Vehicle Motion Detection using Fuzzy Logic and Multi-Class Classification

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***Abstract*—Accurate vehicle motion tracking is essential for various applications, including traffic monitoring and autonomous navigation. This report explores methodologies for analyzing vehicle movement using coordinate data extracted from captured frames. The dataset preprocessing involves selecting data points at specific intervals based on vehicle movement characteristics. Fuzzy logic is implemented to classify movement direction, followed by the utilization of SVM and Random Forest models for direction prediction. Results demonstrate the effectiveness of these models, with Random Forest achieving superior accuracy. This study underscores the importance of robust methodologies for interpreting vehicle trajectories and direction, with implications for real-world applications.**

***Index Terms*—Vehicle Motion Detection, Fuzzy Logic, Dataset Preprocessing, Multi-Class Classification, SVM, Random Forest, Fuzzy Membership Functions, Machine Learning.**

I. Introduction

The accurate tracking of vehicles' motion is crucial in numerous applications, including traffic monitoring, surveillance, and autonomous navigation systems. This report explores methodologies for analyzing vehicle movement based on coordinate data extracted from captured frames. The objective is to develop robust techniques for interpreting the trajectories and direction of vehicles over time.

II. Methodology

A. Dataset Preprocessing and Selection of Data Points

In this section, we describe the dataset, provided to us by Yagnik Bhavsar Ph.D Scholar at Ahmedabad University [1], used for analysis and the methodology employed to preprocess the data for our specific analysis needs.

Dataset Description

The dataset utilized for this analysis consists of vehicle coordinates captured at continuous timestamps from a moving vehicle on the road. Each entry in the dataset represents the location of the vehicle at a specific point in time, recorded at a frequency of 30 frames per second (30 fps), which corresponds to data collected every 0.033 seconds.

Frm	Track	xc	yc	w	h	Velocity(kmph)
1	1	2373	1324	95	128	0
2	1	2376	1331	94	128	22.12735165
3	1	2378	1338	96	127	21.32106834
4	1	2381	1347	96	129	26.45146189
5	1	2384	1356	97	129	28.12338374
6	1	2387	1363	96	128	25.49540046
7	1	2390	1371	95	130	25.49809004
8	1	2393	1379	94	130	25.47731044
9	1	2395	1387	94	128	25.08667118
10	1	2398	1395	94	128	25.14730526
11	1	2402	1403	94	130	25.58595195
12	1	2405	1412	96	130	26.39773612
13	1	2408	1420	97	130	26.16989314
14	1	2411	1428	94	130	25.98810281
15	1	2413	1437	94	130	26.35463835
16	1	2416	1445	94	130	26.15008535
17	1	2419	1453	94	130	25.97926713
18	1	2422	1462	95	129	26.44989327
19	1	2425	1469	95	130	25.66228096
20	1	2427	1477	95	130	25.37886817

Fig. 1. Dataset Description

Dataset Preprocessing

To prepare the dataset for our analysis, we implemented a preprocessing step to select data points at specific intervals. This selection was based on the movement characteristics of vehicles on the road, taking into account average vehicle speeds and lengths.

Calculation for Data Point Selection

1) **Average Speed of Vehicles:** The average speed range of vehicles considered for this analysis is 20 km/h to

30 km/h, which converts to approximately 8 m/sec to 9 m/sec.

2) **Vehicle Movement per Frame:** At 30 fps, the distance a vehicle travels in one frame (0.033 seconds) at an average speed of 8 m/sec is calculated as:

$$8 \text{ m/sec} \times 0.033 \text{ sec} = 0.26 \text{ meters}$$

3) **Determining Window Size:** To ensure significant movement between selected data points, a window size was calculated. The desired window size was set to ensure that the vehicle moves a distance equivalent to its length (4 meters) within the span of the window.

$$0.26 \text{ meters} \times \text{window\_size} = 4 \text{ meters}$$

$$\text{window\_size} = \frac{4 \text{ meters}}{0.26 \text{ meters}} \approx 15$$

Data Point Selection

Based on the calculated window size of 15, we selected coordinates from the dataset at every 15th timestamp. This approach ensures that each selected data point represents a significant movement of the vehicle along the road, considering its average speed and length.

