handling skill. For example, θ_p measures the driver's skill in handling the car orientation angle, \dot{d} measures the driver's skill in correcting the car lateral speed, d measures the skill of handling car position, and lastly, \dot{s} measures the car's speed handling skill.

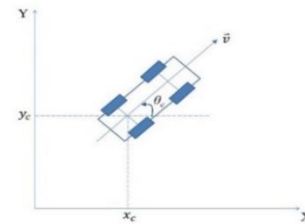


Figure 1 Standard kinematics: Definition of states describing position and orientation of the car [16].

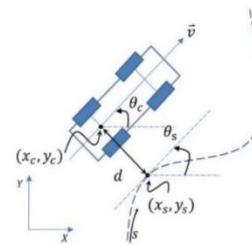


Figure 2 Description of the car kinematics using path coordinates [17]

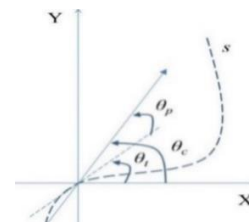


Figure 3 The angle between the car and the tangent to the path, θ_p

3.2 Parameter Normalization

The parameter might not seem to be very useful without reference to any known value, because this is the basic characterization process of human control action skill. Thus, all parameters need to be normalized.

Given $x_1, x_2, \dots, x_i, \dots, x_T$, as the series of raw parameter values logged from a driver at a particular track segment, the normalization process is shown in Equation (5).

$$x_{norm} = \frac{x_{avg}}{x_{true}} \quad \text{and} \quad x_{avg} = \frac{1}{T} \sum_i^T x_i \quad (5)$$

Where;

$T \equiv$ Total number of instantaneous data at a particular track segment

Driving parameter x_{true} is the parameter of a true driver used as a reference for parameter characterization or in other words, giving the driving parameter a meaning. All the parameters (i.e., $\theta_p, d, \dot{d}, \dot{s}$) must undergo this normalization process.

3.3 Parameter Reflection

Monotonicity or magnitude interpretation of the parameter is crucial. For the strictly decreasing index value, it needs to undergo extra processing called reflection. While preserving its distance, the parameter value will be translated to the opposite side of a mirror (i.e. axis of reflection). By using the normalized, x_{norm} and true parameter, x_{true} , it can be proven that, a reflected parameter, x' can be calculated as shown in Equation 6 below [18]:

$$x' = -x_{norm} + 2x_{true} \quad (6)$$

Only the driving parameters of θ_p and d are treated by this process.

3.4 Driving Skill Metric

Driving parameter after the normalization and reflection processes are as in Equation (7) below;

$$x = \{\theta'_p, d', \dot{d}_{norm}, \dot{s}_{norm}\} \quad (7)$$

The skill index, J can be calculated using the driving skill metric, $f(x)$ which is the function of driving parameter x . The previous driving skill metric measured and evaluated the driver's skill index, J as in the equation below (8) [7, 19];

$$J_{old} = a - b(J_T + J_E) \quad (8)$$

Where;

$$\begin{aligned} J_T &= \dot{s}_{norm} \\ J_E &= d' \end{aligned}$$

Generally, this driving skill metric linearly adds two driving criteria index to form a cumulative score of driving skill index, J namely, time criterion index, J_T , and error criterion index, J_E . The metrics are parameterized into scaling factor, b and shifting factor, a . This driving skill metrics assumes a car as a point of mass. In other words, there is no information regarding car orientation and information is taken into account in the metric formulation. The formulation also does not pay attention to the capability of the

driver's agility (related to car lateral speed) skill in correcting the location offset between the car and roadway.

The driving criterion index (i.e. J_E and J_T) formulation can be generally structured into a more generalizable Human Performance Index (HPI) formulation, as shown in Equation (9) below [20].

$$J_l = \frac{\sum_{k=1}^m W_{x_k} \times x_k}{\sum_{k=1}^m W_{x_k}} \quad (9)$$

Parameter (x_k) represents the basic elements of HPI, which are directly measured from human control action. These parameters are then compiled into a cumulative index of performance criterion (J_l), where each of the variables constitute a degree of significance, defined by performance variable weighting factor (w_x).

