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Inductive Classifying Artificial Network for Vehicle Type Categorization

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ABSTRACT

As transportation surveillance technology continues to advance, the measurement of more complete traffic information is becoming increasingly feasible. ICAN stands for Inductive Classifying Artificial Network and is used to conveniently describe a self-organizing feature map (SOFM) for vehicle type categorization using inductive signatures as input. Vehicle type categorization is the separation of vehicles into predefined classes and can be useful for improving transportation efficiency, cost, environmental sustainability, enforcement, safety, and education. ICAN mainly focuses on the challenging task of differentiating between two-axle vehicles such as passenger car, sports utility vehicle (SUV), van, truck, and bus. This is in contrast to systems that classify according to the number of axles. One characteristic of ICAN is the simplicity of the 13 neuron 1-dimensional neural network, and the employment of a small training set of 13 signatures. The overall classification results of 87% (dataset 1) and 82% (dataset 2) for 7 categories coupled with consistent performance across all vehicle categories was significant and

encouraging. Field freeway data was used for testing ICAN, and representative signatures and video images of different vehicle types are presented.

INTRODUCTION

One simple way of summarizing the areas of benefit from Intelligent Transportation Systems (ITS) is by categorizing them into six "E's"; namely, efficiency, economy, environment, enforcement, enhanced safety, and education. The acquisition of more reliable and complete data improves ITS strategies in all the aforementioned categories by reducing assumptions on traffic characteristics. One type of data that is valuable in the effort to improve data quality is vehicle type classification. Vehicle type classification refers to the division of vehicles into useful classes such as passenger car, sports utility vehicle (SUV), van, bus, truck, etc… In terms of efficiency, it is important to model different vehicle types accurately since each vehicle type has differing acceleration, handling, and braking characteristics. Since larger and heavier vehicles incur greater economic costs on the transportation system, it is important to assess the economic impact of these vehicles independently. Regarding the environment, the airborne and noise emissions from different vehicle types differ greatly and should be captured separately in transportation models. Electronic Toll Collection (ETC) is one of many applications of vehicle classification in the area of transportation enforcement. Because the frequency and severity of traffic accidents can depend on the type of vehicle involved, safety research can also benefit from vehicle classification information as part of safety records.

Since vehicle type classification has so many possible implementation areas, it is difficult to present research that is applicable to every area. However, a general approach has been taken in this research to illustrate the process of developing a self-organizing feature map (SOFM) classification scheme. Examples of three particular schemes have been presented without consideration to particular applications. The hope of this research is that readers will find this illustration useful in developing vehicle type classification systems for their own particular need. One goal of this project is to exploit the current inductive loop infrastructure. However, this fact does not preclude the possibility of improving the vehicle classification scheme developed in this research to accept other forms of detector output in the future.

PRECEDING WORK

Vehicle type classification systems have been researched by different agencies and research institutions since the seventies. Some of the technologies for vehicle detection have been in existence since the twenties. Davies (1), presents a good review of earlier vehicle detection technologies and vehicle type classification schemes. Common vehicle detectors include pneumatic tubes, inductive loops, piezoelectric sensors, magnetometers, optical beam curtains, laser/infrared sensors, microwave detectors, and video image processing. Because the inductive loop detector is arguably the most common form of traffic detector, it is the focus of this project. However, as other technologies become more widely implemented, there is the potential for the combination of multiple technologies for detector fusion.

Early vehicle type classification systems consisted of axle counters used in combination with inductive loop detectors. One example was ALICE (Automatic Vehicle Classification System) developed by the Transport and Road Research Laboratory in the U.K. (2). This system consisted of a preferred configuration of one inductive loop with two axle detectors per lane and the associated processing hardware and software. Speed, vehicle length, and wheelbase length(s) can all be derived using this system. The system then compares the recorded inter-axle distances with predefined values of length and distances to derive the vehicle type. This system performs well except when errors are generated during vehicle overtakings.

More recently, there have been investigations with detectors that produce images which can be evaluated using pattern recognition techniques. These systems are increasingly more sophisticated in terms of the classification algorithms and automated software tools. These approaches include video image processing (3 and 4), infrared detection (5), acoustic waveform analysis (6), and inductive signature recognition (7 and 8).

Wei et al. (3) used the three-vehicle class scheme in Table 1 by applying video classification. The feature extraction process involves ground segmentation and background subtraction. The resulting image was quantized by using 16 windows and three characteristics: occupation rate, horizontal image line, and vertical image line. A backpropagation Artificial Neural Network (ANN) with one hidden layer was used. The resulting recognition rates were 98.5%, 96.92%, and 91.94% for heavy vehicles, small cars, and motorcycles using a test set of two hundred images.

