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Multi-Cameras based Decision Making at Mini-Roundabouts for Autonomous Vehicles

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Abstract— **Safety driving in complicated traffic situations such as at roundabouts is crucial in autonomous vehicle design. Utilising multiple cameras for approaching vehicles detection in real-time has been determined the key challenge in this research area. This paper proposes a grid-based image processing approach that effectively learns the movement, position and direction of approaching vehicles, thus supporting an autonomous vehicle to make a human-like decision at mini-roundabouts. 230 video clips recorded in the UK were examined using three Machine Learning models (i.e. Support Vector Machines, Artificial Neural Network, k-Nearest Neighbours). Experiments indicated that SVM was outstanding with 91.32% accuracy rate in 0.7 seconds. This result suggests that the proposed system is reliable for autonomous vehicles to enter mini-roundabouts safely and smoothly.**

I. INTRODUCTION

Interaction provide challenge for autonomous vehicle in recently years, the autonomous vehicle is threated by many meeting-points in normal interaction when it merge a junction[5]. A roundabout is a useful circular design in improving safety in intersections, both in urban and rural areas. A roundabout is a looping junction where vehicles are restricted to go in one direction around a central island with priority is given to the ones have already entered the roundabout [1]. Roundabouts are widely applied in many countries' road systems and associated with a significant reduction of accidents [2] [3].

Traffic safety in roundabouts is an emerging topic in designing autonomous vehicles (AV). Facing a roundabout, the AV must normally handle a number of tasks including traditional vehicle controls (acceleration, deceleration, turning or braking) and situation awareness (approaching vehicles detection, speed evaluation or position keeping) [4]. Of which, the main issue should be judging the priorities and the behaviours of other vehicles around the roundabout [5]. Given that there could be a number of vehicles moving in various directions and speeds at a time, a roundabout can be considered a very complex driving environment. Enabling an AV to enter a roundabout smoothly and safety, therefore, remains a challenging question.

Many studies have been published in AV driving at roundabouts. For example, Gonzalez et al. [6] presented a path planning method that divided the driving process into three stages: entrance, driving within and exit the roundabout. By minimizing curvature steps, it avoided extensive manoeuver and increase smooth movements in roundabouts. Ziegler et al. [7] introduced a motion planning method for AV in roundabouts using camera recording, radar, and digital road maps. Dinh and Tang [8] proposed a Mixture of Gaussian algorithm to detect approaching vehicles in roundabouts using a single fix camera. Although some positive results have been reported, none of them really consider the mini-roundabout scenarios.

A mini-roundabout, as its name, is a smaller roundabout that built at sites lacking room for a conventional roundabout [9]. Mini-roundabouts even pose more challenges to AV than the normal roundabouts do [6]. Firstly, there is no physical centre island but a traversable painted circle (or a low dome) in a mini-roundabout, hence a higher chance of accidents. Secondly, the close gap between vehicles requires extra cautious in entering the mini-roundabout, especially in mini-roundabouts without a traffic light.

Figure. 1. A mini-roundabout (*source: Wikimedia Commons*)

In this paper, we propose a Grid-based system using multiple cameras to support AV in making the right decision at mini-roundabouts (GB-MC-MR). The system can evaluate the movement, position and direction of approaching vehicles at a

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mini-roundabout and then decide whether when it is safe to join. To the best of our knowledge, it is the first study in AV path planning that exploited the use of multiple cameras and focused on the mini-roundabouts traffic. On the other hand, our system is fast and reliable to be applied in real-time traffic scenarios.

The rest of this paper is organized as follows: Section 2 describes the proposed GB-MC-MR system. Section 3 presents the detailed of experiments including data acquisition, preprocessing, feature extraction and classification stages. Important factors of the algorithm are highlighted in Section 4 whilst future work is discussed in the final section.

II. PROPOSED GB-MC-MR SYSTEM

This section presents details about the proposed GB-MC-MR. Basically, mini-roundabout traffic video that captured using two cameras is pre-processed to appropriate images (frames). Image processing techniques are applied to each frame to extract its features, which are the closest approaching vehicle attributes, including the position, the speed, and the direction. For training purpose, each frame will be labelled as safe or unsafe that indicates whether the AV should go or wait at the mini-roundabout. The feature vectors and the corresponding labels generated are fetched a machine learning model so that the system can make a local decision from each camera. The final decision will be an integration of two local decisions using a simple rule: it is safe to go if only all local decisions are Go.

In real-time traffic, it is possible to use the system to inform the AV about the moment it can join the mini-roundabout safely.

