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Quantifying drivers' visual perception to analyze accident-prone locations on two-lane mountain highways

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ABSTRACT

Owing to constrained topography and road geometry, mountainous highways are subjected to frequent traffic accidents, and these crashes have relatively high mortality rates. In middle and high mountains, most roads are two-lane highways. Most two-lane mountain highways are located in rural areas in China, where traffic volume is relatively small; namely, traffic accidents are mainly related to the design of roads, rather than the impact of traffic flow. Previous studies primarily focused on the relationship between actual road geometry and traffic safety. However, some scholars put forward that there was a significant discrepancy between actual and visual perceived information. Drivers greatly depend on what they perceived by their vision to determine driving behavior. Thus, in this paper drivers' visual lane model was established to quantify drivers' visual perception. To further explore drivers' perception of horizontal and vertical alignments, the visual lane model was projected onto horizontal and vertical planes in drivers' vision respectively. The length and curvature of the visual curve were extracted as shape parameters of drivers' visual lane models. Real vehicle driving tests were conducted on typical two-lane mountain highway sections of G318 in Tibet, China. Then the differences of visual perception at black spots and accident-free locations were analyzed and compared. In horizontal and vertical projections of visual lane model, there were 9 shape parameters have significant differences between accident-prone and accident-free locations. A probabilistic neural network (PNN) was formed to identify accident-prone locations on two-lane mountain highways. This study will lay a foundation for the improvement of traffic safety on mountain highways based on the quantification of drivers' visual perception, during the phase of both road design and reconstruction, and can also make a contribution to the automatic driving technique.

1. Introduction

Owing to constrained topography and road geometry, mountainous highways are subjected to frequent traffic accidents, and these crashes have relatively high mortality rates (Rusli et al., 2015). In India mountain highways had a higher fatality index (the ratio of fatalities to road injuries) compared to roads in non-mountainous areas (Rautela and Shikher Pant, 2007). Mountain roads also suffered from high crash rates in Colorado, USA, and from 2006 to 2010, 1171 crashes were documented in a 15-mile mountainous section on I-70 (Yu et al., 2015). In China, one-third of the country is covered by mountains (Meng, 2017), and most roads in mountainous terrain, especially in middle and high mountains, are two-lane highways (Xu et al., 2017). According to statistical yearbooks of road traffic accidents of China between 2012 and 2016, up to 68% of serious crashes occurred in mountainous regions, while serious crashes that happened in non-mountainous areas only accounted for 32% (Traffic Management Bureau of Ministry of Public Security of China, 2013–2017).

Accident-prone locations or black spots refer to geographical locations with highly concentrated traffic accidents (Geurts et al., 2004). Most two-lane mountain highways are located in rural areas in China, where traffic volume is relatively small; namely, traffic accidents are mainly related to the design of roads, rather than the impact of traffic flow. Single-vehicle crashes are a dominant crash type on mountainous roads (Rusli et al., 2017). Thus, a geometric design on two-lane mountain highways plays a vital role in traffic safety. Many scholars have studied the relationship between road geometry and traffic safety. Crashes on mountain roads were primarily attributed to basic road geometric parameters like sinuosity and gradient that differentiate mountain roads from those in the plains (Fu et al., 2011). Roadway

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geometry was strongly correlated with crash risk, and steep downgrades could lead to the growth of crash risk (Ahmed et al., 2011). Drivers' average speed, time headway, time to collision, and distance headway were affected by roadway-related factors, such as horizontal curves, vertical curves, shoulder width, median type and so on (Hamdar et al., 2016). Using naturalistic driving data, Xu et al. (2016) found that road geometrical parameters had a great impact on vehicle travelling tracks on mountain highways. Chen et al. (2007) established a causation model of accident numbers with significant factors including the length of slope, grade, and curvature of horizontal alignments. A hierarchical tree-based regression approach was developed by Karlaftis and Golias (2002) to quantitatively evaluate the impacts of highways geometric features on crash rates and mathematically predicate crash rates on rural roads. With data envelopment analysis technique, curvature ratio and tangent ratio were regarded as geometric indexes to detect black spots (Sadeghi et al., 2013).

The dominant information that drivers obtained during driving mainly comes from their visual perception (Sivak, 1996; Underwood, 2007). Drivers' visual perception has a close relationship with driving safety (Ma and Fu, 2015). On mountain highways, drivers determine driving speeds in accordance with their perceptions of roadway geometry (Castro et al., 2012). Some scholars maintained that there was a significant discrepancy between actual and perceived information, so sometimes an actual roadway geometric design that looks good in terms of design indicators cannot meet the demands of drivers' visual perception, resulting in traffic accidents. Bidulka et al. (2002) emphasized the significance of precise visual information received by drivers, and found that the overlapping vertical alignment had a great impact on the perceived horizontal curvature. The probability of erroneous perception of horizontal curvature was affected by sight distance, actual curve radius, the length of vertical curve and turning direction (Hassan et al., 2002). Current highway geometric design focused on two-dimensional analyses without considering three-dimensional visual quality, which was primarily responsible for inaccurate drivers' visual perception (Hassan and Sayed, 2002). Drivers could generate misperceptions when horizontal and vertical curves were combined, and this might lead to erroneous drivers' speed choice (Hassan and Sarhan, 2012).