Yuan et al. (4) used the six-vehicle class scheme in Table 1 by also applying video classification. Four vehicle extraction models were used to obtain vehicle features. They are: perspective projection, length measurement, width and height estimation, and profile characters. A two-level hierarchical classification scheme was used. Level one separated vehicles into three categories by using lengths and heights. This level used the k nearest-neighbor rule. The reported classification rate for level one was over 90%. Level two further divided vehicles by using profile characters and heuristics.

Lu et al. (5) used an infrared detector with the four-vehicle class scheme in Table 1. This paper also included the possibility of user-defined vehicle categories. A modified Sobel's edge-sharpening method was used to accentuate (or brighten) the engine, emission pipe, and wheels. Features such as size, height, and location of bright clusters, were found through the analysis of the size and position of the bright clusters. Similar to Yuen et al. (4), a k nearest neighbor method was used for classification into four groups. The reported accuracy was 95% for a test sample of 100 vehicles.

Nooralahiyan et al. (6) used acoustic signatures to derive the four-vehicle classification scheme listed in Table 1. Linear Predictive Coding (LPC) was utilized to extract feature vectors through parameter conversion from autocorrelation analysis. A Time Delay Neural Network (TDNN) was used for classification. The reported classification accuracy was 82.4% for 400 test patterns.

Pursula and Pikkarainen (7) used the seven-vehicle class scheme in Table 1 for classification using double inductive loop signatures. Two loop signatures were used in an array configuration that improved classification accuracy over single loop configuration. The physical inductive loops used were 3x2 meters. A 12x12 Self-Organizing Feature Map was used with analog loop signals (inductive signatures) as inputs. The reported percentage of success was around 80% for the training set. An improved algorithm using length windows, SOFM, and Learning Vector Quantization (LVQ) was also discussed.

Sun et. al. (8) also used inductive signatures to differentiate between seven vehicle types as shown in Table 1. This system used a heuristic discriminant algorithm with feature vectors as inputs. The feature vectors were extracted from the inductive signature and were vehicle length, magnitude, variance, skewness, and kurtosis. A multi-objective training scheme for the heuristic was solved by using golden section search. The algorithms yielded overall classification rates of 81%-91%.

There are also commercial products available that use infrared detector or multi-beam vertical light curtain for vehicle classification. Companies such as Schwartz Electro-Optics (9) and Transport Data Systems (10) use 4 and 5 category schemes with subcategories. Details on the algorithms and performance for such commercial systems are often unavailable.

METHODOLOGY

Artificial Neural Networks (ANN) have been employed in problems involving pattern recognition and in several transportation applications. Some examples include traffic control (11), equilibrium assignment (12), incident detection (13), vehicle lateral control (14), origin-destination flow identification (15), traffic classification (16), and pavement management (17). For more examples and evaluations of neural networks in transportation engineering see Faghri and Hua (18).

A helpful taxonomy of neural networks for pattern classification is shown in Figure 1 (19). Classical classification algorithms that are most similar to the neural network are listed in parentheses. Figure 1 is helpful in identifying the type or types of neural network(s) needed for a particular application in pattern recognition. A Self-Organizing Feature Map is an Artificial Neural Network that forms clusters of neurons which reflect similarities in the input vector. SOFM is also known as the Kohonen network. Some references on this subject include (20) and (21). Some reasons for using SOFM in this investigation include:

- ability to detect irregularities in input and adapt responses accordingly
- use of competition to naturally cluster data without supervision
- insight into network weights which represent class templates
- similarity to the well understood k-means statistical algorithm

Since SOFM uses unsupervised learning, it is a mapping that is defined implicitly and not explicitly. This is desirable since this investigation is not restricted to any particular transportation applications or predefined categories. Input vectors are presented sequentially in time without specifying the output. Because of this fact, there is no way of predicting which neuron will be associated with a given class of input vectors. This mapping is accomplished after training the network.

The SOFM has a sequential structure starting with the d input vectors **x** which are received by the n neurons in parallel and are scaled by the weight vector **w**. Thus, the weight matrix is the size of n neurons by d inputs. The n neurons are then entered into competition where only one neuron wins. The architecture of the SOFM is illustrated in Figure 2. SOFM employs the concept of topological neighborhoods, which are equidistant neuron neighborhoods centered around a particular neuron. The neighborhood distance matrix for a one-dimensional case using four neurons is

0 1 2 3
1 0 1 2
2 1 0 1
3 2 1 0

It can be seen that the distance of a neuron from itself is 0, the distance of a neuron from its immediate neighbor is 1, and so on. Unlike simple competitive learning, the weights of the neighborhood neurons are updated in addition to the weights of the winning neuron.

