Performance prediction of vehicle detection algorithms

Peter Klausmann, Kristian Kroschel and Dieter Willersinn

Fraunhofer-Institut für Informations- und Datenverarbeitung,
Fraunhoferstraße 1, 76131 Karlsruhe, Germany

ABSTRACT

Performance prediction of computer vision algorithms is of increasing interest whenever robustness to illumination variations, shadows and different weather conditions has to be ensured. The statistical model which is presented in this contribution predicts the algorithm performance under the presence of noise, image clutter and perturbations and therefore provides an algorithm-specific measure of the underlying image quality.

For the prediction of the detection performance logistic regression using covariates defined by the properties of the vehicle signatures is used. This approach provides an estimate of the probability of a single vehicle signature being detected by a given detection algorithm. To describe the relationship between background clutter and the false alarm rate of the algorithm a severity measure of the image background is presented.

After the construction of the algorithm model, the probability of a vehicle signature being detected and the false alarm rate are estimated on new data. The model is evaluated and compared to the true algorithm performance.

Keywords: Automatic target detection, performance prediction, algorithm assessment, logistic regression, clutter measure.

1. INTRODUCTION

In recent years the computer vision community has been focussed not only on the development but also on the assessment of algorithms.[1–3]

Therefore, methods have been compared and the suitability of algorithms has been investigated, but also explanations why an algorithm works better than another have been tried to be found. Many reasons may cause the algorithm to fail: Data features corresponding to a different object due to noise, inconsistent description of object features, missing contrast, imprecise edge detection and background clutter.[4] Object or target hypotheses are seldomly consistent with all data, not even on a subset for which an algorithm is trained.

Therefore, the characteristics of the targets have been analyzed under different noise and clutter conditions and the performance of automatic algorithms has been compared to the performance of human observers.[5,6] Schmieder and Weathersby[7] first noticed the relevance of the relationship between target signature and background texture for target detection applications. They defined image clutter C as the average gray value standard deviation σ of all N contiguous cells in the scene, where each cell is square and has twice the height of the targets. Therefore, clutter is defined as follows:

$$C = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\sigma_i^2}$$

The "signal-to-clutter ratio" (SCR) was then defined by

$$SCR = \frac{|I_{max} - I_b|}{C}$$

where I_{max} is the maximum target intensity value and I_b the average background intensity. The detection capacity of human observers versus the SCR and several target resolutions have been analyzed. Ratches et al.[8] stated that the signal-to-noise ratio SNR has a basic influence on the detection performance. They defined the signal-to-noise ratio as

$$SNR = \frac{(I_t - I_b)}{I_b}$$

Send correspondence to Dieter Willersinn, E-mail: wil@iitb.fhg.de

where I_t is the average intensity of the target and I_b the average intensity of the background.

Human preattentive vision has been modeled by Conners and Ng[9] on the basis of gray level cooccurrence matrices. These matrices have been used by Shirvaikar and Trivedi[10] to describe the amount of clutter contained in an image using a texture-based image clutter measure (TIC). This clutter measure has been related to the detection and false alarm rates of a vehicle detection algorithm. Another approach is pursued by Waldman et al..[11] They found that spatial extent, contrast, clutter, movement, shape, number of targets and color play a main role in performance prediction.

A first approach to model the performance of corner detection and matching algorithms using probability density functions is given in.[12] Each probability function models a single layer of the algorithm and is derived by applying the algorithm to a large number of synthetic images. But beside this approach criteria to predict the relationship between algorithm performance and image quality aspects are rarely found.

However, all measures of image quality considered so far have not been found to be useful to generally explain algorithm success or failure. Therefore, Ratches et al.[8] claimed that "an active image science that provides image metrics - especially clutter measures -, understanding of scene information, and models- and that performs experiments to generate data that lead to model formulation and validation is needed to indicate the most fruitful scientific endeavors for rapid progress."

Following this guideline the goal of this contribution is to qualify signatures of vehicle targets according to their difficulty in being detected and to model a performance predicition rule for an automatic vehicle detection algorithm. The main topics are the quantification of the influence of noise and perturbations on the detection probability with respect to a given algorithm and the design of a model of the performance variation. Once such a model is constructed it will be possible

- to estimate the probability of a vehicle's signature being detected and to predict the number of false alarms due to background clutter on new data.
- to specify requirements on the vehicle's signature and the background structure to guarantee a good algorithm performance.
- to describe the image quality for the algorithm under consideration.
- to decide how image perturbations influence the algorithm performance.
- to define requirements for imaging sensor systems.