Accordingly, it can be considered that, the following two items are very suitable for analytically evaluating driving skill index, J . The first item is related to car instantaneous position, either in location or angle, against the ideal path or angle. This deviation is viewed as error that needs to be corrected. This error is related to the driver's ability to control the car accurately. Thus, it is then called accuracy criterion, J_A . The second item is more related to speed in compensating the error. As opposed to accuracy control, this type of control deals with the driver's control agility. Thus, it is called quickness criterion, J_Q . Both driving criterion are best in capturing the driver's capability in negotiating changes in immediate future path requirement.

Hence, the completion time driving criterion or, J_T can be referred to as the quickness criterion, J_Q reflects a more generic term of speed related driving skill criterion, while task tracking error, J_E , or car positioning correction, is changed into accuracy criterion, J_A also reflects a more generic term for accuracy related to driving skill index.

From Equations (7) and (9), the driving criteria are as below;

$$\begin{aligned} J_Q &= \frac{w_1 \dot{d}_{norm} + w_2 \dot{s}_{norm}}{w_1 + w_2} \\ J_A &= \frac{w_3 d' + w_4 \theta'_p}{w_3 + w_4} \end{aligned}$$

Assuming $w_1 = 1, w_2 = 1, w_3 = 1$ and $w_4 = 1$, hence;

$$\begin{aligned} J_A &= 0.5(d' + \theta'_p) \\ J_Q &= 0.5(\dot{d}_{norm} + \dot{s}_{norm}) \end{aligned} \quad (10)$$

All the criteria index are then combined into a single index, namely skill index, J with a corresponding performance criterion weighting factor (W_j). From Equations (8), (9) and (10), the new driving skill index, J is then measured using the metric below [21];

$$J = a - b \left(\frac{w_Q J_Q + w_A J_A}{w_Q + w_A} \right)$$

Assuming $w_Q = 1$ and $w_A = 1$, and set $a = 2$, thus J_{new} :

$$J_{new} = 2 - 0.5(J_Q + J_A) \quad (11)$$

4.0 DATA ACQUISITION SYSTEM

This section discusses the data acquisition system that had been used in this study. The hardware and parameters for both car and track environment settings are discussed. This is important to ensure that the test that is carried out is based on the standards of actual driving.

4.1 Driving Simulator Setup

Figure 4 shows the configuration of the driving simulator used in the study for data acquisition. The steering wheel is attached to a desk to avoid rocking or slipping during the experiment (b). The gas pedal and brake are independent of each other (a). The driving simulation gives the user an experience like driving in actual environment. The participants are requested to drive in the testing track depicted in Figure 5. The track is 2.5 kilometers in distance, and 10 meters in width.

Track curvature, $C(s)$ on a track path instantaneous point changes with track deviation angle, $d\theta_s$ and also changes in track path length ds . From Figure 6, the track curvature $C(s)$ is calculated as follow;

$$C(s) = \frac{d\theta_s}{ds}$$

Where;

$$d\theta_s = \theta_s^{j=1} - \theta_s^{j=0}$$

$$ds = \sqrt{(dy_s)^2 + (dx_s)^2}$$

And;

$$dy_s = y_s^{j=1} - y_s^{j=0}$$

For segment severity, k is then simply an average of total track curvature calculated across the track segment which is computed as:

$$k = \frac{1}{N} + \sum_j C(s) \tag{12}$$

Where;

$j \equiv$ Index of instantaneous point on track center line s .

For this study, the track is divided into 5 segments, as depicted in Figures 5 (a - e). Its corresponding severity characteristics are measured using Equation (13) and is tabulated in Table 1.

4.2 Data Collection Process

An example of data collection process on one track segment is depicted in Figure 7. At every instance of car location (within the predefined track segment), all driver parameter data were measured and the driver skill index, J were calculated. Figure 8 shows an example of calculating the angle θ between a line tangent to the curve s with gradient m_1 , and the line that is parallel to the x -axis with gradient m_2 , then;

$$\tan \theta = \left| \frac{m_1 - m_2}{1 + m_1 m_2} \right|$$

Line m_2 is parallel to the x -axis or its gradient is known to be equal to 1, then;

$$\theta = \tan^{-1}|m_1| \tag{14}$$

Where m_1 is calculated as;

$$m_1 = \frac{\Delta y - y}{\Delta x - x}$$

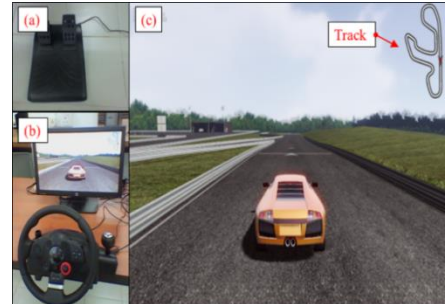


Figure 4 Driving simulator; (a) independent gas and brake pedal; (b) steering wheel and simulator monitor; (c) driving simulator view gives the user a perspective preview of the road ahead.

