Highway Vehicle Classification by Probabilistic Neural Networks

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Abstract

The Federal Highway Administration (FHWA) Office of Highway Planning requires states to furnish vehicle classification data as part of the Highway Performance Monitoring Systems (HPMS). To comply with this requirement, most states use the "F-Scheme" to classify vehicles. This scheme classifies vehicles in 13 classes depending on a number of factors, primarily the number of axles and the axle spacings on each vehicle. Classification of highway vehicles using the "F-Scheme" can be automated by properly using visual information of the number of axles and axle spacing; however, this process is hindered by the absence of a suitable logic to be used in the digital computer. Many computer software vendors rely on sharply defined decision trees that are based on the vehicle number of axles and axle spacing, which often results in misclassifying some vehicles. This paper proposes a classification approach that is based on Probabilistic Neural Networks. The paper explains the design of the neural network for this purpose and how to condition the training data. Field results have shown that the proposed network is effective and can classify the majority of the vehicles as defined in the "Scheme F" guidelines and it outperforms the existing decision tree systems.

Introduction

State highway agencies, metropolitan planning organizations, and various other agencies in charge of overseeing transportation facilities utilize vehicle classification data to design and manage paved roads and to schedule the resurfacing and reconstruction of these roads based on projected remaining pavement life. Other uses of classification data include prediction and planning for commodity flows and freight movements, provision of design inputs relative to the current and predicted capacity of highways, analysis of alternative highway regulatory and investment policies, developing weight enforcement strategies; conducting environmental impact analysis, and reviewing accident records and mitigation strategies.

The standards for collecting and analyzing vehicle classification data vary countrywide due to the fact that vehicle characteristics differ from one state to another. Truck type patterns are heavily affected by local economic activities, weight limits, and truck size specifications imposed by the states. For example, multi-trailer trucks are common in most western states but make up a much smaller percentage of the trucking fleet in many eastern states (FHWA 2001). Also, some trucks are designed to carry specific commodities; for example, coal trucks in Kentucky and Pennsylvania (FHWA 2001). The FHWA Office of Highway Planning requires states to furnish vehicle classification data as part of the Highway Performance Monitoring Systems (HPMS). To comply with this requirement, most states use "F-Scheme" to classify vehicles. This scheme, which classifies vehicles in 13 classes, is essentially a visual classification scheme based on the vehicle types.

To assign a vehicle to one of the 13 classes in "Scheme F," a lookup table implemented through a decision tree is required. In Florida, different vendors supply the Florida Department of Transportation with vehicle classification equipment. The lookup table in each vendor's equipment is unique to that vendor. Each vendor has its decision tree algorithm. Comparison of vehicle classification algorithms used by these vendors revealed discrepancies in the decision thresholds, a factor which might be contributing to misclassification of vehicles. For example, for class 8 vehicles with 4 axles, one vendor (PAT Traffic Control Corporation, Inc.) specifies the range of the first axle spacing to be from 6.01 to 23.0 ft, another vendor (PEEK Traffic Inc.) specifies the same axle spacing to range from 6.0 to 20.0 ft while the third vendor (Diamond Traffic Products) specifies 0 to 199.9 ft as the range of first axle spacing. The Florida Department of Transportation (FDOT) decided to set the common thresholds that could be used with any vendors' equipment; these thresholds are shown in Table 1. However, the thresholds chosen by FDOT were non-optimally selected and set. Field evaluation of these thresholds as shown in the results of this paper revealed that they causes classification errors.

This paper proposes using a Probabilistic Neural Network (PNN) as a classification tool for vehicles using observed patterns on the number of axles, axle spacing, vehicle weights and the vehicle lengths. It documents the method used to develop the neural network, selecting training data, and gives preliminary performance results of the proposed network. It is hoped that the desired thresholds can be established after the proposed neural network has classified a relatively large number of vehicles.

FHWA Guidelines for Vehicle Classification–"Scheme F"

The Federal Highway Administration issued guidelines for vehicle classification in a form known as the 13-category classification scheme. A number of schemes have been developed based on these guidelines, however the most popular is "Scheme F" which was developed by the Department of Transportation of the State of Maine (Wyman, Braley, & Stephens 1985). This scheme is shown in the Appendix which is taken from (FHWA 2001).

