Image Processing for Driver Assistance

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Abstract. Systems for automated image analysis are useful for a variety of tasks and their importance is still growing due to technological advances and an increase of social acceptance. Especially in the field of driver assistance systems the progress in science has reached a level of high performance. Fully or partly autonomously guided vehicles, particularly for road-based traffic, pose high demands on the development of reliable algorithms due to the conditions imposed by natural environments. At the *Institut für Neuroinformatik* methods for analyzing driving relevant scenes by computer vision are developed in cooperation with several partners from the automobile industry. We introduce a system which extracts the important information from an image taken by a CCD camera installed at the rear view mirror in a car. The approach consists of a sequential and a parallel sensor and information processing. Three main tasks namely the initial segmentation (object detection), the object tracking and the object classification are realized by integration in the sequential branch and by fusion in the parallel branch. The main gain of this approach is given by the integrative coupling of different algorithms providing partly redundant information.

1 Introduction

Some systems presented in ref. [4, 23, 3] show the principal feasibility of driver assistance systems based on computer vision. Although exclusively vision based systems and algorithms are not yet powerful enough to solve all driving relevant tasks, a large amount of different scenarios can be interpreted sufficiently. Additionally sensors like RADAR and LIDAR extent the contents of sensor information necessary for building a reliable system. The main focus of our system lies in combining various methods for the analysis and interpretation of images and in the fusion of a large spectrum of sensor data to extract most reliable information for the final planning and for predicting of behavior of other vehicles. The great variety of different scenarios as well as the high degree of reliability necessary for the given task require an encompassing and flexible system architecture. The requirements concerning the reliability of the reached solution, the variety of geometric appearances of involved objects and the environmental constraints of both deterministic as well as statistical nature necessitate a multitude of partial solutions based on different representations of the environment. Consequently, complexity and structure of the overall system have to be adaptable to the increasing system complexity in order to allow accommodation of additional modules without degeneration of already accomplished partial solutions. For this reason, even *simple* applications are encumbered by considerations concerning the overall system architecture. Basically, the overall system architecture can be divided into basic, fusion and integration algorithms. Basic methods are those providing specific partial solutions under given constraints. Results and application of the individual algorithms are not independent, resulting in an increase in redundancy making the overall system secure and reliable given a suitable coupling architecture. The necessary methods for fusion and integration ensure a flexible cooperation of the basic building blocks as well as the integrative derivation of results. In a similar vein, a sequential data transmission and system dynamics are necessary in order to build up an overall system and giving solutions to complex tasks.

2 Image Processing for Driver Assistance

The fusion of different sensor information and preprocessing results increases the performance of the system. Basic algorithms for themselves are *specialist* for a specific kind of sensor information. Figure 1 shows the different types of information principles depending on the spatial relationship to the vehicle. With respect to the requirements of various applications optimally adapted algorithms are built. In the area F1 contour based methods are chosen. On the one hand the sparse coding (edges) of the intensity information is sufficient due to the high resolution of the objects in the image and on the other hand it speeds up computation time for real time applications. Here, we mainly use a feature called local orientation coding (LOC) [8]. In the field F2 we use motion detection algorithms to segment overtaking and overtaken vehicles. In contrary to other applications we use a pattern tracking based algorithm which ensures high stability. The long distance field F3 is analyzed by texture based methods. The low spatial resolution makes an edge based processing infeasible. Nevertheless the integrative

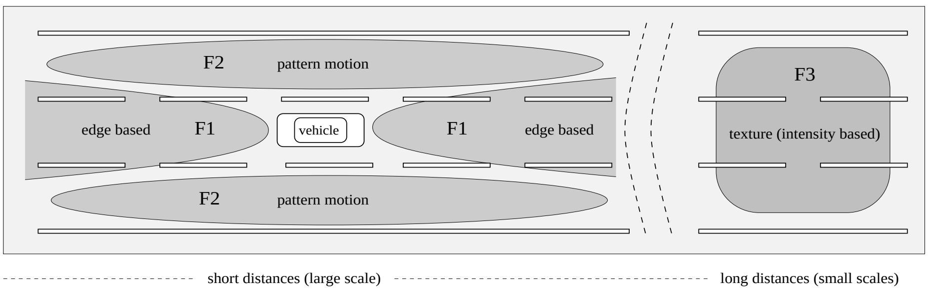

Fig. 1. Separation of the road in fields F1, F2 and F3 in which different algorithms can be applied optimally.

characteristics of texture analysis provides good results by separating the objects from the background by use of their texture. In the area of preprocessing, a multitude of different methods for initial segmentation, object tracking, and object classification has been developed in the context of current research. A few inherent tendencies appear remarkable.

