The Study on Intelligent Vehicle Collision-Avoidance System with Vision Perception and Fuzzy Decision Making

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Abstract—This paper proposes a combination scenario of vision perception and fuzzy decision making for developing an intelligent vehicle collision-avoidance system (IVCAS). In IVCAS, a CCD camera is installed on the following vehicle and used to capture the image of leading vehicles and road information. The features of the leading vehicles and lane boundary are recognized by vision perception method which derived from our previous work on Histogram-based Color Difference Fuzzy C-Means (HCDFCM). HCDFCM is a robust and fast algorithm for detecting object boundary. In this paper, we adopted the coordinate mapping relationship (CMR) with HCDFCM to provide a robust vision perception for the necessary information such as relative velocity, relative distance between leading and following vehicle and absolute velocity of following vehicle, etc. The collision-avoidance strategy is based on the vision perception and implemented by a fuzzy decision making mechanism. In this paper, the necessary information is integrated as a degree of exceeding safe-distance (DESD) to estimate the possibility of collision. A safety coefficient (SC) is defined to indicate the degree of safety. Therefore, the number of fuzzy rules that based on DESD and SC could be reduced to improve the efficiency of decision making.

In addition to robust image processing, abundant information are derived from recognizing image feature using the proposed algorithm in this paper. The fuzzy decision making mechanism abstract useful compact data extracted from these abundant information. Therefore, the main advantage of IVCAS is using less number of fuzzy rules than other systems, and gets more effectiveness in vehicle collision-avoidance.


I. INTRODUCTION

In recent years, vehicle collision-avoidance using electronic devices has become a main stream in the developing Intelligent Transportation System (ITS). The purpose of Collision-Avoidance System (CAS) is to prevent collision accidents, thus how to identify the leading vehicles and measure the relative distance between the leading and following vehicles are important research topics. In [1], Yamaguchi et al. proposed a high-pass filter method to detect the characters of the vehicle plate, and the locations of cars in the meantime. It is often used in Automated Detecting Vehicle System on parking spots. In [2], Kato et al. used Neural Network to recognize the proceeding vehicles. It provided sufficient training samples, and tested the reliabilities of the Neural Network System by testing samples. In [3], the Roma System combined odometer and adopted the optical flow method to distinguish the clusters of moving objects. In [4], the research department of NEC Company reduced the error rate of detecting the vehicles from images by using the feature of the symmetry of vehicles, shadows underneath the vehicles, and the difference in gray-level average intensities. In [5][6] proposed a reliable stereo matching to apart vehicle from overlapping vehicles group.

This paper proposes a combination scenario of vision perception and fuzzy decision making for developing an intelligent vehicle collision-avoidance system (IVCAS). In IVCAS, a CCD camera is installed on the following vehicle and used to capture the image of leading vehicles and road information. The features of the leading vehicles and lane boundary are recognized by vision perception method derived from our previous work on Histogram-based Color Difference Fuzzy C-Means (HCDFCM) [11]. HCDFCM is a robust algorithm for detecting object boundary, used to recognize road edge and boundary of vehicles in this paper. The coordinate mapping relationship (CMR) adopted with HCDFCM to provide a robust vision perception for the necessary information such as relative velocity, relative distance between leading and following vehicle and absolute velocity of following vehicle, etc. The collision-avoidance strategy is based on the vision perception and implemented by a fuzzy decision making mechanism. In this paper, we integrated all of the necessary information as a degree of exceeding safe-distance (DESD) to estimate the possibility of collision. A safety coefficient (SC) is defined to indicate the degree of safety. In IVCAS, the number of fuzzy rules that based on DESD and SC therefore could be reduced to improve the efficiency of decision making.

Besides this section, we discuss the vision perception algorithm in section II. The fuzzy decision making mechanism is presented in section III. The section IV and V are experiment results and conclusion, respectively.