In its basic form this scheme provides information that cannot be quantified in a way suitable for computer application. Therefore, it is in general very difficult to automate the classification process using these guidelines of "Scheme F" alone. For that reason, many software vendors have developed a decision tree that is based on the number of axles and axle spacing. Table 1 shows such a decision tree used by the Florida Department of Transportation. This table can be used to automate the vehicle classification process by using a set of linked IF-THEN rules that can be programmed into a digital computer. However, as is evident from the table, the line of demarcation between the classes is very thin and often has resulted in misclassifications. For example, while the second axle spacing for classes 4 and 6 are overlapping, the upper limit for the first axle spacing for class 6 is 23.0 while the lower limit for class 4 is 23.01. The line of demarcation is therefore within 0.01 ft only.

The objective of this research was, among other things, to develop a better way of automating vehicle classification process that satisfies the guidelines provided by "Scheme F". After an extensive evaluation of the problem and the available classification tools(Michie, Spiegelhalter, & Taylor 1994; Tsoukalas & Uhrig 1997), a Probabilistic Neural Network (PNN) approach was chosen. The following section briefly describes the principles behind PNN.

Probabilistic Neural Networks

A probabilistic neural network (Specht 1990a; 1990b) is a pattern classification network that is believed to provide a general method for pattern classification problems (Tsoukalas & Uhrig 1997). This neural network is based on the classical Bayes classifier, which is statistically an optimal classifier that seeks to minimize the risk of misclassifications. Details of how this network works can be found in many standard textbooks; however, a brief description of this network is given below.

Veh. Type	Class	Num. axles	Description	Axle spacing [ft]								Weight	Max Length
				Ax.1-2	Ax.2-3	Ax.3-4	Ax.4-5	Ax.5-6	Ax.6-7	Ax.7-8	Ax.8-9		
1	1	2	Motorcycle	0.1-6.0								0.1+	10.0
2	2	2	Auto,Pickup	6.01-10.0								1.0+	22.0
3	3	2	Other(Limo,Van,RV)	10.01-13.30								1.0+	26.0
10	4	2	Bus	23.01-40.00								12.0+	45.0
20	5	2	2D	13.31-23.0								1.0+	40.0
3	2	3	Auto W/1 Axle Trlr	6.01-10.0	6.0-25.0							1.0+	32.0
7	3	3	Other W/1 Axle Trlr	10.01-13.30	6.0-25.0							1.0+	60.0
11	4	3	Bus	23.01-40.0	0.1-6.0							12.0+	52.0
	5	3	2D W/1 Axle Trlr	13.31-23.0	6.0-25.0							1.0+	60.0
24	6	3	3 Axle	6.01-23.0	0.1-5.99							12.0+	40.0
30	8	3	2S1, 21	6.01-23.0	11.0-40.0							12.0+	75.0
4	2	4	Auto W/2 Axle Trlr	6.01-10.0	6.0-25.0	0.1-6.0						1.0+	45.0
9	3	4	Other W/2 Axle Trlr	10.01-13.30	6.0-25.0	0.1-6.0						1.0+	60.0
	5	4	2D W/2 Axle Trlr	13.31-23.0	6.0-25.0	0.1-6.0						1.0+	60.0
28	7	4	4 Axle	6.01-23.0	0.1-6.0	0.1-13.0						12.0+	45.0
34	8	4	3S1, 31	6.01-23.0	0.1-6.0	6.01-44.0						20.0+	75.0
38	8	4	2S2	6.01-23.0	11.0-40.0	0.1-10.99						20.0+	75.0
	3	5	Other/W 3 Axle Trlr	10.01-13.30	6.0-25.0	0.1-6.0	0.1-6.0					1.0+	60.0
	5	5	2D W/3 Axle Trlr	13.31-23.0	6.0-25.0	0.1-6.0	0.1-6.0					1.0+	60.0
40	9	5	3S2	6.01-26.0	0.1-6.0	6.01-46.0	0.1-10.99					12.0+	80.0
44	9	5	32	6.01-26.0	0.1-6.0	6.01-23.0	11.0-27.0					12.0+	80.0
60	11	5	2S12	6.01-26.0	11.0-26.0	6.1-20.0	11.01-26.0					12.0+	85.0
50	10	6	3S3, 33	6.01-26.0	0.1-6.0	0.1-46.0	0.1-11.0	0.1-11.0				12.0+	85.0
70	12	6	3S12	6.01-26.0	0.1-6.0	11.01-26.0	6.01-24.0	11.01-26.0				12.0+	110.0
54	10	7		6.01-16.7	0.1-6.0	13.3-40.0	0.1-13.3	0.1-13.3	0.1-13.3			12.0+	85.0
80	13	7	2S23, 3S22, 3S13	1.0-45.0	1.0-45.0	1.0-45.0	1.0-45.0	1.0-45.0	1.0-45.0			12.0+	110.0
84	13	8	3S23	1.0-45.0	1.0-45.0	1.0-45.0	1.0-45.0	1.0-45.0	1.0-45.0	1.0-45.0		12.0+	120.0
90	13	9	PERMIT	1.0-45.0	1.0-45.0	1.0-45.0	1.0-45.0	1.0-45.0	1.0-45.0	1.0-45.0	1.0-45.0	12.0+	120.0
	15		ERRORS OR UNCLASSIFIED										