- Previous work often was based on the use of higher features, meaning the generation of a sequence of features beginning at the iconic (image-based) side and continuing to the symbolic side. There are two main reasons to do this. First the historic rooting of image processing in material and surface inspection for quality control has lead to the existence of theoretically well-founded and practically tested algorithms. Second the symbolic features are commonly used for compact coding purposes, so that processed data amounts can be largely reduced for accommodating limited processing resources. The breath-taking evolution of processors has particularly alleviated the impact of this last constraint. In addition, it appears that particularly in the context of limited sensor resolution (i.e., in long distance regions) algorithms can be employed that rely on statistical measures of extensive 'early' (in the chain of processing) feature sets. These algorithms supplement the spectrum of methods explicitly in more traditionally oriented algorithms.
- Often a formulation as an optimization problem can lead to implicitly robust solutions avoiding disadvantages of explicit methods (e.g., the correlation of model with image features, the correspondence problem). In this area the increase in available computational power has contributed to the scientific progress, as well.
- Particularly in natural environments, flexible algorithms possessing a certain learning capability for input data driven adaption are preferably used.

3 The Basic Algorithms

At the *Institut für Neuroinformatik* algorithms providing partial solutions for object detection, tracking and classification have been incorporated in an driver assistance architecture. Namely the following enumeration gives an overview over the applied methods.

- Initial Object Detection: local orientation coding (LOC) [7][8], polygon approximation of contours [5], use of local symmetry [25], pattern motion analysis [25], texture analysis based on local image entropy [18], local variance analysis [24] and local cooccurrence measures [25], shadow analysis [10], color analysis [12], and RADAR mapping [24].
- Object Tracking: Hausdorff distance matching [10], parametric optimization [21] and cross entropy [19].
- Object Classification: local orientation coding [25], Hausdorff distance [25], cooccurrence analysis [9], and parametric optimization [21].

All algorithms can be parted in methods working on differential information (e.g. edges) and integral measurements (e.g. texture). For the application types, initial object detection, tracking and classification, a description of the actually used algorithms is given.

3.1 Initial Object Detection

The main motivation of using multiple simple methods is that the development of designing one basic method solving all conceivable scenarios seems to be impossible. Therefore in order to provide reliable results and to ensure a fast and robust processing a coupling of *specialists* is carried out. Some methods are described shortly in this section.

Local Orientation Coding: The 'raw' gray scale (intensity) images are preprocessed by a method we call local orientation coding (LOC). The image features obtained by this preprocessing are bit strings each representing a binary code for the directional gray-level variation in a pixel neighborhood. In a more formal fashion the operator is defined as

$$b'(n,m) = \sum_{i,j} k(i,j) \cdot u(b(n,m) - b(n+i, m+j) - t(i,j)), (i,j) \in \text{ neighborhood}$$

where $b(n,m)$ denotes the (gray scale) input image, $b'(n,m)$ the output representation, $\mathbf{k}$ a coefficient matrix, $\mathbf{t}$ a threshold matrix and $u(z)$ the unit step function. The output representation consists of labels, where each label corresponds to a specific orientation of the neighborhood. An adaption mechanism for the parameters $\mathbf{t}$ of the coding algorithm yields a high level of flexibility with respect to lighting conditions [8].

Shadow Analysis: The detection of shadows is realized by thresholding the intensity image, some morphological processing and a region clustering stabilized over time. As already introduced in [20] the shadow underneath a vehicle can be used as a sign pattern. For the task of the initial object detection the grey level of the road is analyzed in order to extract a threshold τ for the shadows. Furthermore we select those LOC features that expose an horizontal orientation and correspond to a light-to-dark transition (scanning the image upwards) and group them in clusters. These clusters are imposed in further constraints (i.e. from the camera geometry [17]) and finally build the initial hypotheses (or Regions Of Interest).

Texture Analysis (Entropy, Cooccurrence): Besides operators like intensity derivation (gradients and the LOC) texture analysis as an integrating operator has been used successfully in image processing. The term *texture* is not explicitly defined. Globally texture is a description of image pixels or texture elements (groups of pixels) belonging to a specific texture class due to their spatial arrangement to other elements. Texture depends inherently on scaling. The spatial and intensity relationship between these elements define the kind of texture. Strong variation of intensity in a small area lead to fine textures and

