Vehicle Classification Based on Multiple Fuzzy C-Means Clustering Using Dimensions and Speed Features

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10 October 2018

Outline

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- Background and applications
- Problem statement and objective
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Introduction

- **Traffic control and management** require detailed information regarding the traffic flow.
- One of the key components is the information about the **class of the passing vehicles** (e.g. passenger car, truck, trailer) .
- Traffic clustering can be **challenging** and **time consuming** for a massive traffic data based on appearance features.

Background and related works

- In [1], a method proposed to eliminate unwanted shadows and then to extract the vehicle size and linearity of edges and accordingly to classify vehicles based on their sizes.
- Jiang et al. [2] presented a vehicle classification into bus, passenger car and truck, using deep features of PCANet deep network, HOG and HU moments that are fed to a SVM classifier.
- In [3], a classification method is introduced for nighttime surveillance. It is based on headlight segmentation, detection and furthermore classification into two-wheeled or four-wheeled vehicles.
- In [4], various deep learning convolutional neural networks are compared for vehicle classification mainly into articulated truck, bus, and passenger car.

(a) Original image (b) Shadow eliminated image

Courtesy of Jun-Wei Hsieh *et al.* [1].

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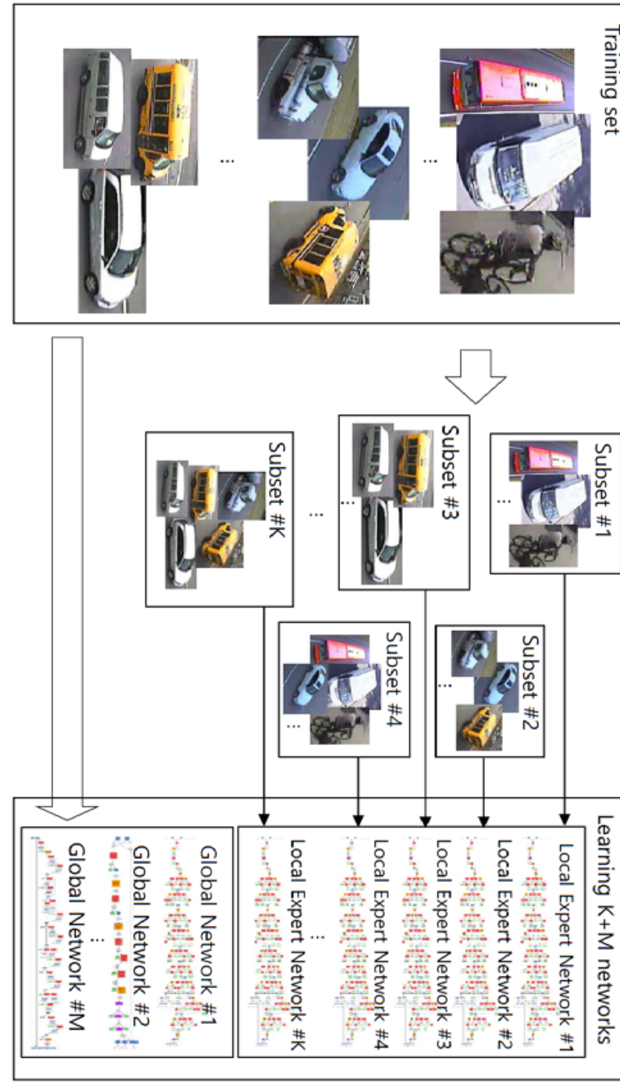


Courtesy of Lee & Chung [4].

Problem statement and objective

- It can be seen that vehicle classification is challenging, particularly for those vehicles that have similar dimensions.
- The main objective of this paper is to propose an efficient classifier in order to cluster vehicles specially for big data.
- The hypothesis of this research is that the speed as an input feature beside the dimensions features can enhance the classification using fuzzy c-means clustering.

Solution

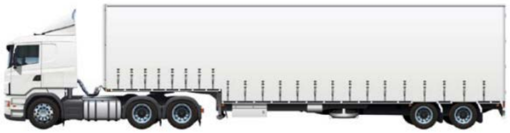
- Traffic authorities provide vehicles definitions in different categories to impose related regulations upon them as presented in Swedish Act (2001:559) such as “private car”, “lorry (light, heavy)”, “bus (light, heavy)”, “motorcycle (light, heavy)”, “trailer (light, heavy)”, etc. [5].
- Due to the similarity of their regulations, we have considered four classes of “private car (including light lorry and light bus)”, “light trailer”, “lorry or bus (both heavy)”, and “heavy trailer”.