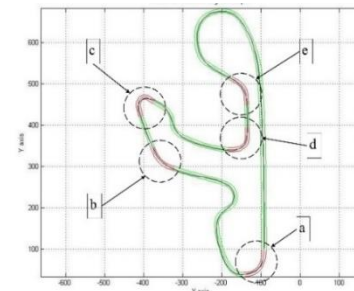


Figure 5 Track course with segment (a, b, c, d and e) used for data analysis

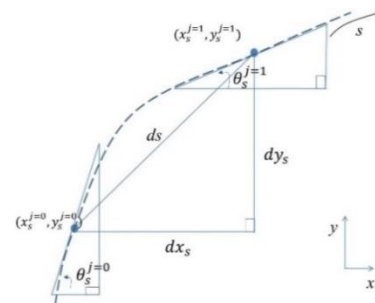


Figure 6 The diagram shows example of measuring the track severity, k

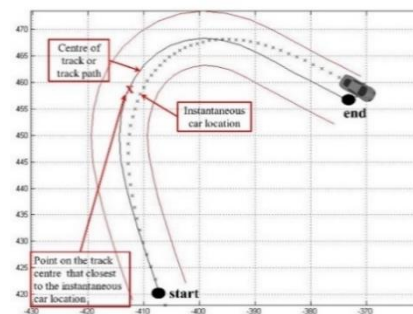


Figure 7 Example of data collection process on track segment c

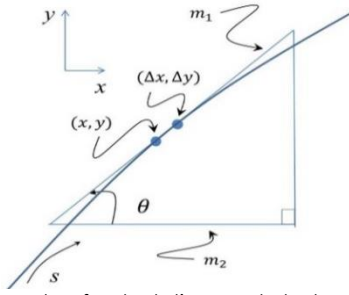


Figure 8 Example of calculating angle between two lines

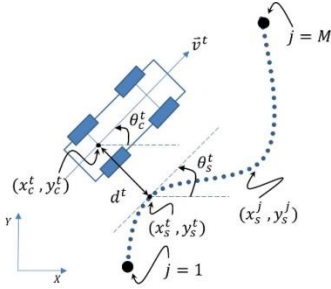


Figure 9 Example of collecting driver raw data at instantaneous position

Table 1 Track segment severity characteristic, k used to study driving skill metric

Segment	a	b	c	d	e
Severity, k (rad/m)	0.0885	0.0620	0.1055	0.0821	0.0547

4.2.1 Measuring the Driving Parameters

From Figure 9, instantaneous car location, (x_c^t, y_c^t) , point, (x_s^t, y_s^t) and car longitudinal speed, \bar{v}^t are continuously measured and used to compute subsequent driver parameter of x (i.e. $\theta_p^t, d^t, \dot{d}^t$ and \dot{s}^t), starting from when the car enters from the segment starting point of $j = 1$ until the segment end point of $j = M$.

Given instantaneous point (x_c^t, y_c^t) and points $\{(x_s^1, y_s^1) \dots (x_s^j, y_s^j) \dots (x_s^M, y_s^M)\}$, d^t can be specifically obtained by searching the position number j which makes the value of

$$d^t := \sqrt{(x_s^j - x_c^t)^2 + (y_s^j - y_c^t)^2}$$

as small as possible. This search problem of minimum distance is easy since the selection of track segment used in this research has only a single local minimum. Thus;

$$d^t = \sqrt{(x_s^{j=t} - x_c^t)^2 + (y_s^{j=t} - y_c^t)^2} \quad (15)$$

Where;

$(x_s^{j=t}, y_s^{j=t})$ is the closest point to the (x_c^t, y_c^t) .