Additionally, such models are extremly important in empirical algorithm assessment to explain and to predict performance differences due to the application of the algorithm to different test data sets.

The approach presented here is divided into two parts. The first part defines properties of the vehicle signatures and investigates their influence on detection probability. The second part investigates background clutter and relates the background properties to the false alarm rate of an automatic vehicle detection algorithm. The models are then applied to estimate the algorithm performance on new and perturbed data. Finally, the predicted and the true algorithm performance is compared.

1.1. Detection algorithm task

For vehicle detection algorithms the main performance measures are the detection rate and the false alarm rate. To compute the detection rate and the false alarm rate achieved by the application of a detection algorithm to a test data set, adequate ground truth data must be available. Then the algorithm results can be compared to this ground truth and the corresponding rates can be calculated. The ground truth was given as polygons surrounding each vehicle signature (see Fig. 1). The algorithm's task is to provide the vehicle's centroids. The algorithm results can now be checked if they are located inside (detection) or outside a truth polygon (false alarm). Truth polygons without any vehicle centroid inside are called non-detections.

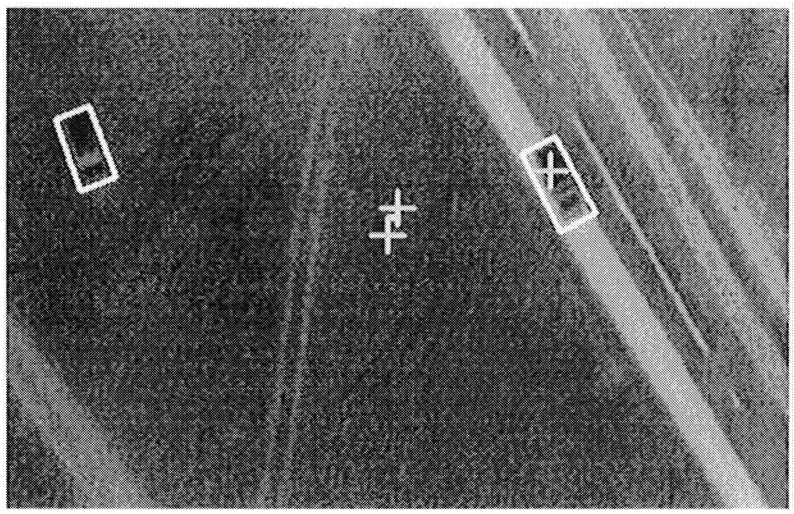

Figure 1. *Clip of an infrared image for vehicle detection. Overlaid onto the image clip are the white ground truth polygons and three algorithm results. Note that there is one detection, one non-detection and two false alarms.*

2. DETECTION PERFORMANCE MODELING

In order to construct a mathematical model of the detection performance based on several vehicle signature properties logistic regression is suggested.[13] In logistic regression these properties are called *covariates*. These covariates are computed using the ground truth of the data set to which the algorithm is applied.

To be detectable, a vehicle should differ significantly from its background. Because the background varies on the image range, a description of the local background has to be used. Therefore, a rectangle tightly surrounding each vehicle is used as local background area (see Fig. 2). The white regions correspond to the vehicle's signature, the black lines form the surrounding truth polygons whilst the light gray area is the associated local background area of each vehicle.

Various covariates may be used to describe the difference between the vehicle signature and the local background.[14] Here, the following covariates x_i, $i = 1, 2, 3$, indicating the detectability of each vehicle have been used:

- x_1: Edge pixel difference $EPD = |E_t - E_b|$ where E_t denotes the number of edge pixels of the vehicle area and E_b the number of edge pixels of the local background. For the computation of the edge pixels the Sobel operator has been used with an adaptive threshold for the gradient magnitude.
- x_2: Variance difference $VD = |\sigma_t^2 - \sigma_b^2|$, where σ_t^2 denotes the variance of the gray values of the vehicle area and σ_b^2 denotes the gray value variance of the local background.
- x_3: The number of pixels belonging to the vehicle area. This number is denoted by PIX.

The relationship of the covariate vector $\mathbf{x} = (x_1, x_2, x_3)^t$ and the detection probability P_D of a single vehicle has now to be estimated. Thus the covariate vector $\mathbf{x}$ has to be related with the dichotomous outcome of the comparison between the truth data (polygons) and the algorithm results (vehicle centroid hypotheses) on the given image data set. Therefore, logistic regression is used which provides an algorithm-specific formula of the relationship between the algorithm's detection performance and the image quality described in terms of the covariates.