The steps in training the SOFM can be outlined as follows:

Step 1. Initialize weights randomly.

Step 2. Present new input.

Step 3. Compute distances between input and neuron weights.

Step 4. Competitive selection of the neuron with the minimum distance.

Step 5. Update neuron weights to winning neuron and neighborhood neurons.

Step 6. Continue iterating by going through steps 2-5.

In describing the training algorithm, it is useful to understand the weight structure of the network. Each neuron has the same number of weights **w** as the dimension of the input vector **x**. The weight structure for each neuron can then be viewed as a matched filter competing against other neurons. A matched filter has the impulse response tuned to input so that it produces the maximal output signal (22). The overall weight structure can be viewed as an array of matched filters with each neuron's weights being adjusted on the basis of current weights and the goodness-of-match of the input.

Given that the feature map is initialized with random weights $\boldsymbol{w}$ for all the neurons, a distance measure, $d(\boldsymbol{x}, \boldsymbol{w}_i)$ can be used to define the goodness-of-match between a particular weight vector $\boldsymbol{w}_i$ and the input vector $\boldsymbol{x}$. The distance measure used can be correlation, Euclidean, city-block or other statistical measures. If the Euclidean distance is used, then the winning neuron from the competition is found at each iteration k by using the following equation

$$\|x(k) - w_c(k)\| < \|x(k) - w_i(k)\|, \forall i$$

where neuron c is the winning neuron. The network weights are then updated as follows:

$$w_i(k+1) = \begin{cases} w_i(k) + \alpha(k)[x(k) - w_i(k)], i \in N_c(k) \\ w_i(k), i \notin N_c(k) \end{cases}$$

where N_c defines the neuron neighborhood and $\alpha(k)$ is the learning rate at each iteration. The weight updating equation shows that $d(\boldsymbol{x}, \boldsymbol{w}_i)$ is decreased for N_c while those outside N_c are left unchanged. The neighborhood size and the learning rate both decrease with increase in the number of training iterations. Typically $\alpha(k)$ start near 1 and go down to 0.1. The size of N_c can start out as large as the greatest distance between weight vectors, and decrease until the neighborhood defines only one neuron.

An interesting feature of SOFM is that the distances between neurons can be interpreted as statistical frequency distributions. In a fully trained network, if input vectors occur with varying frequencies, then the feature map will also allocate neurons to an area in proportion to the frequency of input vectors (23). Another interesting feature of SOFM is that the weights become topologically similar to the input vectors. In a sense, the final weights are analogous to class templates and can be plotted for visual inspection. Because of this feature, the SOFM is less like a black-box and is more like an automated k-means statistical clustering algorithm.

The choice of the particular SOFM configuration is not a precise science and involves engineering judgement. The two major design parameters are the dimension of the network and the number of neurons. As noted by Schalkof (24), powerful results have been obtained by just using 1- and 2-dimensional topologies. In selecting the dimensionality of the network for vehicle classification implementation, the computational intensity and the classification rate are both important. Pursula and Pikkarainen (7) employed 2-dimensional networks for vehicle classification. They presented encouraging results from the use of 5*5 to 12*12 feature maps. However, a 1-dimensional feature map with 1-dimensional inputs can also be applied to the vehicle classification problem using less computational intensity. As the vehicle signatures are interpolated at fixed intervals, there is no need to capture the abscissa. Therefore a 1-dimensional structure can be used to capture the inductance magnitude changes of the vehicle signatures.

The training parameters are the learning rate and the number of training iterations. The initial learning rate should be between 0 and 1, and value of 0.99 was chosen based on experience. Kohonen (24) cites the use of 10,000-100,000 training iterations as typical, and recommends that the number of training cycle should be at least 500 times the number of output neurons. Thus, all the networks have been trained using 100,000 iterations. By looking at the plot of the feature maps for the different networks used for vehicle classification, one could see that the neurons are well-spaced indicating that the training iterations were adequate. Otherwise, the neurons would be bunched up towards the middle of the input vector space where the training originally started.