From Figure 3, hence θ_p^t is;

$$\theta_p^t = \theta_c^t - \theta_s^t \quad (16)$$

Where (By using Equation (14));

$$\theta_c^t = \tan^{-1} \left| \frac{\Delta y_c^t - y_c^t}{\Delta x_c^t - x_c^t} \right| \text{ and } \theta_s^t = \tan^{-1} \left| \frac{\Delta y_s^t - y_s^t}{\Delta x_s^t - x_s^t} \right|$$

From Equation (3), \dot{d}^t and \dot{s}^t are then calculated as;

$$\dot{d}^t = \bar{v}^t \sin \theta_p^t \quad (17)$$

$$\dot{s}^t = \bar{v}^t \cos \theta_p^t + \theta_p^t \dot{d}^t \quad (18)$$

From Equations (17) and (18), the driver's driving parameters computed at instantaneous point of t are then;

$$x^t = \{\theta_p^t, d^t, \dot{d}^t, \dot{s}^t\}$$

4.2.2 Computing the Driver Skill Index

Let x be the average the driver's driving parameter measured from the starting instantaneous time t to T when car entering segment start point j to segment end point M .

$$x = \{\theta_p, d, \dot{d}, \dot{s}\}$$

Where;

$$x = \frac{1}{T} \sum_t x^t$$

The parameter characterizations processing of the driving parameter was conducted using Equations (17) and (18). The processed parameters were then;

$$x = \{\theta_p', d', \dot{d}_{norm}, \dot{s}_{norm}\} \quad (19)$$

From Equation (20), skill index of the old metric can be computed as follows [7, 19];

$$J_{old} = 2 - 0.5(\dot{s}_{norm} + d') \quad (20)$$

While the new skill index of the new metric is computed as (See Equation 11) [21];

$$J_{new} = 2 - 0.5(J_Q + J_A) \quad (21)$$

Where;

$$J_Q = 0.5(\dot{d}_{norm} + \dot{s}_{norm}) \text{ and } J_A = 0.5(d' + \theta_p') \quad (22)$$

5.0 EXPERIMENTAL SETUP

Two types of experiments were developed. For the first one, the driving task parameters were studied. For the second one, the improvement for new driving metric incorporating those parameters was then validated.

5.1 Participant Demographic

The selected participants must reflect a certain level of driving skill. All participants must have knowledge of driving and hold a Malaysian driver's license. Ethical approval was also obtained before the experiment. All participants must also have no history of neurological deficits. Participants who had exceptional skills in gaming and driving were not selected. Participants who had lack of driving knowledge was not considered for this experiment.

5.2 General Instruction to the Participant

Before any test was started, the participants were given five-minutes to gain familiarity with the driving simulated environment. The participants were also explicitly instructed to complete the driving through

the track course for five laps, with a five-minute rest period in between each lap. During the course of driving, the participants must maintain car stability (i.e., overshooting and over steering are not allowed, and they must maintain all four tires on the track) otherwise, the experiment is considered a failure.

5.3 Analysis of Driving Parameters

Nine participants were carefully recruited. All the participants must meet the requirement as discussed in Section 5.1. In short, for this study, a group of people with homogenous driving skills was the main target.

All participants were directed to undergo a driving test, as described previously in Section 5.2. The driving parameter data, $x = \{\theta_p, d, \dot{d}, s\}$ were measured and collected from all five track segments a, b, c, d and e (See Figure 5) as described in section 4.1.

The correlation data analysis between the driving parameter, x and track severity criterion, k is performed to understand how the driving parameters are related to the path tracking driving task. The path tracking driving task would be more meaningful at the curving part of the road, as drivers are brought into higher attentive state, thus, truly reveal their skills [22]. Correlation between parameter, x and track severity, k is defined as follows:

$$\rho_{xk} = \text{corr}(x, k) = \frac{\text{cov}(x, k)}{\sigma_x \sigma_k} = \frac{E[(x - \mu_x)(k - \mu_k)]}{\sigma_x \sigma_k}$$

Where μ_x and μ_k are the expected values of x and k respectively, and σ_x and σ_k are the standard deviations of those parameter value. In statistics, a correlation value -1.00 represents a perfect negative correlation while +1.00 is a perfect positive correlation. If the value of correlation is equal to 0.00, it means that there is no correlation between two random variables. A perfect negative correlation value between two random variables simply means that the relationship that appears to exist between two variables is negative 100% of the time.