2.1. Review of logistic regression

Over the last decade logistic regression has become an integral component of data analysis by modeling the relationship between a discrete dichotomous response variable (e.g. vehicle detected or not) and one or more independent explanatory variables (e.g. the above defined covariates).[13]

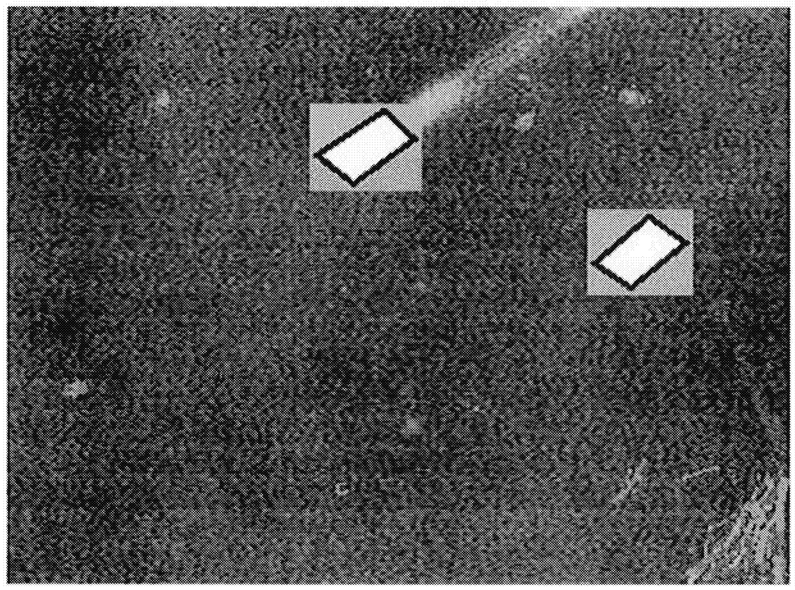

Figure 2. *Clip of a test image. The regions used to compute the vehicle's image features are displayed: White regions correspond to the vehicle location, the black lines form the truth polygons whilst the light gray area defines the associated local background area for each vehicle.*

In the following the probability of a vehicle being detected or missed due to the covariates is modeled on the basis of a given image data set and the dichotomous information, whether the corresponding vehicles have been detected or missed by the algorithm. The prediction rule is constructed using a likelihood function, which maximizes the probability of obtaining the observed data.

Suppose a p-dimensional input random variable X and a scalar dichotomous outcome Y (vehicle detected or not detected) are given. Each of the n observations is assumed to be independent and described by the pair $(\mathbf{x_i}, y_i)$, $i = 1, ..., n$ where the $\mathbf{x_i}$ are realizations of X and the y_i denote the dichotomous outcome, which is assumed to be coded as 1 if a vehicle has been detected and 0 if a vehicle has been missed.

To represent the conditional probability P_D that a vehicle is detected given $\mathbf{x}$, the logistic regression model is used, which is defined by

$$P_D(\mathbf{x}) \quad = \quad \frac{e^{g(\mathbf{x})}}{1 + e^{g(\mathbf{x})}} \tag{1}$$

where $g(\mathbf{x})$ denotes a polynomial and is refered to as the **logit**. Here, in case of continuous covariates, the logit is given by

$$g(\mathbf{x}) = \beta_0 + \beta_1 \cdot x_1 + ... + \beta_p \cdot x_p$$

The regression coefficient vector $\boldsymbol{\beta} = (\beta_0, ..., \beta_p)$, in the case under consideration $p = 3$, has to be estimated from the given data. The conditional probability that the realization y of Y is equal to zero given $\mathbf{x}$ is expressed by $1 - P_D(\mathbf{x})$. Thus, the contribution of each pair $(\mathbf{x_i}, y_i)$, $y_i \in \{0, 1\}$, $i = 1, ..., n$ to the likelihood function is expressed by

$$\lambda(\mathbf{x_i}) \quad = \quad P_D(\mathbf{x_i})^{y_i}[1 - P_D(\mathbf{x_i})]^{1-y_i} \quad = \quad \begin{cases} P_D(\mathbf{x_i}) & if \;\; y_i = 1 \\ 1 - P_D(\mathbf{x_i}) & if \;\; y_i = 0 \end{cases}$$