This preprocessing step allows us to focus on capturing key moments of the vehicle's trajectory while reducing the volume of data for subsequent analysis.

B. Fuzzy logic Implementation

The fuzzy logic system defines membership functions for input variables (changeX and changeY) and output variable (direction), alongside specific rules governing the inference process.

- **Input Membership Functions:**
  - `changeX`:
    - `positive`: S-shaped Membership Function (Sigmoidal)
    - `no_change`: Triangular Membership Function
    - `negative`: Z-shaped Membership Function
  - `changeY`:
    - `positive`: S-shaped Membership Function (Sigmoidal)
    - `no_change`: Triangular Membership Function
    - `negative`: Z-shaped Membership Function
- **Output Membership Functions (‘direction‘):**
  - Directions:
    - `east`: E, `north`: N, `west`: W, `south`: S
    - `north-east`: NE, `north-west`: NW, `south-west`: SW, `south-east`: SE
    - `Nochange`: X
- **Fuzzy Rules:**
  - A set of rules map combinations of ‘changeX‘ and changeY‘ to specific ‘directions‘.
  - Each rule specifies conditions for inferring the movement direction based on input changes.

The following are explanations of used fuzzy membership functions:

- **Gaussian Membership Function:** The Gaussian membership function (see Figure 2) assigns higher membership values to elements closer to the center of the curve and lower values to elements farther away.[2]

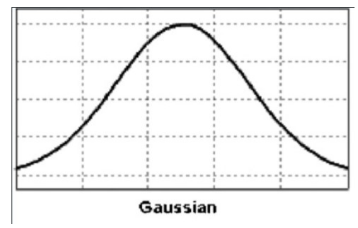

Fig. 2. Gaussian Membership Function

- **Sigmoidal Membership Function:**
The sigmoidal membership function (see Figure 3) assigns membership values to elements based on a sigmoidal curve, typically resembling an ”S” shape. It is useful for representing gradual transitions or uncertainties in fuzzy sets.[2]

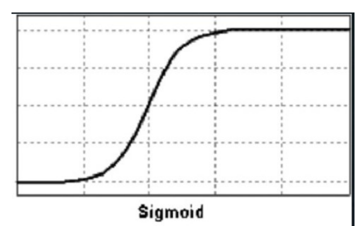

Fig. 3. Sigmoidal Membership Function

- **Triangular Membership Function:**
The triangular membership function (see Figure 4) assigns membership values based on a triangular-shaped curve defined by three parameters: the lower limit, the peak, and the upper limit. Elements closer to the peak have higher membership values, while values decrease linearly as elements move away from the peak. [2]

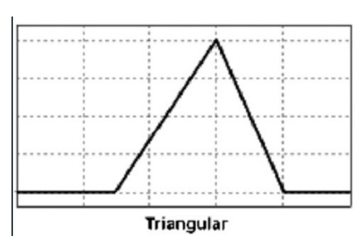

Fig. 4. Triangular Membership Function

As mentioned, the output of the fuzzy logic system helps us classify the direction. The following image represents how we classify each direction.

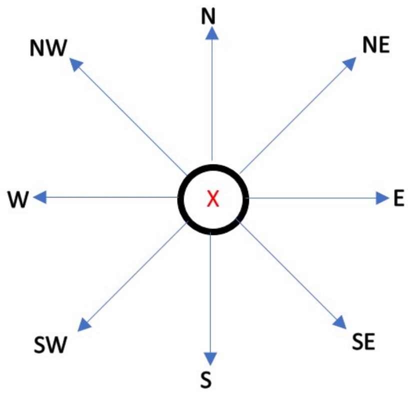

Fig. 5. Direction Predictions

Here, X represents no significant movement of the vehicle for classifying the direction of movement.

Additionally, this is the final dataset created, which contains the changes in x and y coordinates along with their corresponding direction classes.