RESULTS

All feature maps tested had the following general characteristics. First, the input vector was composed of ninety-three components corresponding to the ninety-three equally spaced interpolations of the vehicle signature. This input format was chosen to match directly the output of the detector cards with very little processing. This is in contrast to the preprocessing needed in feature extraction algorithms such as (7) or (8). Second, the number of training iterations was the same for all feature maps. Even though some trials involving as little as 3000 iterations were performed, the resulting feature maps did not exhibit convergent characteristics. Therefore, based on the recommendations of other researchers and on experience, the number of training iterations was chosen to be 100,000. A 300Mhz personal computer was used for implementing ICAN, and the training took only a few minutes for each feature map configuration. Third, the training set is composed of only thirteen vehicles signatures. The 13 vehicles included one signature from each of the following categories: passenger car, station wagon, minivan, sports car, Sports Utility Vehicle (SUV), cargo van, limousine, pickup, full-size truck, vehicle towing trailer, bus, box truck, and truck with trailer.

The field data used for this investigation were collected in Lafayette, California, in December of 1996 and is the same data used in (8). A section of the four lane SR-24 freeway was instrumented with signature-capable detector cards, dataloggers, and video ground truth cameras. Existing octagonal loops of 1.8mx1.8m (6'x6') dimensions were used in acquiring inductive signatures. None of the loops were calibrated with respect to each other in terms of sensitivity. The data collection setup for a single lane of traffic is shown in Figure 3. Data were collected for several days and a particular dataset was further processed and manually verified. The dataset used for this investigation consisted of approximately 2000 vehicles in moderate flow traffic (~1000VPHPL). Since the majority of traffic was composed of passenger cars, this dataset was further reduced to a more interesting dataset containing approximately 300 vehicles from different vehicle classes. The process of visual verification of signature and ground truth coupled with the extraction of more unique vehicle signatures took several months to accomplish. Figure 4 shows examples of signatures and video ground truth for different vehicle classes. The y-axis in all the vehicle signature plots represents the amount of change in the inductance magnitude of the loop. The x-axis represents the electronic length of vehicles since vehicle speeds and vehicle traversal times are collected.

The first implementation of the SOFM involved a one-dimensional feature map composed of four neurons. Therefore a maximum of four vehicle classes could be derived from this feature map. Four distinct clusters resulted from the training, and the representative vehicle classes are listed in Table 2.

One advantage for using SOFM is that the weights actually represent the categorized inputs and can be interpreted as class templates. This makes the graphical analysis of the SOFM possible, and gives insight to the so-called neural network blackbox. The weights from the four neuron ICAN are plotted in Figure 5a. By comparing Figure 5a to Figure 4, it can be seen that the weights look similar to the vehicle signatures that they try to represent.

A test set composed of 124 vehicles was used for testing this first ICAN. The overall classification rate was 77%. This result is significant in view of the small size of the SOFM and the training set. All of the misclassifications were incorrectly assigned to an adjacent category. This is encouraging since this implies that a shifting of the classification boundaries might improve the classification rate. The shifting of the classification boundaries is accomplished by re-training ICAN. This is perhaps one disadvantage of using neural networks, since these boundaries are not specified explicitly as in statistical approaches but are embedded in the neuron weights. A more detailed analysis of the results show that ~5% of the misclassifications were due to full-size trucks incorrectly classified as class 3 (van).

Due to the manageable size of the test data, detailed analysis of the signatures from the misclassified vehicles was performed. The first group of misclassifications involve cargo vans incorrectly classified as class 2 (truck/SUV). By analyzing the signature of the training set for the vehicle type "cargo van", it was found that the van was an ambulance which had a signature that had features of both a van and a truck. Therefore, the training set was modified by replacing the ambulance with a cargo van that was more representative of the signature of the cargo van.

Another group of misclassifications involves passenger cars being incorrectly classified into group 2. The magnitudes of these signatures are low compared with a normally centered passenger vehicle. This indicates that the vehicles were traveling off the center of the lane or switching lanes. Since the inductance change is proportional to the inverse of the distance from the loop detector, pickups and SUV's also exhibit such low magnitude signatures. These two examples demonstrate one weakness of using the inductive signatures, namely that lateral offset causes low magnitudes in vehicle signatures which leads to misclassifications.

After analyzing the error from the first ICAN implementation, the training set was changed by replacing the "cargo van" signature with a more representative signature. The change in training set also produced a new four-category classification scheme shown in Table 2. After changing the training set by one vehicle the reidentification rate increased to 81%. All the misclassifications were again one-class misclassifications, meaning that the class was assigned erroneously to a neighboring class. The results reported are similar to those reported by Pursula and Pikkarainen (7). In their study, they reported successful classifications of around 80% by using two-dimensional self-organizing feature maps. The 4-neuron ICAN was also tested with a second test set composed of 137 vehicle signatures. The classification rate of 80% on the second data set is similar to the results from the first test set.