Since the observations are assumed to be independent, the likelihood function $l(\boldsymbol{\beta})$ is obtained by

$$l(\boldsymbol{\beta}) = \prod_{i=1}^{n} \lambda(\mathbf{x_i})$$

	estimated coeff. $\hat{\beta}_i$	$S.E.(\hat{\beta}_i)$	$(\hat{\beta}_i/S.E.(\hat{\beta}_i))^2$ (Wald)	$Sig.$
EPD	0.0498	0.0220	5.1	0.023
VD	0.1122	0.0431	6.7	0.009
PIX	0.0014	0.0009	2.4	0.140
const.	-2.956	1.0775	7.5	0.006

Table 1. *Estimated logistic regression coefficients $\hat{\beta}_i$, $i = 0, 1, 2, 3$ and the corresponding standard error (S.E.). Also the univariate Wald-statistic and the achieved significance level (Sig.) are given.*

To simplify mathematical handling, the **log likelihood function** L is used, which is defined by

$$L(\boldsymbol{\beta}) = ln[l(\boldsymbol{\beta})]$$

The task is now to find a value of $\boldsymbol{\beta}$ that maximizes the log likelihood function. Therefore, the $p+1$ likelihood equations are computed by differentiating the log likelihood function L with respect to $\boldsymbol{\beta}$ and are set to zero, i.e.

$$\begin{array}{rcll} \sum_{i=1}^{n} y_i - P_D(\mathbf{x_i}) & = & 0 & \\ \sum_{i=1}^{n} x_{ij}[y_i - P_D(\mathbf{x_i})] & = & 0 \quad j = 1, ..., p & \qquad with\ p\ =\ 3 \end{array}$$

where $\mathbf{x_i} = (x_{i1}, x_{i2}, x_{i3})$. An iterative algorithm to solve these nonlinear equations can be found in[16] and is implemented in most statistical software packages.

2.2. Detection model estimation

From the covariates mentioned above, a logistic regression model has been estimated for the algorithm KLMDET[15] and a test data set consisting of 51 real infrared images containing 106 vehicles. The estimated coefficients $\hat{\beta}_i$, $i = 0, 1, 2, 3$ and the corresponding standard errors $(S.E.)$[17] are shown in Tab. 1. Additionally, for every coefficient $\hat{\beta}_i$ the univariate Wald-statistic $(\hat{\beta}_i/S.E.(\hat{\beta}_i))^2$ is given which is χ^2-distributed.[13] With this statistic the hypothesis that a single coefficient is zero is tested. The achieved significance level of this test is given for each coefficient in the column $Sig.$ of Tab. 1 indicating a high significance for EPD and VD. A lower significance is given for PIX.

The final model which describes the correspondence of the detection probability P_D of a vehicle due to its signature described by the covariate vector $\mathbf{x}$ is given by equation (1) with the following logit:

$$g(\mathbf{x}) = -2.9566 + 0.0498 \cdot EPD + 0.1122 \cdot VD + 0.0014 \cdot PIX$$

For example, suppose given a single vehicle with signature description $EPD = 30$, $VD = 13$ and $PIX = 900$. This yields a logit of

$$g(\mathbf{x}) = 1.256$$

The probability of this vehicle being detected by the algorithm KLMDET is estimated by the model equation 1

$$P_D(\mathbf{x}) = \frac{e^{1.256}}{1 + e^{1.256}} = 0.78$$

The detection performance of an algorithm on a new set of data can be estimated by computing the covariate vectors $\mathbf{x_i}$, $i = 1, ..., n$ for each vehicle in the image data set. Then the corresponding detection probabilities have to be computed using the logistic regression formula. An estimate of the detection rate of the algorithm on the whole data set is given by the mean of the individual detection probabilities. Results of such a performance prediction are discussed in Section 4.

Very often desired is a guideline, how vehicle signatures must look like to be detected with a high reliability. This is of major interest e.g. when a specification of an optimal algorithm-adapted sensor configuration is needed or the quality of the vehicle signatures has to be determined.

The values of EPD, VD and PIX yielding a detection probability larger than e.g. 95 % can be easily computed by a simple Monte-Carlo-Simulation. Therefore, many random values of EPD, VD and PIX have been produced. The admissible range of these random values corresponds to the range of EPD, VD and PIX on the given data set.