II. IMAGE INFORMATION EXTRACTION

2.1 Coordinate Mapping Relationship

Coordinate mapping relationship (CMR) performs the transformation between two dimensional and three dimensional
coordinates systems. If the information of one of coordinates is given, the other is obtained by mapping procedure. Comparing with [7][8], the CMR proposed in this paper not only derive the distance between image plane and leading vehicle but also the height and width of leading vehicle could be measured. We discuss CMR into three parts individually.

A. The determination of distance

The geometric relationship between two-dimensional image plane and three-dimensional real-world illustrated as Fig.1, where the image plane and real world coordinate are presented as \((x',y')\) and \((x^*,y^*,z^*)\). \(O'\) and \(O\) are center of image plane and the geometric center of CCD lens, respectively. Assume that point \(D\) and \(F\) are the location of leading vehicle and CCD lens installed at following vehicle, where point \(D\) is mapping to point \(E\) in image plane. If the height of installed CCD is fixed in \(CH\), then the distance between \(D\) and \(F\) can be obtained by (1), where the depression angle of CCD \( \theta \) is calibrated by (2). \( \theta \) is derived from pixel length \( lp \) and the distance between adjoining pixels \( \Delta p \) with focal length of CCD lens \( f \). A fixed quantity of \( \Delta p \) is according to the resolution specification of image plane, example for 640×480 image plane can be calculated by (3).

\[
L = \frac{H_c}{\tan(\theta_1 + \theta_2)}
\]

\[
\theta_1 = \tan^{-1}\left(\frac{H_c}{L_1}\right), \quad \theta_2 = \tan^{-1}\left(\frac{l}{f}\right) = \tan^{-1}\left(\frac{p_j \times \Delta p_j}{f}\right)
\]

\[
\Delta p_j = S \times \frac{p_j}{\sqrt{p_j^2 + p_j'^2}} \times \frac{1}{3} \times \frac{2}{\sqrt{13}} \times \frac{1}{480} = 3.852 \times 10^{-7} \text{mm}
\]

B. The determination of width

The line \(KG\) and \(DE\) in Fig. 1 are enlarge upon Fig. 2. The width between \(D\) and \(K\) is derived by (4), where \( \theta_i \) can be obtained from (5).

\[
W = H_c \csc(\theta_1 + \theta_2) \tan \theta_3 = \frac{w \times \sqrt{H_c^2 + L^2}}{\sqrt{f^2 + l^2}}
\]

\[
\theta_3 = \cos^{-1}\left(\frac{n \cdot \overrightarrow{a}}{|n| \cdot |a|}\right)
\]

C. The determination of height

From image plane illustrated in Fig. 3, the height of leading vehicle \(d_{vw}\) is according to various distances between leading and following vehicle. \(d_{vw}\) can be calculated by (6), where \( c \) is the half value of horizontal length of image plane, e.g., \( c \) is 120 in the case of 320×240 image plane. \( i \) is the vertical coordinate value of the vehicle rear, and \( p_j \) is calculated by (7), where \( H_c \) and \( H_f \) are the width and height of vehicle, respectively. \( L_p \) is the distance between point \( i \) mapping to the point of real-world coordinate system and shown as (8).

\[
dl_{vw} = c + p_i - i
\]

\[
\frac{f}{\Delta p_j} = \begin{cases} 
\frac{f}{\Delta p_j} \times \tan(\theta_i - \tan^{-1}\left(\frac{H_f - H_c}{L_p}\right)), & \text{if } H_f \leq H_c \\
\frac{f}{\Delta p_j} \times \tan(\theta_i + \tan^{-1}\left(\frac{H_f - H_c}{L_p}\right)), & \text{if } H_f > H_c 
\end{cases}
\]

\[
L_p = \frac{H_c}{\tan(\theta_i + \theta_3), \quad \text{if } i \in \{0, 119\}}
\]

\[
L_p = \frac{H_c}{\tan(\theta_i - \theta_3), \quad \text{if } i \in \{119, 239\}}
\]

2.2 Vision Perception for Vehicles

The essential work of IVCAS is to extract the necessary features of leading vehicles and make decision for collision avoidance. Our previous work on HCDFCM [13] for lane boundaries detection is adopted with CMR to perform the vision perception for feature extraction. There are three methods for detecting vehicles.