Table 1: Axle spacing limits as defined by Florida DOT

Any pattern classifier places each observed vector of data $\mathbf{x}$ in one of the predefined classes $c_i, \quad i = 1, 2, \cdots, n$ where n is the number of possible classes in which $\mathbf{x}$ can belong. The effectiveness of any classifier is limited by the number of data elements that vector $\mathbf{x}$ can have and the number of possible classes n. The classical Bayes pattern classifier implements the Bayes conditional probability rule that the probability $P(c_i|\mathbf{x})$ of $\mathbf{x}$ being in class c_i is given by

$$P(c_i|\mathbf{x}) = \frac{P(\mathbf{x}|c_i)P(c_i)}{\sum_{j=1}^{n} P(\mathbf{x}|c_j)P(c_j)} \tag{1}$$

where $P(\mathbf{x}|c_i)$ is the conditioned probability density function of $\mathbf{x}$ given set c_i, $P(c_j)$ is the probability of drawing data from class c_j. Vector $\mathbf{x}$ is said to belong to a particular class c_i if $P(c_i|\mathbf{x}) > P(c_j|\mathbf{x}),\ \forall j = 1, 2, \cdots, n,\ j \neq i$ This classifier assumes that the probability density function of the population from which the data was drawn is known a priori; this assumption is one of the major limitations of implementing Bayes classifier.

The PNN simplifies the Bayes classification procedure by using a training set for which the desired statistical information for implementing Bayes classifier can be drawn. The desired probability density function of the class is approximated by using the Parzen windows approach (Parzen 1962; Murthy 1965; 1966; Cacoullous 1966). In particular, the PNN approximates the probability that vector $\mathbf{x}$ belongs to a particular class c_i as a sum of weighted Gaussian distributions centered at each training sample, i.e.,

$$P(c_i|\mathbf{x}) = \frac{1}{(2\pi)^{\frac{N}{2}} \sigma^N n_{t_i}} \sum_{j=1}^{n_{t_i}} \exp\left[-\frac{(\mathbf{x} - \mathbf{x}_j^i)^T (\mathbf{x} - \mathbf{x}_j^i)}{2\sigma^2} \right] \tag{2}$$

where $\mathbf{x}_j^i$ is the j-th training vector for the patterns in class i, σ is known as a smoothing factor, N is the dimension of the input pattern, and n_{t_i} is the number of training patterns in class i. For nonlinear decision boundaries, the smoothing factor σ needs to be as small as possible. In this work, the shape of the decision boundary was assumed to depend on the standard deviation of the data being classified. In particular, since a small value of the standard deviation indicates that the data points are clustered at well defined points, then it is associated with a decision boundary that is almost linear calling for a large value of σ. Similarly, a high value of the standard deviation which indicates that the data points are widely scattered calls for a nonlinear decision boundary with a very small value of σ. In general, σ is inversely proportional to the standard deviation of the data being classified. In the results reported in this paper σ was calculated as

$$\sigma = \frac{1}{||\Sigma||} \tag{3}$$

where $||\Sigma||$ is the Frobenius norm of a matrix formed by concatenating the standard deviation vectors for each training set; it corresponds to the maximum standard deviation in the training patterns. Therefore, σ became automatically small when the training set had large variances, which called for nonlinear decision boundaries. The computational structure of the PNN is shown in Figure 1. The network has an input layer, a pattern layer, a summation layer and an output layer. The input $\mathbf{x}$ to the network is a vector defined as