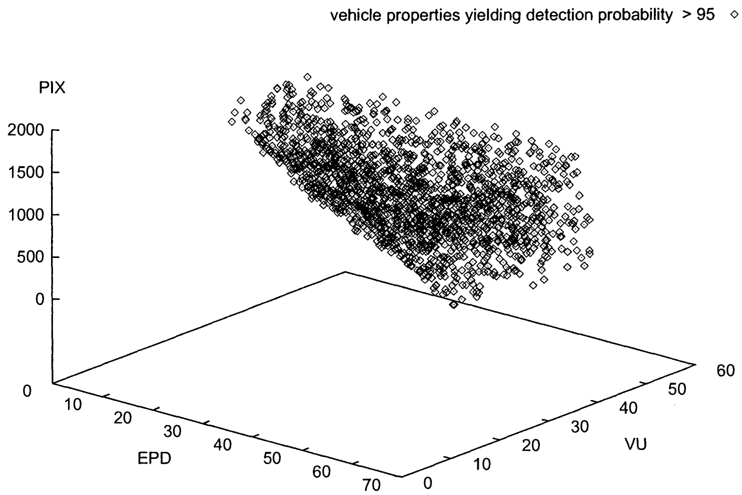

Figure 3. *Vehicle properties in terms of the described covariates yielding a probability to be detected of $\geq$ 95 %. 20000 Monte Carlo samples have been used here.*

Then the corresponding detection probability of the vehicles has been computed by the estimated logistic regression formula. All combinations of EPD, VD, and PIX yielding a lower detection probability have been rejected. Fig. 3 shows all signature property combinations yielding a detection probabiblity $\geq$ 95 %. These values specify the vehicle signature properties corresponding to a high probability of a vehicle being detected. Additionally, the clustering of these set of points indicate a robust and stable behaviour of the logistic regression model.

So far, only the detection probabilities have been considered, although the false alarm rate is equally important. The following section concentrates on a description of the background structure which is related to the achieved false alarm rate.

3. BACKGROUND CLUTTER DESCRIPTION

In a very general sense the amount of clutter in an image is given by the set of signatures which are wrongly guessed by the algorithm to belong to a vehicle. If an algorithm works perfectly on an image data set, one cannot say that there is clutter in the image anymore. Therefore, a definition of the amount of clutter is always related to the algorithm under consideration. In the following, statistical parameters of the features which are extracted by the algorithm on its low-level processing stage are used to construct a false alarm prediction model.

To get an adequate description of the structure of the image background, gradient direction blobs have been used. Such gradient direction blobs are also used by KLMDET for a knowledge-based construction of the detection hypotheses. In[18] these gradient direction blobs are called *line-support regions.* The computation of these line-support regions requires the gradient directions and the gradient magnitude at each pixel. Here, they are computed using the Sobel-Operator. Pixels with similar gradient direction are combined to regions. The 360°-range of the gradient directions is divided into four sections and each pixel is assigned to such a partition according to its gradient orientation. Adjacent pixels which belong to the same partition are grouped to simple-connected components. A selection of the direction blobs due to their attribute sets (e.g. size, average gradient magnitude, maximum pixel intensity) provides a decomposition of the background into finer and coarser structures.

A fast visualization of these direction blobs can be achieved by intersecting two planes. Therefore, the gray value

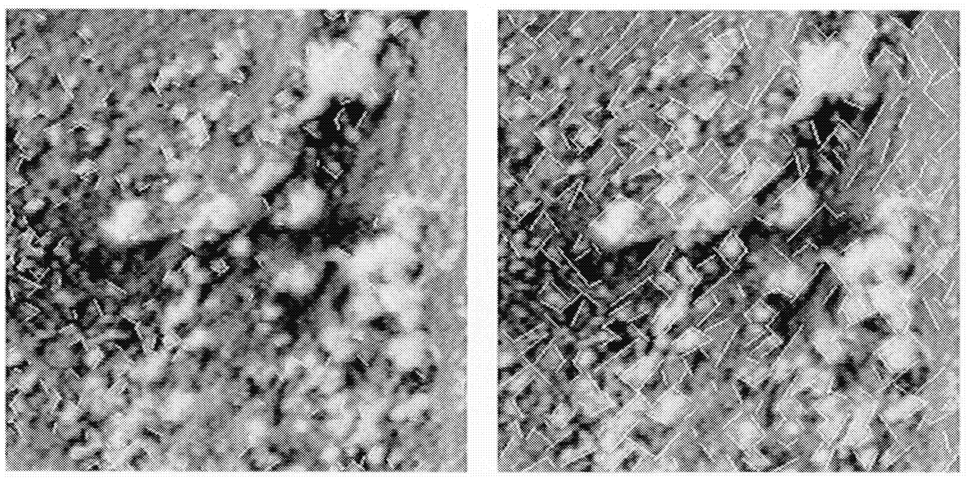

Figure 4. *Line-visualization of direction blobs according to the attribute "size". The image clip on the left-hand side shows all direction blobs of size 21-45 pixels, the image clip on the right-hand side is overlaid by the line-visualization of all direction blobs larger than 45 pixels. The variation of the attribute "size" provides a decomposition of the background from finer to coarser structures.*