A. Usage of image vehicle width

Most width of vehicles are about 180cm, thus the pixel lengths of vehicle width (PLVW) is a fixed quantity. As to the pixel lengths, they can be calculated according to CMR. Follow HCDFCM horizontally scan the image plane from bottom to up, and create a group of detected boundaries. If a boundary has the nearest compatible with PLVW, the location of vehicle is found.

\[
E = (x',y') = (0, L)
\]

\[
G = (x',y') = (-\eta, L)
\]

\[
D = (x^*,y^*,z^*) = (0, H_c, L)
\]

\[
K = (x^*,y^*,z^*) = (-W, H_c, L)
\]

Fig. 2. The width calculation according to CCD camera image

Fig. 3. \(d_{vw}\) is according to variety distance
The method was also mentioned in [4] [9]. The flowchart is depicted as Fig.4. Consequently, the method is described in detail.

\[ Q = \{ q_r = b \beta_j \mid i \neq j, r = 1,2,..., n_2 \} \]  
\[ P = \{ p_i = R(b_j) - V_{1} \max R(b_j) \mid i = 1,2,..., n_1 \} \]  
\[ S = \{ s_q = p_i \times p_j \mid i \neq j, q = 1,2,..., n_2 \} \]  
\[ |BI - IWWV| \leq c_2 \]  

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The flowchart of PLVH processing algorithm is illustrated as Fig. 7, and experiment result shown as Fig. 8.

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(a). Define the scan line area  
(b) Boundary detected by HCDFCM  
(c) Analyzed data

Fig. 5. HCDFCM Preprocessing

(a) Result of HCDFCM  
(b) Leading vehicle rear detected  
(c) Analyzed data

Fig. 6. Leading Vehicle Detection

B. Usage of image vehicle height

Assumed that the pixel length of vehicle height (PLVH) in the image plane is a constant value, and most vehicles’ height are about 134cm, the PLVH expressed as (16) can be calculated by CMR, where \( i \) is the vertical coordinate in image and \( c \) is the half value of image resolution. For example, \( c \) is 120 in the case of 240×320 image plane. The location of vehicle is detected by scanning vertically HCDFCM, and grouping pairs from any two boundaries. The location is obtained from any pair that has the most compatible result. Besides, the number of defined line is constraint to (17), and \( C_1 \) is preset as 1.1 in this case.

\[ PLVH = \frac{C_1 + f \tan(i) - \tan(\theta) - H_i}{L_p} \]  
\[ |I_{line-i} = C_1 \times I_{dw} \]  
\[ i = 0 \]  

The flowchart of PLVH processing algorithm is illustrated as Fig. 7, and experiment result shown as Fig. 8.
C. Usage of boundary distribution of image vehicle rear

This procedure detects leading vehicle using the boundary distribution of vehicle rear, not vehicle height. The algorithm flowchart is illustrated as Fig. 9. As shown in Fig. 10.(a) and (b), the closer the distance between CCD and leading vehicle, the more boundaries can be found. On the contrary, the numbers of boundary get fewer when the distance is getting far. The vehicle can be detected according to (18), where \( C_2 \) indicates the least boundary number that can be obtained in its scanning area. In this case, as experiment results, \( C_2 \) is chosen to 7. \( l_{d_{v_m}} \) shown as (19) indicates the scanning length formed in the location of leading vehicle rear when \( r=0 \).

\[
N_{d_v} \begin{cases} \geq C_2 \times \frac{l_{d_v}}{l_{d_{v_m}}} & \text{it may be a vehicle} \\ < C_2 \times \frac{l_{d_v}}{l_{d_{v_m}}} & \text{it isn't a vehicle} \end{cases}
\]

(18)

\[
l_{d_{v_m}} = l_{d_{v,0}}
\]

(19)