Key components of the system are illustrated in the following figure:

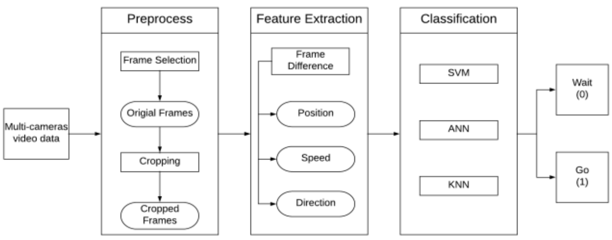

Figure. 2. The proposed system

A. *Data acquisition and preprocessing*

Two identical Nextbase 312GW cameras were utilised to record the traffic video in mini-roundabouts. To simulate the view from the UK driver seat, the cameras were installed on the frontal windscreen (camera A) and the right hand side window (camera B). The cameras worked synchronously, they started recording when the ego vehicle stopped (Wait) at a roundabout. When the ego vehicle started to enter the roundabout (Go), the recording was halted.

Figure. 3. Camera settings from inside the autonomous vehicle

230 pair of video clips were captured at 20 different mini-roundabouts in Leicestershire, UK. The video was recorded in different time frames in the day including peak hours (5 pm to 6 pm) to confirm the robustness of the system in busy traffic conditions.

Data were converted from video to images. In each second of an HD quality video 30fps, six frames were extracted (one in every five frames). Since there were two separated cameras used, each moment was represented by two single frames, frame A and frame B, respectively. The system should, based on the traffic condition showed in the two frames, inform the AV whether it is a safe moment to enter the roundabout.

Frames were manually labelled before passing to the next components. Each pair of frames were labelled as Wait (0) or Go (1) that reflect the decision the AV should make in facing a traffic scenario like what showed in the frames. It is noticed that the camera settings (car stops cameras on – car move cameras off) considerably simplify the labelling process. Only the last frame of each video clip was flagged as Go and the rest were all Wait.

From 230 pair of short clips, 632 samples pairs of frames were generated, providing 230 positive frame samples (Go), and 402 negative frame samples (Wait). Details about processed data are demonstrated in the following table.

TABLE 1. Learning sample statistics for 2 cameras at mini-roundabout (VN: The number of videos, RN: The number of roundabouts, SN: The number of samples, PSN: The number of positive samples, NSN: The number of negative samples, TR: Training sample, TR.P: Training positive sample, TR.N: Training negative sample, TE: Test sample, TE.P: Test positive, TE.N: Test Negative)

VN	RN	SN	PSN	NSN	TR		TE	
					TR.P	TR.N	TE.P	TE.N
230	20	632	230	402	506		126	
					182	324	45	81

B. *Feature Extraction*

That component discloses the descriptions of the closest vehicles to the AV in the pair of frames, including position, speed and direction of that vehicle.

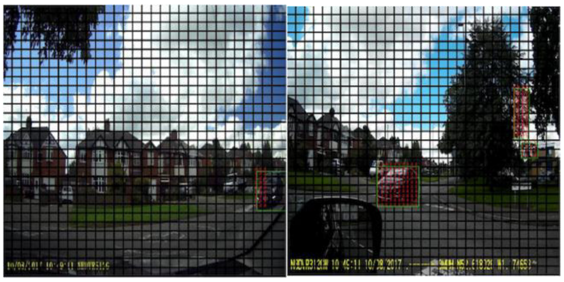

Figure. 4. Approaching vehicle detection in the frontal frame (frame A - left hand side) and the side view (frame B - right hand side)

Various ways of vehicles detection technologies are employed previously, for intense, frame difference method [13], average background method [13] and Gaussian mix method [6]. Gaussian mixture model works the best, but it works more slowly than difference frame algorithm [6]. Therefore, to detect the closest vehicle in each frame, the frame difference technique proposed in [10] was employed. The key advantage of that technique lies in its computational speed [11] which is important in maintaining the system's capability of performing in real-time situations. By applying the frame difference technique, the bounding box of the closest vehicle to the AV in each frame can be obtained. The centre point of the bounding box was used to represent that box.

After that, the position (Px, Py), the speed (S) and the direction (D) of the detected vehicle were computed. In the grid-based map, (Px, Py) denotes the coordinates of the above-mentioned centre point. S shows the distance between two centre points in that frame and the previous frame. D can be defined by the change of Px in that frame and the previous frame. D can take one value as follows:

- D = -1: Px current > Px previous. The direction of the closest vehicle was from left to right.
- D = 0: Px current = Px previous. The closest vehicle does not move horizontally.
- D = 1: Px current < Px previous. The direction of the closest vehicle was from right to left.

Finally, the closest vehicle in each frame can be described by a set of feature (Px, Py, S, D).

Samples of feature vectors generated using the frontal camera (camera A) are exhibited in the following table.

TABLE 2. Feature vector samples – camera A (frontal view) (FN: frame number, PxA: horizontal position. PyA: vertical position, SA: speed, DA: Direction)

FN	PxA	PyA	SA	DA
1	16	15	0	0
2	14	18	5	1
3	13	20	3	1
4	12	22	3	1

After that, the feature vectors and their corresponding labels are fetched a binary classifier. Signal from two cameras will generate to local decision DeA and DeB, each of which could either be 1 (Go) or 0 (Wait). The integrated final decision can be made using a simple logical AND rule: De = DeA *AND* DeB.