Delta X	Delta Y	Direction
170	3	E
-185	0	W
-201	-18	W
-22	56	N
158	3	E
-233	14	W
-13	25	NW
-261	-8	W
16	-20	SE
106	3	E
1	3	X
-215	-13	W
121	-48	E
-179	-11	W
201	2	E

Fig. 6. Created Dataset for Classification

This created dataset contains about 3,000 data points, which will be then used for a classification task.

C. Classification models and training

We are now utilizing models such as Support Vector Machines (SVM) and Random Forests for predicting direction based on changes in x and y coordinates.

- **Support Vector Machines (SVMs)** are effective for multiclass classification as they aim to find an optimal hyperplane that maximizes the margin between multiple classes, promoting clear separation. SVMs handle high-dimensional data well and can handle non-linear separability through kernel functions, making them suitable for various applications.

- **Random Forest**, on the other hand, is a robust ensemble learning method for multiclass classification. It constructs multiple decision trees during training and aggregates their predictions to determine the final class. Random Forest is known for its ability to handle noisy data, large datasets, and provide insights into feature importance, making it a popular choice for multiclass classification tasks in different domains.

D. Model Comparison

In comparing Support Vector Machines (SVM) and Random Forest for vehicle motion detection using fuzzy logic and classification, both models demonstrated strong performance, with SVM achieving an accuracy of **92.389 %** and Random Forest achieving **97.699 %**.

TABLE I
ACCURACY COMPARISON OF SVM AND RANDOM FOREST

Model	Accuracy (%)
SVM	92.389
Random Forest	97.699

E. Results

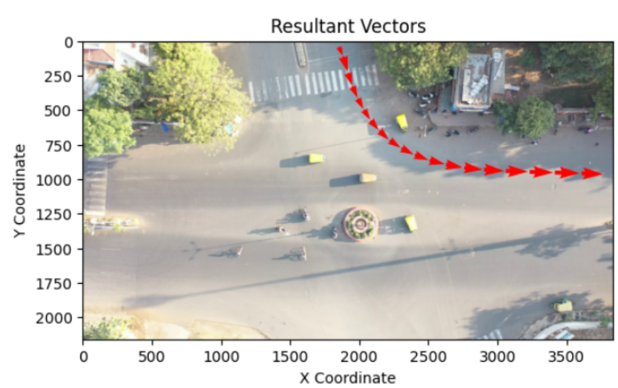

Fig. 7. Tracking objects movement within image

For the given image the Random forest Classification gave us the following direction classes: SE, S, S, SE, SE, SE, SE, SE, SE, SE, SE, E, E, E, E ...

III. Discussions

Generally, SVMs are known for their effectiveness in handling high-dimensional data and finding optimal hyperplanes, while Random Forest excels in capturing complex relationships and handling noisy datasets. The accuracy difference highlights Random Forest's ability to capture intricate patterns, making it a promising choice for this task.
However, factors such as computational complexity and interpretability should also be considered when selecting a model for real-world applications.

IV. Conclusion

In conclusion, our study on vehicle motion detection using fuzzy logic and classification has yielded promising results. We employed robust methodologies for dataset preprocessing, fuzzy logic implementation, and classification using Support Vector Machines (SVM) and Random Forest models. Our analysis showed that both SVM and Random Forest performed well, with Random Forest achieving a higher accuracy of 97.699 % compared to SVM's accuracy of 92.389 %. This difference underscores Random Forest's effectiveness in capturing intricate patterns and handling noisy data, making it a favorable choice for vehicle motion detection tasks. However, considerations such as computational complexity and interpretability must be weighed when deciding on a model for real-world applications.

References

[1] Yagnik M Bhavsar et al. "Vision-based investigation of road traffic and violations at urban roundabout in India using UAV video: A case study". In: *ScienceDirect*. Available: https://www.sciencedirect.com/science/article/pii/S2666691X23000477. 2024.

[2] *Four types of fuzzy membership functions: Gaussian, sigmoid, triangular, and trapezoidal*. ResearchGate. Available: https://www.researchgate.net/publication/230905093/figure/fig3/AS:667805544353810@1536228657895/Four-types-of-fuzzy-membership-functions-Gaussian-sigmoid-triangular-and-trapezoidal.png [Accessed: April 8, 2024].