level is approximated by the following skew plane[19]:

$$\begin{pmatrix} x \\ y \\ z \end{pmatrix} = \begin{pmatrix} \bar{x} \\ \bar{y} \\ \bar{m} \end{pmatrix} + q \cdot \begin{pmatrix} 1 \\ 0 \\ \bar{gx} \end{pmatrix} + r \cdot \begin{pmatrix} 0 \\ 1 \\ \bar{gy} \end{pmatrix}$$

where $\bar{x}$ and $\bar{y}$ describe the centroid coordinates and $\bar{m}$ the mean gray value of the direction blob. This plane is intersected by the horizontal plane defined by the mean gray value $\bar{m}$ of the direction blob. Lastly, the intersecting line is projected into the image. The line-visualization of selected regions according to the attribute *"size"* are shown in Fig. 4. From this visualization one can see, that by the variation of the attribute *"size"* of the line-support regions a decomposition of the underlying textural background structure is provided.

3.1. False alarm prediction

Highly related to the false alarms are direction blobs having attributes which may occur also on the vehicle signatures. For this reason the statistical distribution of such direction blobs in the image background is investigated. In this section two easily computable image statistics are combined to a prediction rule for the false alarm rate with respect to the considered KLMDET-algorithm.[15]

As the first statistical image background parameter which is computed for each image, the number n_{db} of direction blobs consisting of more than n_p pixels is used. The number n_p equals to the pixel size of the direction blobs which are provided by the vehicles in the image data set. Additionally, for each direction blob an average gradient magnitude higher than a threshold depending on the gray value variance of the image is required.

The second image background statistical parameter used here is the variance of the average gradient orientation o_{db} of the selected direction blobs. The higher the variability o_{db} of the orientations, the more false alarms will be expected.

For the false alarm prediction the derived image statistics are linked by means of transformations which are well-known in knowledge-based fuzzy-set applications.[20] The image statistics n_{db} and o_{db} were both rescaled and transformed to the interval [0, 1] by fuzzy membership functions T_n and T_o, respectively. The type of fuzzy membership function used here is shown in Fig. 5. Then they are combined to a severity measure $S = min[T_n(n_{db}), T_o(o_{db})] \in [0, 1]$ such that for a difficult background structure a large number of selected direction blobs as well as a high orientation variability has to be present. A high value of the severity measure S indicates a high difficulty of the background, a lower value indicates an easy job for the algorithm. A data flow diagram of the construction process of the false alarm model is given in Fig. 6. The relationship of this severity measure S and the number of false

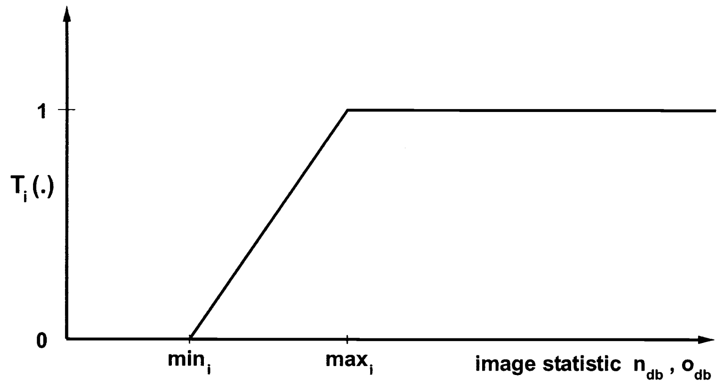

Figure 5. *Fuzzy membership function $T_i(.)$, $i \in \{n, o\}$, which is used to transform the number of direction blobs per image n_{db} and the orientation variance o_{db} to the interval $[0, 1]$. To transform n_{db} to $[0, 1]$, $min_n = 20$ and $max_n = 200$ have been found to be appropriate. For o_{db} $min_o = 300$ and $max_o = 2000$ have been used.*