low variations produce coarse textures. Furthermore textures can be parted into properties weak and strong. Weak textures are described mostly by statistical methods. In strong textures the spatial interaction of elements are somewhat regular. Their recognition is usually accompanied by an exact definition of texture primitives (grammars). Actually two different methods for analyzing are commonly used: statistical and syntactic. In our applications we mainly work with statistical texture description. Every kind of texture is represented by a multidimensional feature vector in order to evaluate a statistical pattern recognition for every texture class based on suitable decision rules.
The *local image entropy (LIE)* has been developed at our institute [18]. In this method an estimation of the information contents of a pixel and its neighborhood is given. A saliency map is calculated so that a separation of objects and background can be evaluated. A detection of road-users and the free driving space can be easily done.
One of the fundamental tools in texture analysis, the cooccurrence matrices, were suggested by ref. [13]. In here, the probability of the cooccurrences of pixel pairs under predefined geometrical and intensity constraints are measured. These constraints are determined by the intensity ratio and the spatial relationship (angle and distance) of two image points. A definition of the cooccurrence matrix follows. In an image window $\mathbf{I}$ of size $M \times N$ and a maximum number of different gray values Q the cooccurrence matrix $\mathbf{P}$ is calculated under parameters angle α in a given distance d as follows

$$P_{d,\alpha}(i,j) = \frac{\text{number of pairs}_{((x,y),(x',y'))},\ \text{verifying}\ {}_{(d,\alpha)}\ \text{and}\ {}_{I(x,y)=i}\ \text{and}\ {}_{I(x',y')=j}}{\text{number of all pairs in image window}_{((x,y),(x',y'))}}$$

A calculation of texture features is performed in most of the applications under four directions ($\alpha = 0, 45, 90,$ and 135) and different distances $d = 1, 2, \ldots$. A rotation-invariance can be obtained by accumulation of the matrices of the four directions. The amount of scaling variance can be reduced by calculating the matrices over different distances. Julesz showed that the human perception of texture is based on cooccurrence statistics. Haralick, Shunmugan, and Dinstein suggested in [13] 14 different statistical features which can be obtained from the cooccurrence matrices. In our field of research cooccurrence matrices are mainly applied to the initial segmentation. The matrices are calculated in overlapping windows. Features like energy, entropy, contrast, correlation and the highest cooccurrence of [13] are combined for the segmentation process.

3.2 Object Tracking

Algorithms for object tracking are the most important if a stabilization over time or a prediction of e.g. trajectories are demanded. Some methods for object tracking are introduced in this section. As it can be seen in figure 1 the tracking algorithms find their applications depending on the spatial resolution of the images. In the near distance field the Hausdorff distance or order statistics are used as a measurement based on contour codes (LOC). Here we proceed to present the more stable Hausdorff distance tracker that has been tested successfully on a large set of different image sequences (figure 2). For further details of the approach using order statistics see ref. [26]. Supplementary in the long distance field the texture based cross entropy provides optimally results.

Hausdorff Distance: The geometric comparison of shapes is a fundamental tool for model-based object recognition. Most of the methods used in object recognition systems refer to a similarity measure between the model features and the image features [22]. The Hausdorff distance measures the divergence of a set of features with respect to a reference set of features [16]. These sets mostly describe object contours in our application. The comparison of similar object contours yields small distance values, whereby objects with different contours yield larger distances. The directed Hausdorff distance h of one point set A against a point set B is the maximum of the minimum distances of each point of set A to the points of set B. The final Hausdorff distance H is simply the maximum of the two directed distances.

$$h(A,B) = \max_{p \in A} \min_{q \in B} \|p - q\|, \;\; H(A,B) = \max(h(A,B), h(B,A))$$

The partial Hausdorff distance performs a ranking of these minimum distances and considers a fraction of them instead of the maximum. Unlike the classical correlation methods the Hausdorff distance uses Min-Max operations instead of multiplications, so it is more efficient in time. The partial Hausdorff distance is robust against partially occluded objects and outliers that may arise at the contours due to noise or insufficient feature extraction.

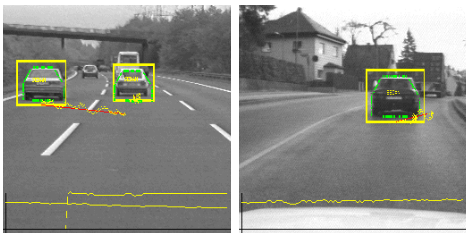

Fig. 2. Objectdetection, objectclassification and objecttracking on german Autobahnen and german Landstraßen

The partial Hausdorff distance can examine object hypotheses in a complex scene. This method was tested successfully with highway-traffic scenes. It was able to recognize vehicles on highways and track them over time. Two degrees of freedom were considered in our schema: translation and scaling of models.