A more complicated ICAN configuration with 13 neurons was also trained and tested. The resulting weights are plotted on Figure 5b. The thirteen outputs were mapped to two vehicle categorization schemes, one with 9 vehicle classes and the other with 7 vehicle classes. The two schemes are listed in Table 2. The classification rate using 9 vehicles classes was 71% for the first data set. Most of the error is due to ICAN's inability to distinguish between 3 vehicle classes. These vehicle classes are classes 2, 3, and 4. In other words, cargo vans, SUV's, pickups, and full-size pickups exhibit very similar signatures. This is not surprising, since smaller SUV's share platforms with pickups, and bigger SUV's share platforms with full-size pickups. By expanding the SUV/pickup cluster to include cargo vans and full-size pickups, a 7 class scheme results. The overall classification rate for that scheme is 87%. The overall test result from using the second data set was 82%. The rates for individual classes are presented in Table 3. One major reason for errors was the misclassification of off-center passenger cars as SUV's or pickups. As was mentioned before, such vehicles produce smaller inductance changes and confuses ICAN. The results obtained from this research are similar to the results reported by Sun and Ritchie (8) from their heuristic algorithm; however, the training size used by the ICAN is much smaller.

CONCLUSION

It is difficult to compare ICAN directly to previous research for several reasons. First, the classification schemes used by previous researchers differed significantly with most schemes utilizing three or four different classes instead of the seven or nine used in this research. The purpose of this research was not to use the FHWA thirteen-class taxonomy which can be easily performed with an axle counting system. Instead, the purpose was to try to differentiate between two-axle vehicles which is a much more challenging task. Vehicle classes such as SUV's are becoming increasingly popular and need to be classified accurately for traffic analysis and modeling purposes. Second, the different surveillance technologies, such as inductive loop and video, capture different aspects of vehicles. Therefore it will be helpful to identify the abilities of each technology in feature identification and possibly fuse multiple detector data for building a more robust classification system.

The results of testing ICAN were encouraging. In addition to the overall classification rates of 87% and 82% for the two test datasets, the classification rates for individual vehicle classes were also consistent. In other words, this system was not biased toward the class with the most samples, namely passenger cars.

One advantage of ICAN is the simplicity in the implementation and training. The architecture of the network is composed of one dimension with 13 neurons in contrast to previous neural network implementations. ICAN was implemented on a standard personal computer with a 300 MHZ microprocessor. Also, only 13 samples were used for training as compared with 400 for the 12x12 feature map (7), about 150 for the heuristic algorithm (8), and 450 for the LPC/TDNN (6).

It was important to use field data from a freeway to show the complexity of real world data and the incompleteness of real world signatures in testing ICAN. The acquired traffic traveled at high speeds (average of 106kph or 66mph) which resulted in very few samples recorded per vehicle. This is in contrast to higher resolution arterial data. The real world data was also useful in showing the limitations of ICAN such as in instances where vehicle straddling occurred. Also, it is often easy to disregard the enormous effort expended in data collection and verification of real world data. In addition to the task of instrumenting a freeway section, the task of visual verification and data reduction of about 2000 vehicles was a formidable process.

The authors hope that the graphical presentation of representative vehicle type signatures along with the video images will be helpful for other researchers interested in using signatures for vehicle classification, reidentification, preemption, and other applications. The differing characteristics of signatures between vehicle classes can be clearly seen from the samples. The effort of this research was in the automation of this visual process.

Even though ICAN was initially designed for using inductive signatures as inputs, other inputs can be added to the system as they become available. The SOFM structure is general enough so that feature vectors from another detector technology can be used to augment the inductive signature information. For example, information derived from video images, such as projected width or front shape (4), can be added to ICAN to improve classification results.

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The contents do not necessarily reflect the official views or policies of the State of California or New Jersey. This paper does not constitute a standard, specification, or regulation.