Fig. 9. Boundary distribution processing algorithm

2.3 Features Extraction

After the vehicle detecting procedures the actual distance between the leading and following vehicle can be extracted by (20), where the CCD depression angle \( \theta_i \), height of CCD \( H_c \), focal length of lens \( f \), and distance between pixels \( \Delta p \) are known, and \( p_i \) can be obtained from location of vehicle in image. Therefore, the relative velocity (RV) can be derived by (21), where \( \Delta t \) and \( \Delta M(t) \) are the time interval of the consecutive image frames and distance between following and leading vehicle, respectively.

\[
L = \frac{H_c}{\tan(\theta_i + \theta_j)} = \frac{H_c}{\tan(\frac{H_c}{L_i} + \tan^{-1}(\frac{D_i \times \Delta p_i}{f}))}
\]

(20)

\[
RV = \frac{\Delta M(t)}{\Delta t}
\]

(21)

The absolute velocity of following vehicle is derived as below. For the two consecutive images shown as Fig 11, the \( AB \) is a predefined segment in vertical line, example for \( A_1B_1, A_2B_2, \ldots \), and \( A_{n+1}B_{n+1} \) are also defined individually in the next image. Besides, the results shown in Fig. 12 are the pixel values processed by HCDFCM, and the fig_1, fig_2…fig_N are the results of \( A_1B_1, A_2B_2, \ldots, A_{n+1}B_{n+1} \), respectively. In (22), the factor indicates that the diffusion factor between two different segments. By adopting this factor, the Euclidean distance is calculated in (23), and it means that the similarity between two different templates. When the similarity is the largest at \( n=M \), it means the modal template in the first image is moved to \( A_{M+1}B_{M+1} \) in real-world space and the pixel length is \( M-1 \). In this case, the real distance mapped from \( A_{M+1}B_{M+1} \) by using CMR is calculated. Then absolute velocity is obtained from (24), where \( D^i, V^i \) and \( \Delta M^i \) are actual absolute distance, absolute velocity and time interval, respectively.

\[
a_n = \frac{A_nB_n}{AB}, n = 1, 2, \ldots, N
\]

(22)

\[
D_n = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (E[k] - E[a_n \times k])^2}
\]

(23)

\[
V^i_n = \frac{D^i_n}{\Delta M_{f,ab}}
\]

(24)
III FUZZY DECISION MAKING

This section builds a fuzzy decision-making mechanism which abstracts the drivers’ expertise to simulate human’s action before the occurrence of collision. From many existed features extracted previously, we can construct a safety decision-making assistant system. Fuzzy inference system has effectively resolved the nonlinear and/or complex system such as this study, and adopts the expertise into fuzzy knowledge base (FKB). The Fuzzy Inference System (FIS) is proposed based on fuzzy logic and approximate reasoning [10]. FKB and Fuzzy Inference Engine (FIE) is the core of FIS. FKB contains the domain knowledge composed of fuzzy database described by linguistic variables for input and output, and fuzzy rule base is composed of many fuzzy production rules as (25) to describe the behavior of system, where \( X \) and \( Y \) are all linguistic variables. The essential work of approximate reasoning is to calculate the strength of fired rules and computes the degree of each fired rule’s conclusion as (26), and defuzzified the output real value by (27).

\[
R_i: \text{IF } X \text{ is } A_i \text{ THEN } Y \text{ is } B_i \\
\mu_B(y) = \max_{x} \left\{ \mu_A(x) \cdot \mu_{A \rightarrow B}(x,y) \right\} \\
\sum_{y \in Y} y \cdot \mu_B(y) \\
\sum_{y \in Y} \mu_B(y)
\]

According to the image information extracted in section II, the FIS system is described in Fig.13. The three inputs are relative velocity, absolute velocity, and relative distance. The outputs are two kinds of warning approaches. Using too many input factors will yield more fuzzy rules, and heavy computation cost. Considering the real time requirement, we combined these three input factors to define a degree of exceeding safe-distance (DESD) as (28). While the DESD \( \geq 0 \) means the possibility of collision exists. In general, DESD \( \leq 100\% \) and getting closer to 100% the possibility of collision is higher. The output factors are replaced by a safety coefficient (SC) expressed as (29) to judge the degrees of warning, and reducing or increasing the velocity of following vehicle as (30). In other word, when the SC value is higher, the degree of warning and reducing velocity is lower. Therefore, in Fig.14 DESD is defined by three fuzzy sets and SC is defined by three singleton values. The fuzzy rules are presented as Fig.15.