Class	Private car	Light trailer	Lorry or bus	Heavy trailer
Speed limit*	100 km/h	80 km/h	90 km/h	80 km/h

*At the measurement site.

Solution

- In addition, a set of rules for initialization of each partition matrix are employed considering the regulations and permitted dimensions for each vehicle category as presented [6].

Vehicle	Maximum permitted length	Maximum permitted width	Side-view	Front-view
Bus with two axles	13.5 m	2.55 m		
Bus with more than two axles	15.0 m	2.55 m		
Power-driven truck	12.0 m	2.55 m		
Heavy trailer	25.25 m	2.60 m		

Solution

- **Fuzzy c-means clustering algorithm** is used for partitioning of the vehicles in fuzzy clusters.
- The algorithm minimizes the objective function J and updates cluster centers b_i and partition matrix U recursively.

$$J = \sum_{k=1}^{N} \sum_{i=1}^{C} \left(\mu_{S_i}(x_k)\right)^m d(b_i, x_k)$$

- $\boldsymbol{N}$ = number of data points, $\boldsymbol{C}$ = number of clusters, $\boldsymbol{m}$ = weighting exponent which determines fuzziness of the resulting clusters, $\boldsymbol{x_k}$ = data point (length, width, velocity), $\boldsymbol{\mu_{Si}(x_k)}$ = membership degree of x_k in cluster S_i and $\boldsymbol{d(b_i, x_k)}$ is the distance between cluster center b_i and x_k.

Solution

- After the objective function J is minimized, we obtain the following outputs.
  - **Cluster centers**

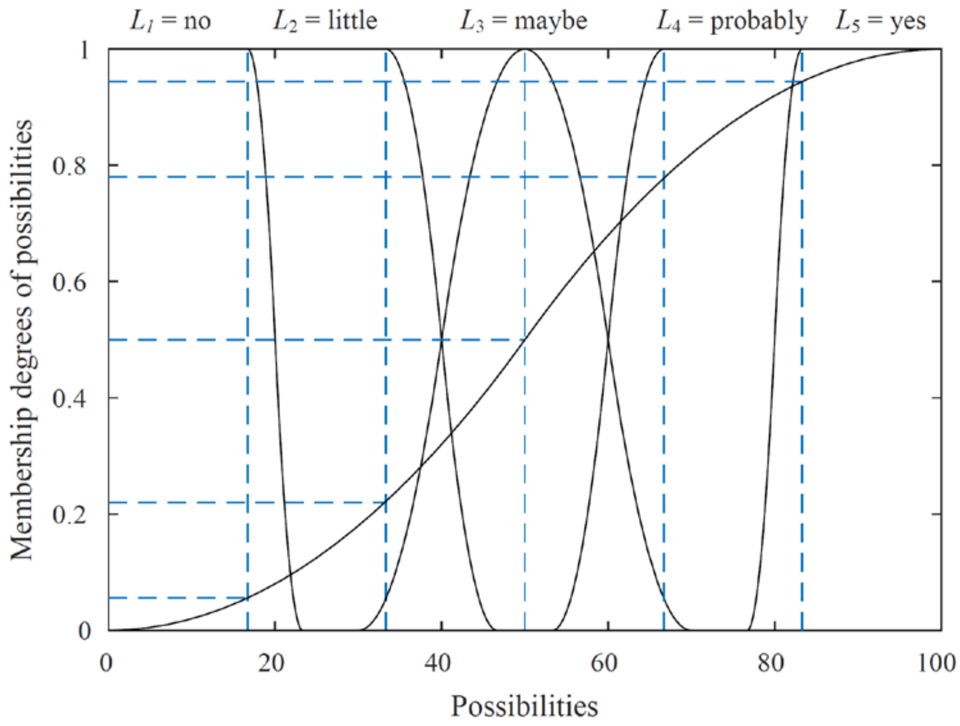
$$b = \{b_1, b_2, \dots, b_C\}$$

  - **Partition matrix U** of size C × N which gives membership degrees in each cluster for all data elements.