C. Classification and Results

The processed data were divided to 80% for training set (506 samples) and 20% for test set (126 samples).

Three classifiers were employed: Support Vector Machines (SVM), Artificial Neural Network (ANN), and k-Nearest Neighbours (kNN). To guarantee that our system is qualified in real-time traffic scenarios, the accuracy and the computational time must be balanced. In our experiments, we focus on reaching the highest accuracy within roughly one second.

Among the three, SVM achieved the highest accuracy rate at 88.44% in 0.9 seconds. ANN and kNN obtained various results based on different parameter settings, but none of them accomplished the tasks within 1 second. The fastest ANN spent 1.1 seconds to reach 85.12% accuracy rate. It only consisted of only 2 layers of 6 input nodes and 2 output nodes. Deepen the ANN by adding another layer lead to running time increasing. In kNN, the most reasonable outcome was 83.76% in 1.3 seconds, obtained with k=64. Adjust the value k would either decelerate the system or deteriorate the performance.

The three classifiers were re-examined using cropped frames. Realising that the closest vehicles almost never entered the top quarter of a frame (unless it was a big size vehicle such as a lorry), we removed the top 25% of each frame and repeated the experiments. Again, SVM was outstanding with 91.32% accurate after 0.7 seconds. The outputs for the above mentioned ANN and KNN were 87.05% in 1 second and 85.84% in 1.2 seconds, respectively.

The results of the experiments are demonstrated in the following table.

TABLE 3. GB-MC-MR output (Cla: classification, Acc: accuracy rate. TT(s): training time, TD: Average decision-making time, FNS/TS: False Negative rate)

	Original frames				Cropped frames			
Cla	Acc	**TT(s)**	**TD(s)**	FNS/TS	Acc	**TT(s)**	**TD(s)**	FNS/TS
SVM	88.44%	1401.13	0.9	7.14%	91.32%	1135.13	0.7	5.56%
ANN	85.12%	1396.26	1.1	9.52%	87.05%	1154.26	1.0	7.93%
KNN	83.76%	1529.71	1.3	10.32%	85.84%	1298.71	1.2	7.93%

Also, the result is compared with Cross Validation (K=10), the 632 samples is divided by 10 subsets. the highest accuracy are provided in table 3.

III. DISCUSSION

In experiments with the two types of frames, SVM was the leading classifier that reaches approximately 90% accuracy rate within the 1-second threshold. That result is satisfactory in applying the system to real-time traffic scenarios.

Cropping the frames obviously improve the performance of the system. In our experiments, the most reasonable removal area was the top quarter of the frame. Exceeding that portion might reduce the reliability of the system since it was unable to effectively detect the approaching vehicles, especially big size vehicles such as Lorries, trucks or buses.

Using the logical AND rule significantly improve the safety in AV driving. It indicates that the AV is ready to go if only decisions made using each camera are all Go. Making the final decision in such way also reflect the way our system simulate the human driver's behaviour. At a mini-roundabout, the driver should always examine vehicles from the front and the right hand side (where other vehicles are given priority in the UK). Once it is safe in both sides, the drive can start entering the mini-roundabout.

One of the key factors in our algorithm is how to effectively and efficiently detect the closest approaching vehicle. Although there were several options, we recruited the frame difference technique [10] due to its simplicity and speed. However, it is not the most sensitive car detection technique, especially when the video quality is low [11]. For example, the poor lit condition in rainy weather can seriously interfere with its robustness. In such cases, other vehicle detection methods such as average background method [11] and Gaussian mix method [12] might be considered.

Another important factor in our algorithm is how to combine the frames captured by multiple cameras. In this study, we extracted features from each frame and accumulated them in a single feature vector. Initially, we also considered the well-known image stitching method which applied in handling multiple images [13] [14]. Image stitching can produce a wide-angle image whilst maintaining the quality of the source images. However, that method was rejected due to the fact that handling the distortion at the corners of the stitched image was a non-trivial task, and it significantly increases the computational cost.

Figure. 5. Image stitching distortion

IV. CONCLUSION

This paper proposed a grid-based decision-making system for an AV to safely enter a mini-roundabout (GB-MC-MR). It is the pioneer system that utilised multiple cameras in AV driving at roundabouts. Three classifiers were evaluated using 230 videos captured by multiple-cameras. SVM showed a promising result with a 91.32% classification accuracy in 0.7 seconds. That outcome suggested that the proposed system can support the AV to make a proper human-like decision when reaching a mini-roundabout in real-time. In the future, other complex driving scenarios including interaction and T-junction roundabouts will be investigated.

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