\[
DESD = \frac{\text{Safety distance} - \text{Relative distance}}{\text{Safety distance}} \\
ALARM = 1 - SC, SC \in [0,1] \\
V_{A, \text{new}} = V_{A, \text{now}} \times SC, SC \in [0,1]
\]

IV EXPERIMENT RESULTS

A visual simulation environment depicted as Fig.16 is developed to simulate the vehicles interactive situation on the road. User can setup parameters to observe the operation of collision-avoidance strategy. The environment is divided into vehicle simulation interface and parameter manager. In the simulation interface, box A and B are the following vehicle and leading vehicle, respectively. The road is represented as symbol C. The parameters manager is composed by three divisions. The F division indicates a lot of features provided by vision perception; include the relative distance between A and B (RD), the velocity of A (VA), the relative velocity between A and B (RVAB), and the equivalent velocity (EV) obtained from VA and RVAB, and the variable safety distance (VSD) can be derived from EV. The DESD is obtained by (28) and SC is inferred from collision-avoidance fuzzy inference system.

Fig. 16. Simulation visual interface

The simulation result of collision-avoidance strategy for common occurrence cases: the distance between leading and following vehicle is 60 meter, the same direction with initial velocity for vehicles are all 100KM/hr. Suppose the leading
vehicle is reducing velocity by the step time 0.2 seconds for {100, 90, 80, 70, 60, 50, 40, 30, 20, 10, ..., 10}. If the following vehicle holds the original velocity, then the collision occurred after three seconds. Owing to the simulation result the collision-avoidance is working correct. Fig.17 (a) indicates RD is larger than VSD from begin to end, Fig.17 (b) and (c) illustrates VA is reducing smoothly than VB and SC is still maintaining above 90%.

(a) RD vs. VSD (b) VA vs. VB (c) DESD vs. SC
Fig. 17. The result of same direction simulation

Follow the previous experiment shown in Fig. 17, the intelligent collision-avoidance strategy was tested another situations with many various considerations, such as: initial relative distance, original velocity of following vehicle, velocity changing schedule of leading vehicle, etc.

1. Compare with various relative distances

Here we compare with various relative distance situations involve many equivalent considerations, such as: the sampling time, initial velocity of following vehicle, and various velocity changing steps of leading vehicle. Fig. 18 and Fig. 19 are simulated results with 65M and 30M, respectively. Following the experiments results, in the case of various relative distances do not influence the collision-avoidance performance: RD is closer VSD all the time, VA is reducing smoothly similar to VB. Although DESD vs. SC curves are different with various relative distance, but after three seconds the SC is improved up to 90%.

Fig. 18. Relative distance = 65M
Fig. 19. Relative distance = 30M

2. Compare with various velocity change

The various velocity changing steps of leading vehicle is by the step time 0.2 seconds for {100, 90, ..., 20, 10, 10, ..., 10} (KM/hr). The simulation results illustrated in Fig. 20 and Fig. 21 are the initial velocity of following vehicle begins with 150KM/hr and 50KM/hr, respectively. No matter how the begin initial velocity of VA; the proposed fuzzy decision making is unquestionably a robust collision-avoidance mechanism.

Fig. 20. The initial velocity of following vehicle with 150(km/hr)
Fig. 21. The initial velocity of following vehicle with 50(km/hr)

V CONCLUSION

This paper combines CMR and HCDFCM algorithms as a vision perception mechanism for capturing the feature information, and takes them as input data to infer outputs according to the fuzzy decision making, in order to prevent the collision accidents. In this study, we regard the vehicles’ velocities and relative distances as primary features extracted by vision perception, and derive into DESD. Besides, a relationship between DESD and SC is induced into three fuzzy rules. Therefore, the main advantage of IVCAS is using less number of fuzzy rules than other systems, and gets more effectiveness in vehicle collision-avoidance.

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