$$\mathbf{x} \triangleq [x_1,\ x_2,\ x_3, \cdots, x_p]^T. \tag{4}$$

This input is fed into each of the patterns in the pattern layer. The summation layer computes the probability $f_i(\mathbf{x})$ of the given input $\mathbf{x}$ to be in each of the classes i represented by the patterns in the pattern layer. The output layer picks the class for which highest probability was obtained in the summation layer. The input is then classified to belong to this class. The effectiveness of the network in classifying input vectors depends highly on how the training patterns are chosen. The next section describes how the training patterns for the vehicle classification problem were chosen.

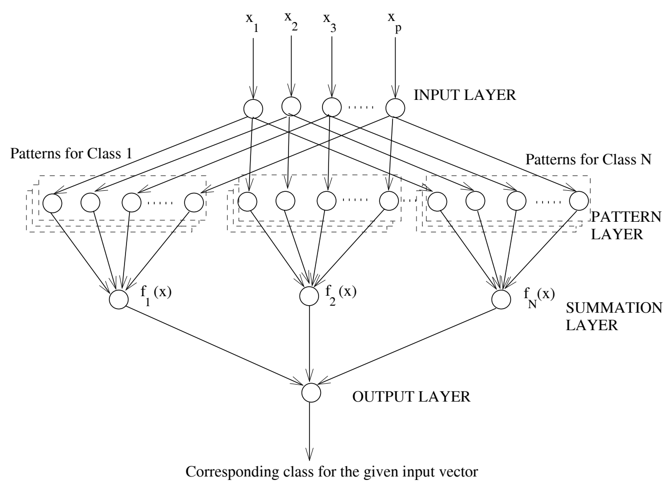

Figure 1: Computational structure of the PNN

Choosing Training Patterns for the PNN

Field data were collected from different calibrated Weigh-In-Motion (WIM) sites along the major highways in the State of Florida. The WIM sites provided individual vehicle records that included the number of axles, axle spacing, vehicle length, and the overall vehicle weight. In addition,video data were collected at the same sites simultaneously. A test vehicle of known axle spacing was run over the sensors during the time which the video was logged on for verification of the accuracy of the axle sensors in detecting axle spacing. Each monitored vehicle was visually classified by using video data and compared to field machine classification that implements the Florida DOT axle spacing table. Misclassified vehicles were identified and recorded. Information for more than 4,000 vehicles was collected.

Since the axle spacing for some vehicles were wider than for others, certain vehicle types were represented by using more data than others. In order to create uniformity in the patterns, all vehicles were assumed to have 9 axles, which is the observed maximum number of axles for all vehicles recorded. Vehicles with less axles were assumed to have additional fictitious axles so that the total number is 9; axle spacings for these fictitious axles were fixed to be 0.

Some of the classes in "Scheme F" span over different number of axles. For example, class 2 covers vehicles with two to four axles depending on the number of axles per trailer. It is difficult to automatically classify the two axle vehicles in the same group as the four axle vehicles. Because of this, such classes were broken down to simple subclasses and redefined as shown in Table 2. A total of 28 subclasses were defined based on the 13 predefined standard classes. Therefore, the PNN patterns were drawn to reflect these subclasses and the network was asked to classify the vehicle into one of these 28 subclasses. To reduce chances of possible misclassification, the mean values and standard deviations of the training patterns were carefully controlled. Each training pattern was chosen to have a sufficiently low standard deviation, and with a mean that was sufficiently far from those of the adjacent training sets in the Euclidean space. Classes that involved wider axle spacings had more training patterns than those with narrow axle spacings. In total, there were 147 training patterns for the 28 classes, which on average suggests that each class was represented by about 5 patterns.