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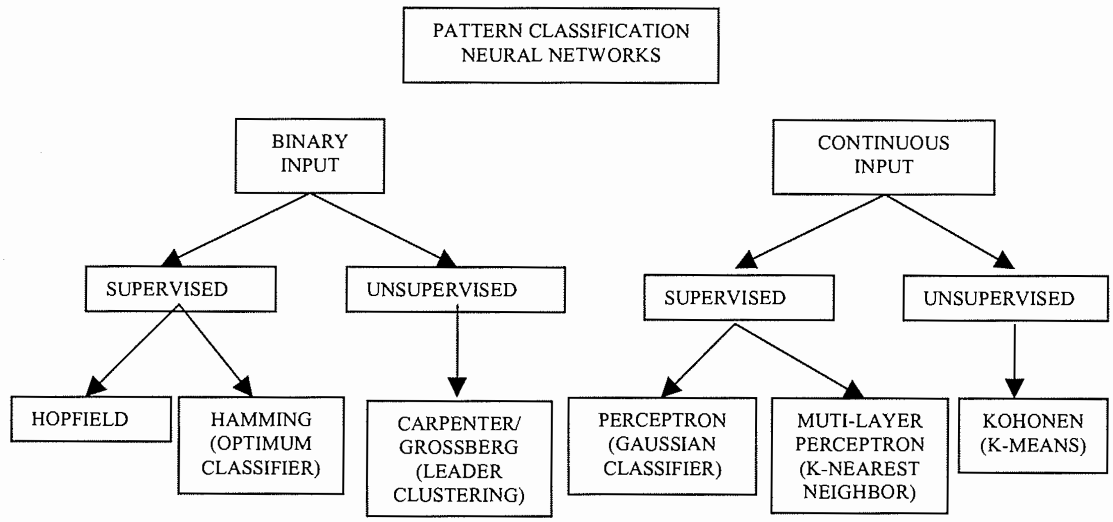


Figure 1. Taxonomy of Pattern Classification Neural Networks (19)

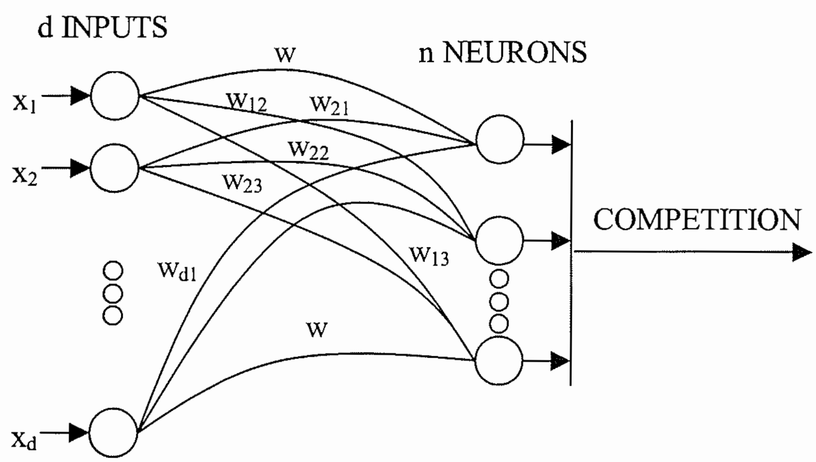


Figure 2. 1-D Self-Organizing Feature Map Architecture

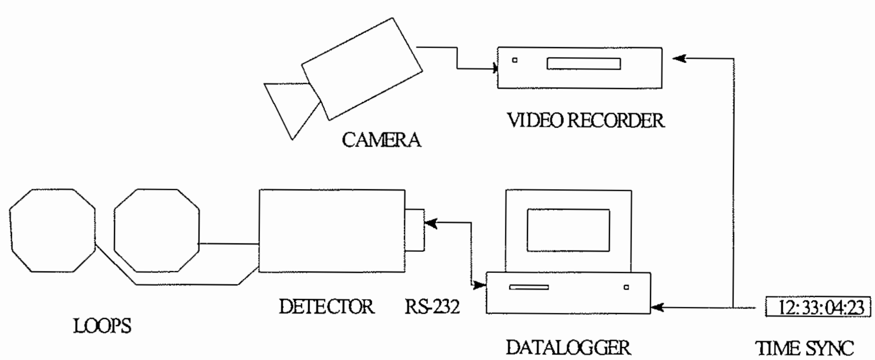


Figure 3. Data Collection Setup

Figure 4a. Sports Car

Figure 4b. Sports Utility Vehicle

Figure 4c. Van

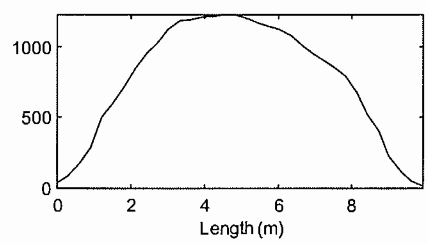
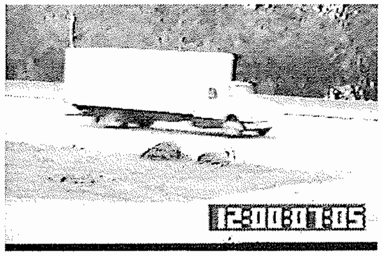