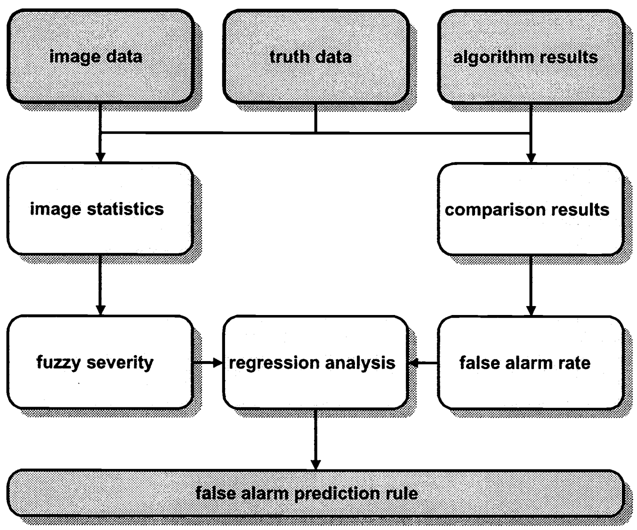

Figure 6. *Data flow diagram of the development of the false alarm prediction rule. Firstly, the image statistics are derived from the image and are combined to a fuzzy severity measure S. The false alarm rate of the considered algorithm on the test data set is computed by comparing the truth data to the algorithm results. Finally, a regression function is used to model the relationship between the false alarm rate and the severity measure S.*

alarms N_F of the algorithm KLMDET for the 51 infrared vehicle images is shown in Fig. 7. Also, the first order regression $N_F(S) = -1.4 + 49.5 \cdot S$ and the second order regression $N_F(S) = 2.4 + 17.2 \cdot S + 49.9 \cdot S^2$ are displayed. Both regression functions may be used as a false alarm prediction model. A comparison of the first and second order regression function shows that the second order false alarm model yields a reduction of the residual mean square error from 25 to 24. This indicates a robust behaviour of the model.

4. RESULTS

To illustrate the power of the prediction models, the 51 infrared images on which the models have been estimated have been perturbed with JPEG data compression, white noise addition and contrast reduction. For the JPEG compression a compression factor of 10 has been used. In Fig. 8 and Fig. 9 this data set is denoted by *jp10*. For the noise-perturbation white noise with standard deviation $\sigma \in \{3, 6, 9\}$ has been added (*wn3, wn6, wn9*). The contrast

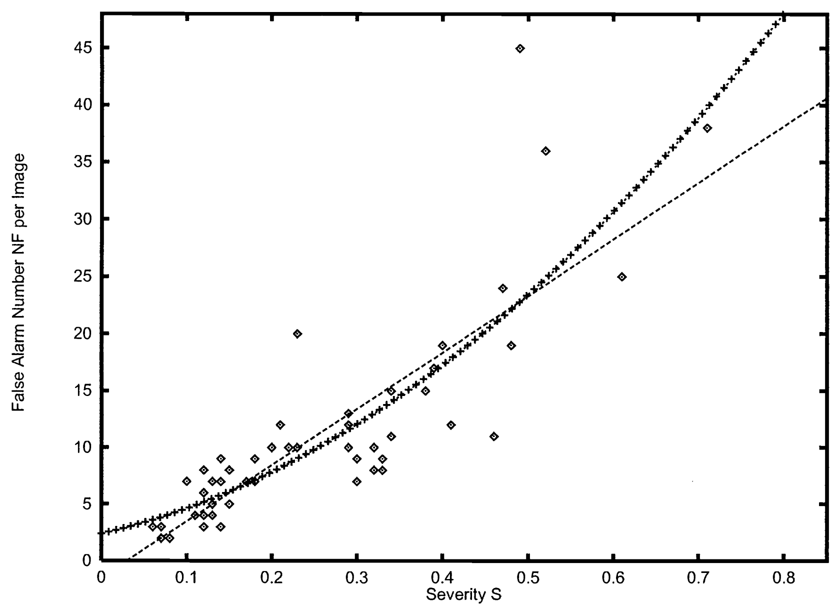

Figure 7. *Relationship between the severity measure S and the number of false alarms $N_F(S)$ for the infrared vehicle data set. Also the first and second order regression functions are displayed. These functions are used as false alarm prediction models.*

reduction has been introduced computing the mean gray value of the image and reducing the distance of each gray value to the mean value to 90, 80, ..., 50 per cent of its original distance. These data sets where denoted by *c90, ..., c50.*

Then the covariates and the direction blobs have been computed as described above. The detection rate has been estimated using the logistic regression model and the false alarm rate has been estimated using the first order regression. Finally, the algorithm KLMDET has been applied to the perturbed data sets and the achieved rates have been compared to the predicted ones. This comparison is illustrated in Fig. 8 and Fig. 9. These figures show that in the considered cases the detection model was able to predict the detection rate with an error of less than 10 % depending on the perturbation. Higher accuracy is given for the JPEG data compression and the contrast reduction, lower accuracy up to an error of 16 % is achieved for the white noise addition. For the false alarm prediction high accuracy is given for every considered perturbation.