Field Performance Results

Data collected from the field were used to test the performance of the PNN as compared to methods that follow the FDOT decision tree. Video data were collected in the vicinity of the WIM sites and used as ground truth. Individual vehicle axle information, weight and the classes assigned by the FDOT decision tree were obtained from the WIM sites. The axle information and weight for each vehicle were supplied to the neural network and the assigned class was recorded. The classes obtained by using the PNN and those due to the FDOT decision tree were verified using the ground truth data. Two sets of performance for the PNN were obtained; the first set used axle information only, which is the same criterion used with FDOT decision tree and the second set used both axle information and weight. All custom made vehicles that do not fall in any of the standard classes 1 to 13 are classified as Class 15 by both the FDOT decision tree and the PNN. The FDOT decision tree was unable to detect all 23 vehicles that would have been in Class 15 while the PNN was able to place some of these vehicles in their correct classes. It is possible that the failure to classify a vehicle in its correct standard class may also result in the vehicle being misclassified as Class 15. Table 3 shows a sample of the results that were obtained. As seen from these results, for both of its data sets the neural network performs better compared to the FDOT decision tree methods. While currently the FDOT decision tree methods are limited to axle information only, the PNN was able to easily incorporate the vehicle weight in the classification process. This as shown in the table of results improved further the performance of the PNN in comparison to the FDOT decision tree. In general, the FDOT recorded a 4.9% misclassification rate while the PNN had a misclassification rate of 3.0% when the vehicle weight was not used and 1.6% when vehicle weight was used as an additional classification variable. It is hoped that PNN will eventually be adopted by FDOT as a classification tool for highway vehicles, or at least the results from the PNN in the long run will be used in setting up better thresholds for the classification decision trees.For establishment of more accurate thresholds, it is necessary to run the network many times. It is understood that the data used in the results reported herein is not sufficient to justify accurate definition of the thresholds for some subclasses; therefore more data are still being collected and field tests are still in progress.

Conclusions

This paper presented a probabilistic neural network design for classification of highway vehicles according to FHWA "Scheme F". The network accepts information about axle spacing and vehicle weight to determine the class into which the vehicle belongs. The proposed network can use the vehicle axle information only or with vehicle weight. Field results showed that the proposed network outperforms the current FDOT decision tree methods; the difference in performance between the proposed PNN method and the FDOT decision tree becomes more conspicuous when the vehicle weight is used in the classification. Accurate classification by the PNN can help the FDOT to establish better axle spacing thresholds in the decision tree. Due to the better performance showed by the PNN, it is hoped that after extensive field tests and validation, the FDOT may eventually consider adopting it as a classification tool to replace the existing classification methods in the State of Florida. The success of the network depends on both its design (i.e., selection of the smoothing factor (σ)) and selection of representative training patterns. The smoothing factor was selected as a function of the variances of the training patterns, and the pattern set for each class was chosen to have a sufficiently small variance and a mean that is sufficiently far from the mean of the pattern for the adjacent class.

Class	Subclass	Mean Axle Spacing [ft] Ax.1-2	Ax.2-3	Ax.3-4	Ax.4-5	Ax.5-6	Ax.6-7	Ax.7-8	Ax.8-9	Weight [Kips]
1	1	2.95								0.47
2	2a	8.50								3.00
	2b	9.35	14.87							5.51
	2c	9.4	18.7	2.56						8.78
3	3a	12.0								11.34
	3b	11.69	16.59							11.71
	3c	11.75	19.47	2.53						14.00
	3d	11.60	22.33	2.63	2.70					16.25
4	4a	24.77								27.85
	4b	25.40	4.06							39.87
5	5a	18.61								16.12
	5b	13.80	17.10							9.18
	5c	13.88	20.90	2.78						10.98
	5d	13.53	24.90	2.80	2.77					20.16
6	6	18.77	4.27							30.76
7	7	12.44	4.08	5.64						39.32
8	8a	13.67	25.23							31.88
	8b	17.14	4.26	31.04						21.00
	8c	15.94	22.76	4.89						23.69
9	9a	15.63	4.33	27.3	4.51					53.35
	9b	16.17	3.47	14.67	19.00					58.65
10	10a	17.83	4.48	29.31	4.15	4.11				61.75
	10b	16.31	4.44	35.16	5.73	9.19	5.79			62.34
11	11	14.13	21.33	9.52	22.25					56.34
12	12	16.26	4.24	20.19	9.04	20.87				64.02
13	13a	16.02	4.40	18.42	23.64	5.96	4.30			74.94
	13b	17.15	4.30	8.45	8.20	7.90	8.35	8.95		104.85
	13c	16.30	4.07	21.13	6.60	24.63	18.58	4.55	22.00	116.05

Table 2: “Scheme F” vehicle classes and the defined subclasses.