Given the above, current studies mostly focus on the actual road geometry and traffic safety, neglecting to consider that information perceived by drivers' eyes is not always consistent with the actual geometric design. However, drivers greatly depend on what they perceived by their vision to determine driving behavior. Thus, it is meaningful for us to analyze traffic accidents on two-lane mountain highways from drivers' visual perception. In this paper, drivers' visual lane model is established to quantify drivers' visual perception. The differences of visual perception at black spots and accident-free locations are analyzed and compared, and then a probabilistic neural network is used to identify hazardous road locations.

2. Methodology

2.1. Drivers' visual lane model

In our previous study, the drivers' visual lane model was established based on Catmull-Rom spline (Yu et al., 2016). This model can be used to quantify and describe road alignments perceived by drivers' vision, shown in Fig. 1. In the following paragraph, a brief introduction of this model is to be presented. The validity of drivers' visual lane model in quantifying drivers' visual perception has been demonstrated by us (Yu et al., 2016). We have also calculated the deviation between horizontal visual perception and the actual information by an index called the horizontal visual component (Chen et al., 2015). In this research, the drivers' visual lane model is improved and refined (see in Fig. 2), and it can better depict the horizontal and vertical alignments from drivers' visual perception.

In the drivers' visual lane model, the bottom-left corner in drivers'

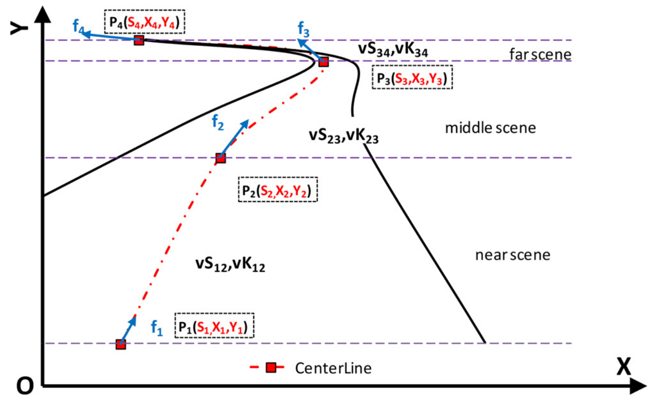

Fig. 1. Drivers' visual lane model.

visual field is set as the origin of coordinate, as shown in Fig. 1. There are four control points (P_1, P_2, P_3, P_4) in Catmull-Rom spline. The matrix equation of the Catmull-Rom Spline is as follows:

$$P(k) = [1\; l\; l^2\; l^3]\, M \begin{bmatrix} P_1 \\ P_2 \\ P_3 \\ P_4 \end{bmatrix} \tag{1}$$

$$M = \frac{1}{2} \times \begin{bmatrix} 0 & 2 & 0 & 0 \\ -1 & 0 & 1 & 0 \\ 2 & -5 & 4 & -1 \\ -1 & 3 & -3 & 1 \end{bmatrix} \tag{2}$$

where l denotes the interpolation variable, $l \in [0,1]$; $\{P_1, P_2, P_3, P_4\}$ are control points of the Catmull-Rom Spline.

Locations of control points (P_1, P_2, P_3, P_4) are determined by the shape of Catmull-Rom Spline, so positions of control points are diverse when drivers' visual lane models change. Four horizontal lines pass through four control points and divide drivers' visual field into three different regions - namely, "near scene", "middle scene" and "far scene". Curve length and curvature of visual lane centerline in three regions are chosen as shape parameters of drivers' visual lane model, denoted by $[vS_{i(i+1)}, vK_{i(i+1)}]$ ($i = 1,2,3$), and computation formulas are as follows:

$$vS_{i(i+1)} = S_{i+1} - S_i \tag{3}$$

$$vK_{i(i+1)} = \frac{f_{i+1} - f_i}{vS_{i(i+1)}} \tag{4}$$

Where, $i = 1,2,3$; $vS_{i(i+1)}$ denotes visual curve length between control point P_i and P_{i+1} (pixels); $vK_{i(i+1)}$ denotes visual curve curvature between control point P_i and P_{i+1}, namely, the unit rate of change of tangential angle (radians); f_i is the tangential angle at control point P_i(radians); S_i is visual curve cumulative length at control point P_i(pixels).

As shown in Fig. 2(a), in this paper, the drivers' visual lane model is projected onto driver's visual horizontal and vertical planes respectively. Then horizontal and vertical alignments in drivers' visual perception can be obtained, illustrated in Fig. 2(b) and (c). During the process of calculation, there are two important steps: (1) acquiring projection points of control points; (2) extracting shape parameters in different planes. The specific computational method is as follows:

Fig. 3(a–c) show the horizontal projection of the driver's visual lane model in three different regions ("near scene", "middle scene" and "far scene"). (P_{1L}, P_{2L}, P_{3L}, P_{4L}) and (P_{1R}, P_{2R}, P_{3R}, P_{4R}) are control points of the left-side and right-side lane markers respectively. P_{12} is the intersection point of two lines $\{P_{1L}P_{2L}, P_{1R}P_{2R}\}$. Likewise, P_{13} and P_{14} are intersection points of lines $\{P_{1L}P_{3L}, P_{1R}P_{3R}\}$ and $\{P_{1L}P_{4L}, P_{1R}P_{4R}\}$. ($P_{1\_H}$, P_{2_H}, P_{3_H}, P_{4_H}) represent the horizontal projection points of control points (P_1, P_2, P_3, P_4). The calculation of P_{2_H} is taken as an example to

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