Figure 4d. Limousine



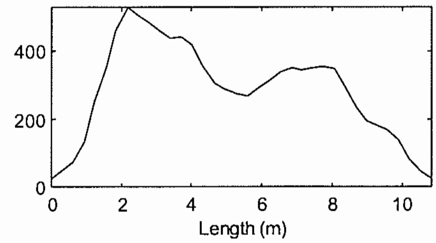


Figure 4e. Bi-axle Truck

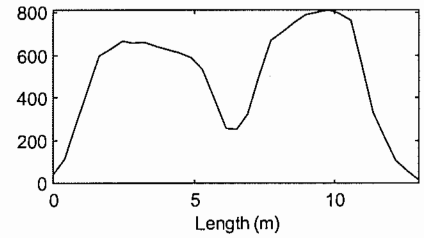
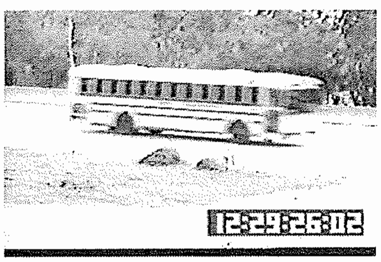


Figure 4f. Vehicle with Trailer



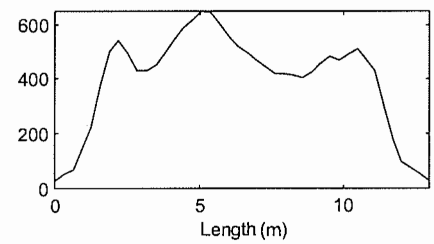
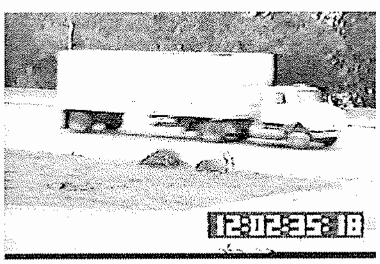