Fig. 3. Tracking of pedestrians based on the cross entropy based on intensity distributions and LOC features

Texture based Object Tracking - Cross Entropy: One of the simple description of textures is obtained by intensity histograms (first order statistics). Especially non-rigid objects like pedestrians and two-wheeled vehicles which consist of a further rotational degree of freedom compared to other road-users can be tracked using the cross entropy. As described in [19] a matching process can be performed by comparison of two probability distributions. In our application a model distribution at time step $(t-1)$ is compared to several hypotheses at time t. Figure 3 show tracking of pedestrians using intensity and edge probability distributions. As an extension to the proposed method we use instead of statistics given by a histogram correlated statistics given by the cooccurrence matrices. The quality of the estimate of position and scale increases but the calculation time increases as well.

3.3 Neural Classifiers for Vehicles

For the task of classification different methods are used. Feature based and model based solutions have been developed. The LOC-classifier is computational fast method used for a fast estimate of given ROI. It is aimed at separating possible objects from the background. It is independent from the resolution of the objects due to a normalization in size. Additionally two classifiers with higher computational costs perform a reliable classification. The Hausdorff distance classifier processes objects in the near field with high spatial resolution enhancing the ROI image coordinates.

LOC-Classifier: With the given local orientation coding [8], described in section 3.1), a classification of vehicles is realized. The classifier has to cope with partial occlusions, varying illumination conditions, tilt of an object, differently resolved structures depending on the distance of the object under consideration, noise and perturbations induced by the recording and processing equipment, different viewpoints and different kind of cars with different shapes and colors. Additionally, the classifier should be able to generalize from relative few training examples to the necessary features characterizing a car. Therefore, a neural network has been chosen for solving the classification task. It is a feed-forward neural network with one hidden layer trained by the error back-propagation algorithm [14]. These networks are known to be universal approximators for any continuous valued function [15]. Furthermore, it is shown that these structures can, with some small modifications, approximate a-posteriori probabilities in the sense of a Bayesian classifier [6].
The inputs for the classifier are certain subsets of the histograms. The output is the class of the region. The complete system has been implemented and extensively tested on the Mercedes Benz VITA II test vehicle [2]. Different classes of vehicles have been trained. For a further evaluation of the system see ref. [1].

Hausdorff Distance Classifier: Furthermore, the geometric property of the Hausdorff distance leads to the idea of classifying various vehicles into separate classes according to the imposed dissimilarity measure. Because of the need of defining a reference contour for each class we deal here with a model based approach. The design of accurate models (prototypes) is of great importance for our task. At a first step, the Hausdorff distance is used for the classification of cars and trucks. Due to the fact that rear views of cars differ significantly from rear views of trucks, one can expect that the design of generic models for each class can accomplish the separation of the objects of both classes. The classification works according to the following scheme: Each region is compared with two models, i.e. a car model and a truck model. The features of the region and the models have been extracted using the Local Orientation Coding. For more robust results the horizontal features are separated from the verticals, for both the region and the models.

Fig. 4. Hausdorff distance classifier: each region is compared with two models

The Hausdorff distance is computed for each model over all the possible translations inside the region and a certain range of scales. The fractions of the features of the forward and the backward match that verify a given distance threshold constitute the criteria for its classification for each model. These values are learned by a multi-layer perceptron (MLP) network using the back-propagation algorithm.

4 The Concept of Fusion

Data fusion is one of the main goals to be achieved if a large amount of stability and reliability is necessary like in this application of driver assistance systems. On one hand a gain in robustness is reached by creating by creating high redundancy so that poor or missing results of one data stream do not affect the overall result decisively [9]. On the other hand the varying types of objects and background constellations demand a large spectrum of data to be processed to solve the given task. Three different types of neural coupling mechanisms are introduced [11]. The high flexibility, the facility of expansion and the adaptive retraining processes have led to the choice of neural networks.

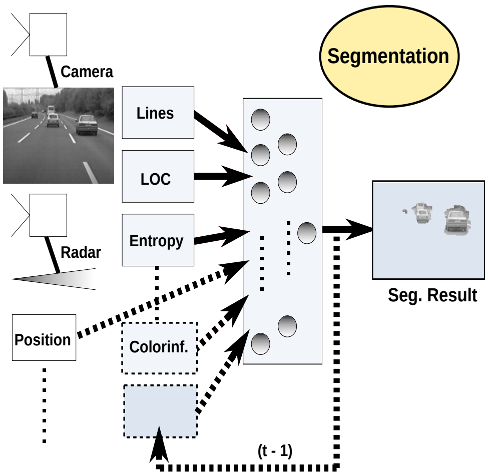

Fig. 5. Coupling model

The aim of fusion in computer vision is to get an improvement of special solutions and single methods with a coupling net (parallel branch). Especially the modular coupling of single processing steps generates redundancy necessary for object recognition.