5.4 Analysis of Driving Skill Metric's Performance

The objective of this analysis is to evaluate the improvement of new path tracking driving skill metric performance. Two types of test involving the analyzing of the estimation accuracy of both metrics at one segment and at all five segments were done in this experiment.

To measure the improvement of the metric, an improvement index must be devised. Metric estimation accuracy is defined as the fractional percentage of actual index against true index. From the accuracy definition, the metric performance accuracy score can be formulated as;

$$A(\%) = \left[\frac{J_{true} - |e|}{J_{true}} \right] * 100\% \quad (23)$$

Where;

$$e = J_{true} - J_{actual}$$

In this research, the value of skill index 1 is used to represent the true driver skill index. To evaluate the improvement index of the new against old one, Equation (24) is used as follows:

$$I = \frac{\mu_{new}}{\mu_{old}} \quad (24)$$

Where μ_{old} and μ_{new} are the average of index value of old and new metric score from all tests respectively.

5.4.1 Analysis of Metric Score Estimation Accuracy

The objective of this analysis is to validate the skill metric estimation accuracy improvement in the new metric over the old one.

A participant was carefully recruited, who must meet the requirement as discussed in Section 5.1. The participant was directed to undergo a driving test, as described previously in Section 5.2. At each lap for five laps, the driver's index skill was measured from old, J_{old} and new, J_{new} metric was computed from track segment c only (Figure 7– Segment c) as discussed in Section 4.1. Equation (23) was then used to calculate its respective estimation accuracy, A against the true driver's skill index. The skill metric estimation accuracy improvement index, I was then analyzed using Equation (24).

5.4.2 Analysis of Metric Score Reliability

The objective of this analysis is to study the effect of track severity criterion, k against both skill metric performances.

A participant was carefully recruited, who must meet the requirement as discussed in Section 5.1. The participant was directed to undergo a driving test, as described previously in Section 5.2. At each lap for five laps, the driver's skill index was measured from old, J_{old} and new, J_{new} metric was computed from all track segments (Figure 5) as discussed in Section 4.1.

Let J_{old_k} and J_{new_k} be the driver index skill from old and new skill metric respectively of a particular track segment k . Equation (23) is used to calculate its respective estimation accuracy, A against the true driver's index skill. The skill metric estimation accuracy improvement index I was then analysed using Equation (24).

6.0 RESULT AND DISCUSSION

This chapter presents the results of data analysis conducted in Section 5. Two fundamental goals lead to the collection of the data and subsequent analysis. The first is analysing parameter related to the path tracking driving task. The second further extends into analysing the skill metric performance by estimating the skill index. These goals were used to develop a base of knowledge about a better driving skill metric formulation.

6.1 Result of Driving Parameter Data Analysis

The data result of driving parameter values at all track segments are tabulated in Table 2. Furthermore, Table 3 shows the results of the correlation data analysis between each of those parameters against track segments. A negative sign in a correlation value indicates anti-correlation.

From the results, it can be observed that θ_p has a higher correlation magnitude over d for accuracy criterion J_A , with 0.63 and 0.61 respectively. While \dot{d} also has a significantly higher correlation value (0.33), where \dot{s} is only 0.30 for quickness criterion J_Q . A good correlation between driving parameter and track severity criteria indicate that the parameters demand more control in negotiating track curving. Technically, the driver is more attentive towards regulating car orientation angle, θ_p for path tracking accuracy when facing curving track circumstances, while emphasizing more agility on quickly compensating car position (related to car lateral speed control \dot{d}).

Thus, the selection of those parameters to be the integral part of the metric is a suitable choice. In addition, the new parameter θ_p and \dot{d} are better in representing the driving task as compared to the other two parameters. In other words, it can be argued that car orientation control θ_p and lateral speed control \dot{d} carry more information regarding driving skill.

6.2 Result of Metric's Estimation Accuracy Data Analysis

Table 4 presents the results of the index skill for both skill metrics for a five lap driving test. Their respective accuracies in percentage are tabulated below with each of their indexes.

Table 5 presents the analysis results of the new metric improvement, against the old metric. The estimation accuracy mean, μ_A of the old skill metric is only 44.40%, while the new metric is significantly increased to 95.44% in estimation accuracy. It is shown that the new metric is 2.15 times better than its predecessor (Improvement index, $I = 2.15$). The new metric shows a great performance improvement; it manages to overcome bias error that might avert its estimation performance in the first place.