$$U = \begin{pmatrix} \mu 11 & \mu 12 & \dots & \mu 1N \\ \mu 21 & \mu 22 & \dots & \mu 2N \\ \vdots & \vdots & \ddots & \vdots \\ \mu C1 & \mu C2 & \dots & \mu CN \end{pmatrix}$$

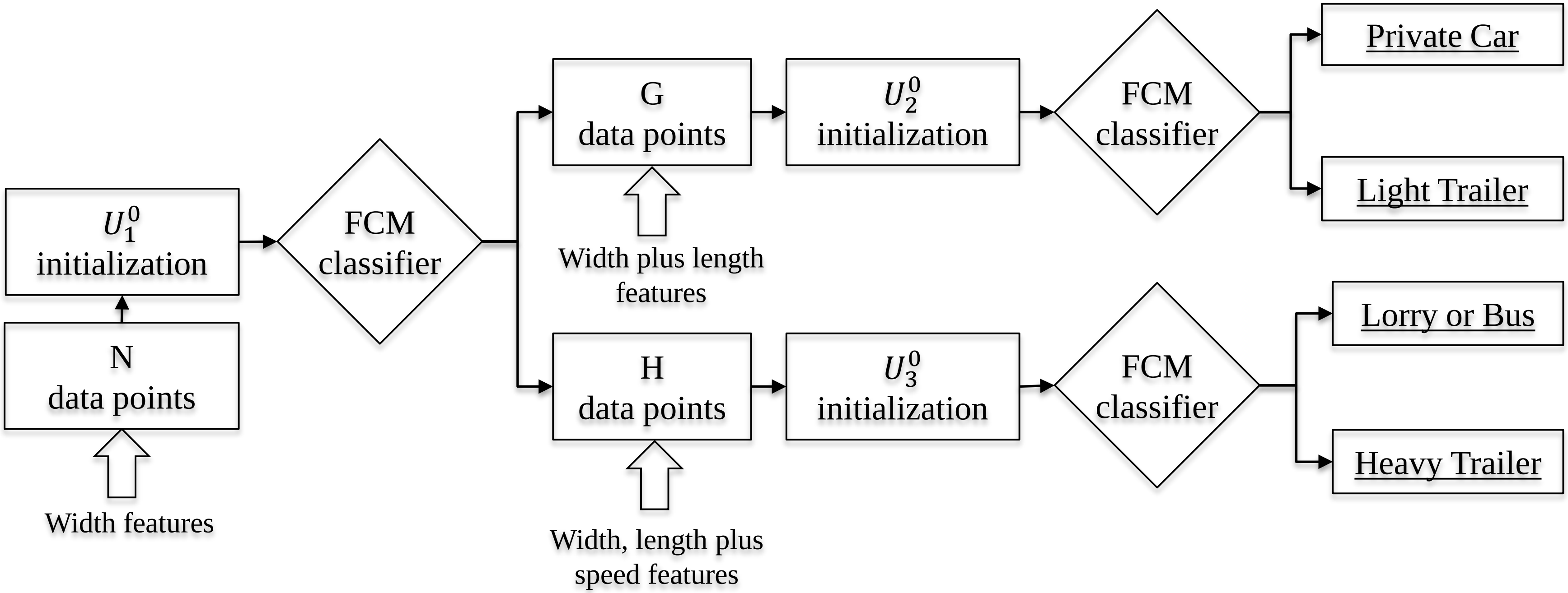
Solution

- To initialize the partition matrix U, let us assume $L = L_1, L_2, L_3, L_4, L_5$ as a list of linguistic terms containing L_1 = "no", L_2 = "little", L_3 = "maybe", L_4 = "probably" and L_5 = "yes" to demonstrate the initial degree of association of a vehicle's feature to a defined cluster [7].



Solution

- In order to exploit the vehicle features for classification, multiple FCM classifiers are designed and their respective partition matrices are initialized.