Figure 4g. Bus



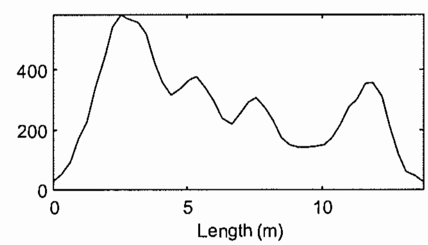


Figure 4h. Semi-trailer Truck

Figure 4. Signatures and Images from Representative Vehicles

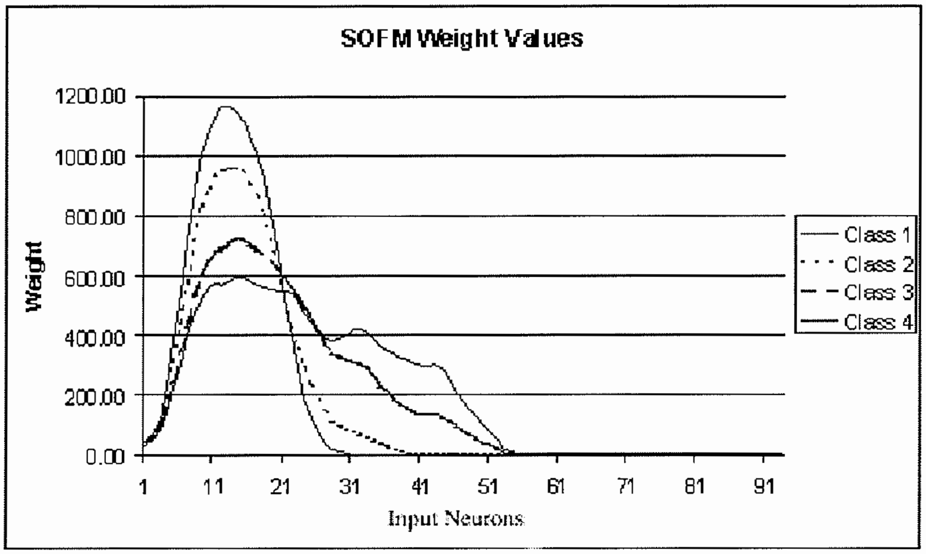


Figure 5a. Four Neuron

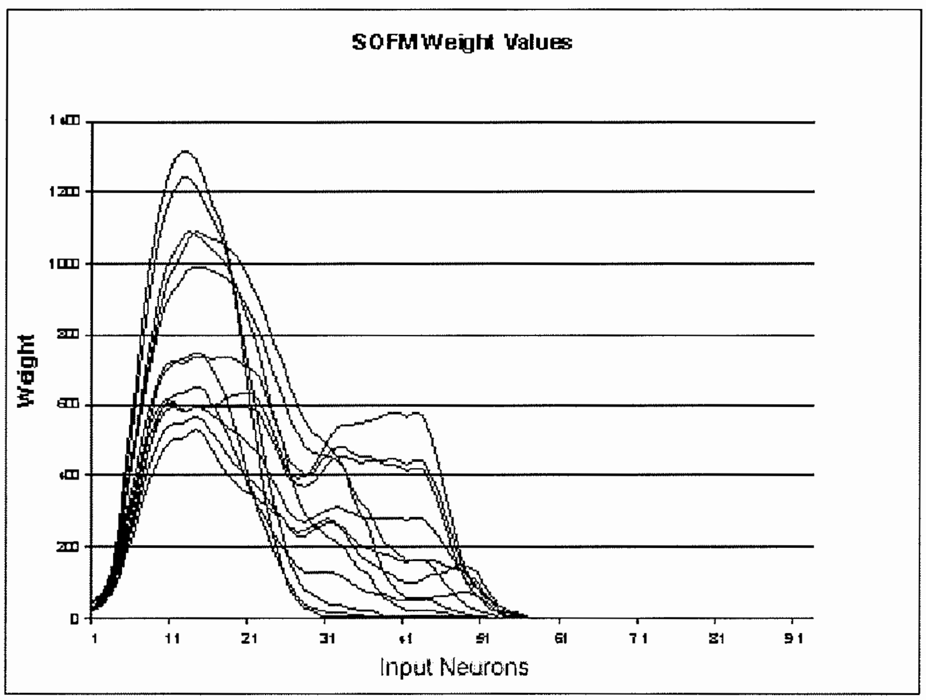


Figure 5b. Thirteen Neuron

Figure 5. Plots of ICAN Neuron Weights

Table 1. Vehicle Categorization Schemes

Category	Description
Three-Vehicle, Wei et al. (3)	
1	heavy vehicles
2	small cars
3	motorcycles
Six-Vehicle, Yuan et al. (4)	
1	2 axle vehicles: car, van, pickup, ambulance, and single-unit truck
2	buses
3	3 axle truck
4	one-unit truck, four or more axles
5	two-unit truck, four or more axles
6	three-unit truck, four or more axles
Four-Vehicle, Lu et al. (5)	
1	passenger cars
2	buses with new engines and trucks without upright pipes
3	trucks with upright pipes and trailer trucks
4	unidentified
Four-Vehicle, Nooralahiyan et al. (6)	
1	buses or lorries
2	small or large saloons
3	Motorcycles
4	light goods vehicles or vans
Seven-Vehicle, Pursula and Pikkarainen (7)	
1	car or van
2	truck
3	bus
4	truck with semi-trailer
5	truck with trailer
6	car with trailer
7	car with mobile home
Seven-Vehicle, Sun et al. (8)	
1	car, minivan, sports car, station wagon
2	SUV, pickup
3	van, full-size pickup
4	limousine
5	2 axle truck
6	vehicle with trailer, bus
7	> 2 axle truck

Table 2. ICAN Vehicle Categorization Scheme

First Four-Vehicle Class Scheme	
Class	Vehicle Types Represented
1	passenger car, minivan, sports car, station wagon
2	SUV, full-size truck, pickup
3	van, limousine
4	cargo truck, vehicle with trailers, bus, and trucks with >2 axles
Second Four-Vehicle Class Scheme	
Class	Vehicle Types Represented
1	cargo truck, vehicle with trailers, bus, and trucks with >2 axles
2	limousine
3	van, SUV, full-size truck, pickup
4	passenger car, minivan, sports car, station wagon
Nine-Vehicle Classification Schemes	
Class	Vehicle Types Represented
1	passenger car, minivan, sports car, station wagon
2	van
3	sports utility vehicle, pickup
4	full-size pickup
5	truck
6	> 2-axle truck
7	bus
8	vehicle with trailer
9	limousine
Seven-Vehicle Classification Schemes	
Class	Vehicle Types Represented
1	passenger car, minivan, sports car, station wagon
2	van, sports utility vehicle, pickup, full-size pickup
3	truck
4	> 2-axle truck
5	bus
6	vehicle with trailer
7	limousine

Table 3. ICAN Test Results

Overall	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7
First Data Set							
87%	80%	98%	100%	67%	100%	100%	100%
Second Data Set							
82%	74%	94%	88%	75%	100%	100%	100%

LIST OF FIGURE CAPTIONS

LIST OF TABLE TITLES