Vehicle Class	Total Observed	FDOT Decision Tree Total misclassified	FDOT Decision Tree Percentage misclassified	PNN (Without Weight) Total misclassified	PNN (Without Weight) Percentage misclassified	PNN (With Weight) Total misclassified	PNN (With Weight) Percentage misclassified
3	2224	80	3.6%	50	2.2%	25	1.1%
4	29	11	37.9%	3	10%	0	0%
5	366	94	25.7%	66	18%	33	9%
6	78	4	5.1%	2	2.6%	0	0%
7	19	0	0%	0	0%	0	0%
8	112	0	0%	0	0%	0	0%
9	1395	1	0.1%	0	0%	0	0%
10	25	0	0%	0	0%	0	0%
11	25	0	0%	0	0%	0	0%
12	12	0	0%	0	0%	0	0%
13	4	0	0%	0	0%	0	0%
15	23	23	100%	10	43.5%	10	43.5%
TOTAL	4312	213	4.9%	131	3.0%	68	1.6%

Table 3: Summary of the PNN classification performance compared to the FDOT decision tree methods

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Appendix: FHWA Guidelines for Vehicle Classification

Class 1 - **Motorcycles (*Optional*):** All two- or three-wheeled motorized vehicles. Typical vehicles in this category have saddle type seats and are steered by handle bars rather than wheels. This category includes motorcycles, motor scooters, mopeds, motor-powered bicycles, and three-wheeled motorcycles.This vehicle type may be reported at the option of the State.

Class 2 - **Passenger Cars:** All sedans, coupes, and station wagons manufactured primarily for the purpose of carrying passengers and including those passenger cars pulling recreational or other light trailers.

Class 3 - **Other Two-Axle, Four-Tire, Single Unit Vehicles:** All two-axle, four-tire, vehicles other than passenger cars. Included in this classification are pickups, panels, vans, and other vehicles such as campers, motor homes, ambulances, hearses, carryalls, and minibuses. Other two-axle, four-tire single unit vehicles pulling recreational or other light trailers are included in this classification. *Because automatic vehicle classifiers have difficulty distinguishing class 3 from class 2, these two classes may be combined into class 2.*

Class 4 - **Buses:** All vehicles manufactured as traditional passenger-carrying buses with two axles and six tires or three or more axles. This category includes only traditional buses (including school buses) functioning as passenger-carrying vehicles. Modified buses should be considered to be trucks and be appropriately classified.

Note: In reporting information on trucks the following criteria should be used:

a. Truck tractor units traveling without a trailer will be considered single unit trucks.

b. A truck tractor unit pulling other such units in a saddle mount configuration will be considered as one single unit truck and will be defined only by axles on the pulling unit.

c. Vehicles are defined by the number of axles in contact with the roadway. Therefore, floating axles are counted only when in the down position.

d. The term trailer includes both semi- and full trailers.

Class 5 - **Two-Axle, Six-Tire, Single Unit Trucks:** All vehicles on a single frame including trucks, camping and recreational vehicles, motor homes, etc., having two axles and dual rear wheels.

Class 6 - **Three-axle Single unit Trucks:** All vehicles on a single frame including trucks, camping and recreational vehicles, motor homes, etc., having three axles.

Class 7 - **Four or More Axle Single Unit Trucks:** All trucks on a single frame with four or more axles.

Class 8 - **Four or Less Axle Single Trailer Trucks:** All vehicles with four or less axles consisting of two units, one of which is a tractor or straight truck power unit.

Class 9 - **Five-Axle Single Trailer Trucks:** All five-axle vehicles consisting of two units, one of which is a tractor or straight truck power unit.

Class 10 - **Six or More Axle Single Trailer Trucks:** All vehicles with six or more axles consisting of two units, one of which is a tractor or straight truck power unit.

Class 11 - **Five or Less Axle Multi-Trailer Trucks:** All vehicles with five or less axles consisting of three or more units, one of which is a tractor or straight truck power unit.

Class 12 - **Six-Axle Multi-Trailer Trucks:** All six-axle vehicles consisting of three or more units, one of which is a tractor or straight truck power unit.

Class 13 - **Seven or More Axle Multi-Trailer Trucks:** All vehicles with seven or more axles consisting of three or more units, one of which is a tractor or straight truck power unit.