Experimental results and discussion

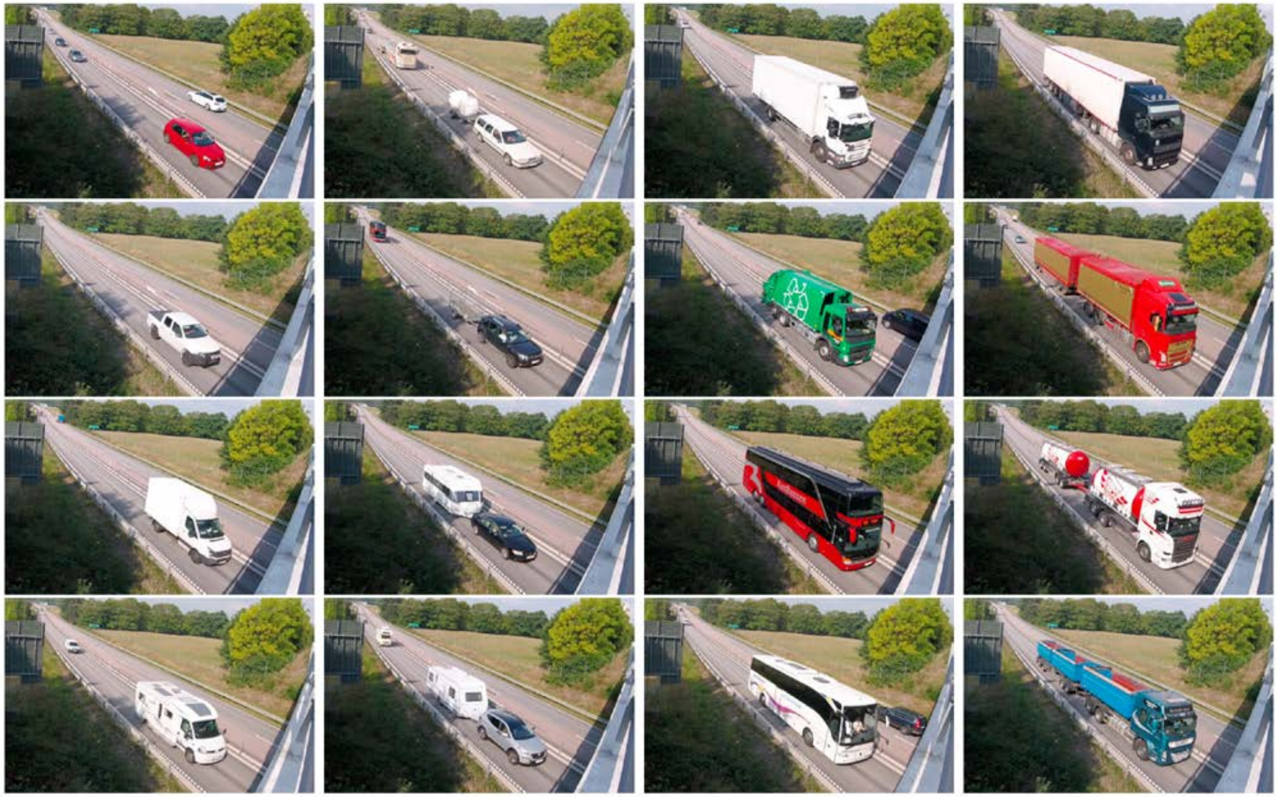
- This experiment used collected traffic data over a major highway in order to evaluate the proposed model.
- As described earlier, the proposed system has employed multiple FCM clusterings for classification of vehicles into $S_1 =$ “private car”, $S_2 =$ “light trailer”, $S_3 =$ “lorry or bus” and $S_4 =$ “heavy trailer”.
- Equal number of 100 vehicles per class from the available data and consequently, the total number of $N = 400$ vehicles are labeled as the ground truth as $X = x_1, \dots, x_{400}$.

Experimental results and discussion

- For every vehicle the features of width, length and speed are collected as the inputs such as $x_k = \{x_{k1}, x_{k2}, x_{k3}\}$.