5. CONCLUSION

In this contribution an algorithm-dependent performance model has been developed. The model consists of two parts.

The detection model considers the influence of vehicle signature characteristics on their probability of detection using logistic regression. Once such a model is constructed, the algorithm's detection performance can be estimated due to the vehicle characteristic. The accuracy of the detection model varies depending on the perturbation. This shows that some sort of noise are not well-intercepted by the covariates. Therefore, a replacement of covariates or the inclusion of additional ones might be useful.

The second part of the model concentrates on false alarms caused by background clutter. A prediction of the number of false alarms is computed using image background statistics which are combined to a fuzzy degree of severity.

This framework can be used in a wide area of computer vision applications to predict and to model the algorithm performance. In general, in the case of modeling various algorithms or working with different imagery, different covariates or an improvement of the background clutter description might be required.

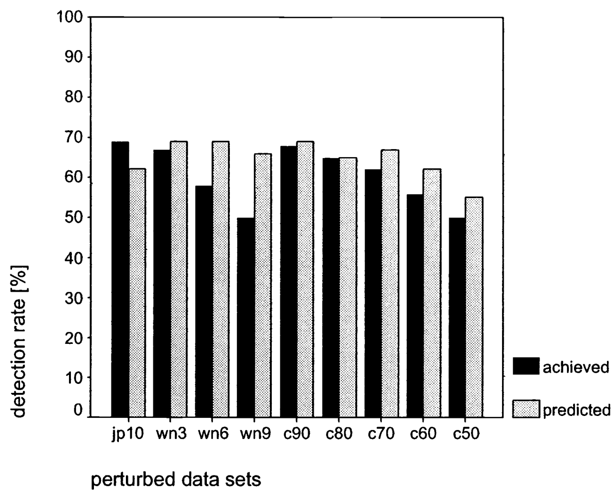

Figure 8. *Predicted and actually achieved detection rates in percent for the perturbed data sets. The JPEG compressed data set is denoted by jp10, the data sets with white noise added are denoted by wn3, wn6, and wn9, where e.g. wn3 indicates white noise with a standard deviation of $\sigma = 3$. The contrast reduced data sets are denoted by c90, ...,c50, where e.g. c90 indicates a reduction of the contrast to 90 per cent.*

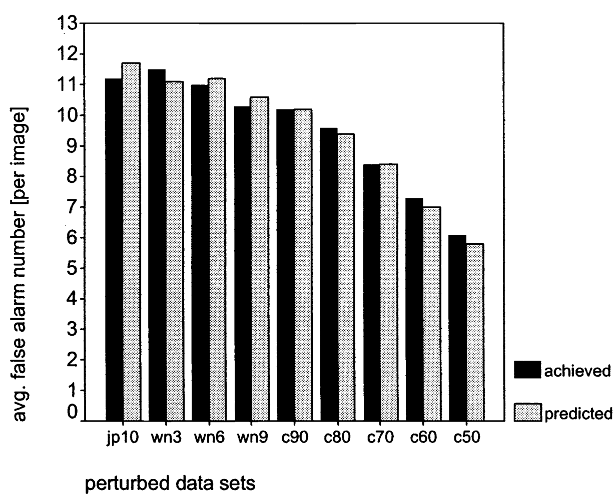

Figure 9. *Predicted and actually achieved false alarm rates for the perturbed data sets. The JPEG compressed data set is denoted by jp10, the data sets with white noise added are denoted by wn3, wn6, and wn9, where e.g. wn3 indicates white noise with a standard deviation of $\sigma = 3$. The contrast reduced data sets are denoted by c90, ...,c50, where e.g. c90 indicates a reduction of the contrast to 90 per cent.*

The covariates computed from the vehicle's signatures and the severity of the background can be used as quality measures for the images with respect to a given algorithm. These measures indicate whether or not the image is a difficult or an easy job for the algorithm.

Further research will include additional covariates and incorporate additional background information to enlarge the scope of this method. In addition, a further study of the effects of data compression on image processing algorithms will be adressed.

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