6.3 Result of Metric's Reliability Data Analysis

The effect of road severity is taken into consideration in this data analysis, and how the metric performances are affected is investigated. Table 6 shows the index of both metrics for all five segments gathered from the driving test. The estimation accuracy analysis of these metrics is depicted in Table 5.7.

According to the results, the old and new metrics have mean estimation accuracy, of 48.30% and 95.69% respectively. The new metric is significantly improved in accuracy, and is 1.98 times better than its predecessor despite of variation in track severity.

7.0 CONCLUSION

This paper introduces two new parameters into the driving skill algorithm structure, namely, orientation angle and lateral speed. The new group of parameter was then called as driving parameter which is denoted by $x_{new} = \{\theta_p, d, \dot{d}, \dot{s}\}$. The new driving skill metric is a function of driving parameter, x which is $J \rightarrow f(x_{new})$. These parameters are then grouped into two distinct driving criteria, namely, accuracy and quickness criteria. The accuracy criterion, J_A is composed of the orientation angle control, θ_p and the position control, d ; while the quickness criterion, J_Q is composed of lateral speed control, \dot{d} and velocity control, \dot{s} .

From the data analysis, driving parameter, θ_p has a higher correlation magnitude over d for accuracy criterion, J_A . While \dot{d} also has a significantly higher correlation than \dot{s} for quickness criterion, J_Q . A good correlation between driving parameter and track severity criteria indicate that the parameters demand more control in negotiating track curving.

Technically, the driver is more attentive towards regulating car orientation angle, θ_p for path tracking accuracy when facing curving track circumstances, while emphasizing more agility on quickly compensating car position (related to car lateral speed control, \dot{d}). Furthermore, it is proved that the skill metric employing a method of accuracy and quickness criterion based modelling methodology achieves greater performance at almost double compared to previous methods

This study however, is limited to path tracking driving skill of drivers holding a Malaysian driver's license. In order to test the behaviour that represents vehicle path tracking control, a scenario of open car track similar to that of a normal roadway, with different conditions of curving severity had been chosen. This study was conducted in a limited experience of driving environment (i.e., the use of a simulated driving environment). There is however still a need to study the practical life application although the experience of driving simulator is quite similar to driving in a real environment.

Table 2 Result of driving parameters data at all track's segments

Segment	Driving parameter, x			
	d'	θ'_p	\dot{d}_{norm}	\dot{s}_{norm}
a	0.95	1.16	0.74	0.84
b	0.86	1.26	0.58	0.77
c	1.02	1.06	0.84	0.97
d	0.85	1.03	1.02	1.01
e	1.16	1.15	0.83	0.96

Table 3 Result of correlation data analysis between driving parameters and track severity

DCI ρ_{xk}	J_A		J_Q	
	d'	θ'_p	\dot{d}_{norm}	\dot{s}_{norm}
	-0.61	-0.63	0.33	0.30

Table 4 Result of skill index of both metrics

Metric score (Index)	Lap				
	1	2	3	4	5
J_{old}	1.53	1.52	1.48	1.54	1.52
J_{new}	1.07	1.04	0.98	1.07	1.02

Table 5 Result of metric estimation improvement data analysis for both metrics

Accuracy, A	Lap					μ_A
	1	2	3	4	5	
$A_{old}(\%)$	47.48	48.42	51.96	45.92	48.22	44.40
$A_{new}(\%)$	93.35	95.64	98.08	92.61	97.54	95.44
Improvement index, I						2.15

Table 6 Result of skill index for both metrics across all five track segments

Metric score (Index)	Segment				
	a	b	c	d	e
J_{old}	1.55	1.52	1.50	1.53	1.47
J_{new}	1.08	1.07	1.03	1.02	0.98

Table 7 Result of skill index for both metrics across all five track segments

Accuracy, A	Lap					μ_A	σ_A
	a	b	c	d	e		
$A_{old}(\%)$	44.82	47.66	49.73	46.53	52.78	48.30	3.07
$A_{new}(\%)$	92.39	93.43	97.30	97.71	97.61	95.69	2.57
Improvement index, I							1.98

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