Experimental results and discussion

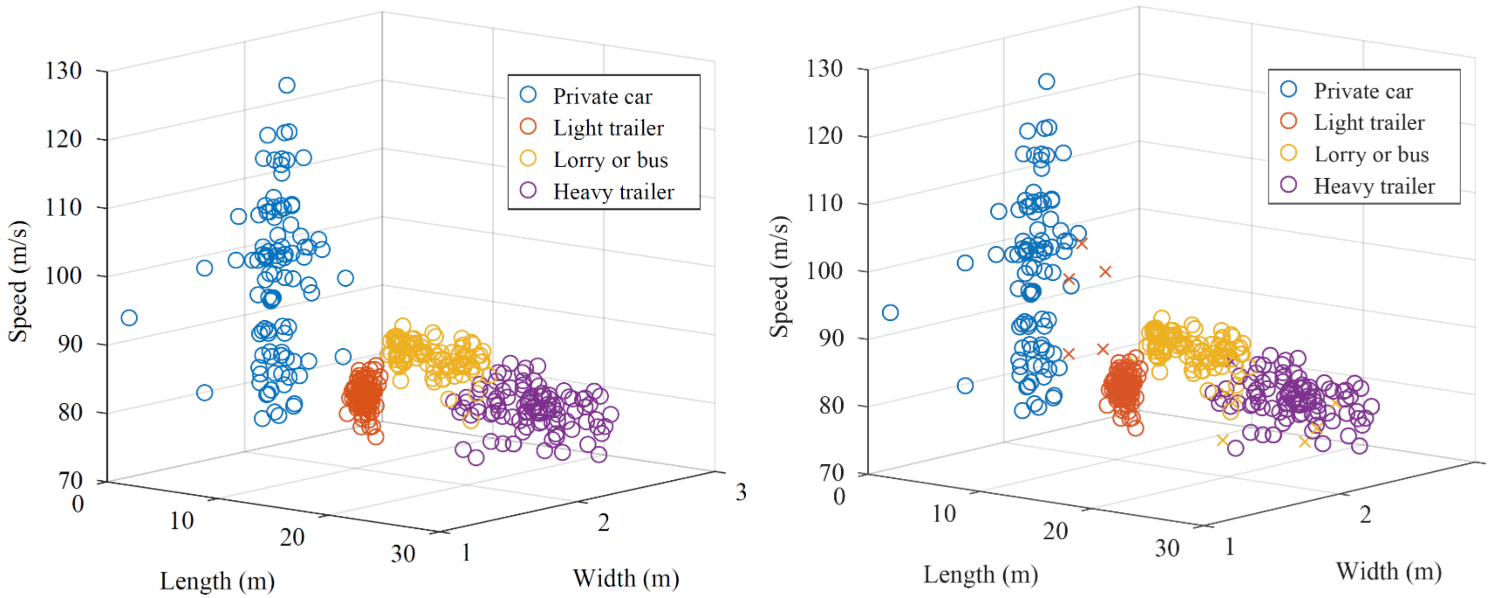
- Some samples of different classes of vehicles.



(a) Private car (b) Light trailer (b) Lorry or bus (b) Heavy Trailer

Experimental results and discussion

- The 3D representation of clustering based on the three given features.



(a) Ground truth

(b) Predictions

Experimental results and discussion

- The confusion matrix of the detected results is presented as below. According to the evaluation, the performance of the FCM clustering is promising for vehicle classification especially for “light trailer” against “lorry or bus”.
- However, the classification between “private car” and “light trailer” seems to be challenging because of the vast variety of dimensions for “private car”.

	Classified				Accuracy
	Private car	Light trailer	Lorry or bus	Heavy trailer	
Private car	95	5	0	0	95%
Light trailer	0	99	1	0	99%
Lorry or bus	0	0	99	1	99%
Heavy trailer	0	0	7	93	93%
				Average accuracy	96.50%

Conclusion and future work

- In this paper, a method based on fuzzy c-means clustering algorithm is proposed for vehicle classification using dimensions and speed features suitable for considerable amount of data.
- The proposed classifier is able to classify vehicles in four classes of "private car", "light trailer", "lorry or bus" and "heavy trailer".
- The classifiers performance was promising for different classes with average accuracy rate of 96.5% and average positive predictive value of 96.66% that outperforms some other traditional machine learning algorithms for the same dataset.
- Furthermore, it has been shown that using prior knowledge of traffic regulations and speed feature can enhance the classification between vehicles from different classes with similar width and length (e.g. straight truck and articulated truck).
- For future work, using the proposed method in combination with others such as vision-based approaches can be used to improve the performance.

References

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[5] “Lag (2001:559) om vgtrafikdefinitioner.” Notisum. Available from: http://www.notisum.se/rnp/sls/lag/20010559.htm.

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[7] Rakus-Andersson, E. “Selected algorithms of computational intelligence in gastric cancer decision making.”, In: Thomas Brzozowski (ed) New Advances in the Basic and Clinical Gastroenterology. InTech; 2012.

Questions and answers

Thank you for your attention!