Within this, greater flexibility and robustness of the image processing modules and high adaptation of the modules regarding to the problems should be achieved. In figure 5 a principle of a fusion process for segmentation is shown [11]. Computer vision modules, generating lines (polygon approximation of the contour) [5], local orientation coding [8], and local image entropy are coupled in a neural network to solve the initial object detection. A feedback over time is realized, additional sensor information could be easily integrated at this level.

5 The Concept of Integration

The overall system is shown is figure 6. The concept of integration (sequential branch) of single steps to a reliable working system is mainly based on feedback of results. As a sensor input the intensity image and radar signals are used. The results of basic preprocessing algorithms are fed into a neural fusion architecture, the initial object detection, that provides hypotheses of possible location of vehicles.

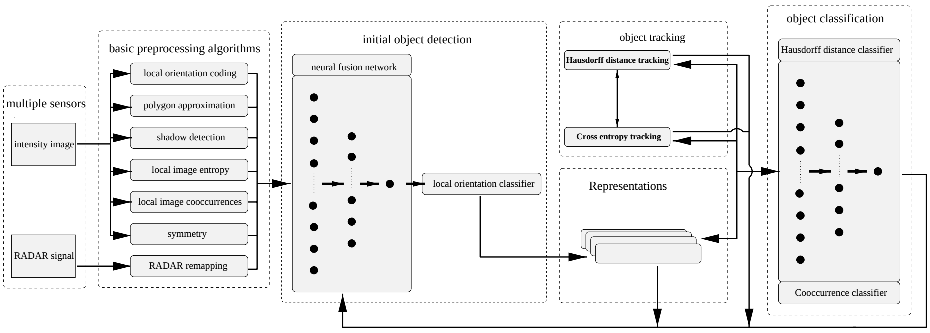

Fig. 6. Overall system

The very fast calculating LOC-classifier reduces the set of hypothesis. An internal stabilization over time ensures further robustness. In order to confirm the hypothesis an object tracking is performed where the object size and type decides whether the Hausdorff tracking or the cross entropy tracking have to be used. The results scale, position, and confidence are fed into the main stream and to the modular classifier. A neural network determines depending on the results of the object size, the Hausdorff and cooccurrence classifier what type of vehicle has been tracked.

Concerning the calculation rates the object tracking has to be performed for every time step. The initial object detection can work on a slower time rate. Finally the classification provides results on larger time steps due to the fact that a tracked object with high confidence values will not change its class. So the object tracking is the most important task next to the detection process. To ensure a stable tracking over time a Kalman filter is implemented.

The main recoupling stream gathers all the results of the single tasks and is increasing over time. The type of information is changing from an iconic (preprocessing) to a symbolic (classification) description. A global data representation is built. Here the integration of the different processing steps is solved. Task depending pixel oriented maps of attention are implemented. In figure 7 an example of a representation for object tracking of vehicles in front is shown.

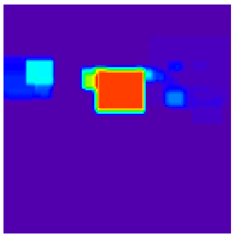

Fig. 7. Representation for object tracking

6 Results and Discussion

We presented an overall system integrating the results and experiences of a long period of research in computer vision. Due to the increase of computational power and the development of reliable algorithms a fusion and integration of basic methods each solving specific problems can be performed to realize an overall stable system. The stability and robustness is largely increased. Because the overall computational time is still quite long by using actual standard hardware a spin off was realized. So if a real time operation system is the goal the whole processing has to be restricted to some algorithms due to limited computational power and time. In this application the initial object detection is restricted to a shadow analysis including a LOC-classification. The objects are tracked by the Hausdorff tracker and classified by the Hausdorff classifier in order to use just one preprocessed feature map. On a standard DEC Alpha (500 MHz) the system uses 10 ms for the initial segmentation including a time stabilization, then the LOC-classification needs 2 ms for every ROI, the tracking is performed in about 2 ms per object (we restrict the number of objects to five so that 10 ms for tracking is realistic) and finally the classification takes about 8-12 ms per object. As mentioned before the classification has not to be calculated for every frame. The organization of the global data representation needs 1 ms per frame. This system is quite capable to obey the real time requirements but the processing cannot cope with all different scenarios and we have restricted this application to extra-urban roads and motorways. Nevertheless if the performance of the hardware components will increase the presented overall system is able to cope with most of the scenarios even in more complex situations.

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