Efficient Level of Service Classification for Traffic Monitoring in the Compressed Video Domain

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***Abstract*—This paper presents a new method for estimating the level of service (LOS) on motorways in the compressed video domain. The method performs statistical computations on motion vectors of MPEG4 encoded video streams within a predefined region of interest to determine a set of four motion features describing the speed and density of the traffic stream. These features are fed into a Gaussian radial basis function network to classify the corresponding LOS. To improve the classification results, vectors of moving objects are clustered and outliers are eliminated. The proposed method is designed to be executed on a server system, where a large number of camera live streams can be analyzed in parallel in real-time. Evaluations with a comprehensive set of real-world training and test data from an Austrian motorway have shown an average accuracy of 86.7% on the test data set for classifying all four LOS levels. With a mean execution time of 48 μs per frame on a common server, hundreds of video streams can be analyzed in real-time.**

***Keywords*-real-time traffic information, level of service estimation, compressed domain video analysis, feature extraction**

I. Introduction

Traffic state - also known as level of service (LOS) - detection has been a well investigated research area in computer vision for several years. Numerous methods and techniques for estimating the vehicles speed, the traffic density, and the level of service on the roads exist, both in the uncompressed and in the compressed video domain. Speed, density, and LOS detection in the uncompressed domain typically rely on background modeling, vehicle detection, or feature-based tracking. The applied methods in this area exploit various information available in and between successive raw frames (like edges, textures, and color distributions) [1], [2]. A disadvantage of these uncompressed domain approaches is that they are computationally expensive and hence real-time performance in large camera networks is sometimes difficult to achieve.

In the compressed video domain there is much less information to exploit for determining the speed, density, and LOS. Compressed domain methods typically utilize statistical features about motion vectors of macro blocks and DCT coefficients of blocks to determine the speed and density of a traffic stream. In the MPEG video encoding domain, various approaches exist which reach LOS classification accuracies up to 92% [3], depending on the number of levels being classified and the illumination conditions of the camera (see section II for details).

However, the existing approaches do not reflect the typically used LOS levels on the high- and motorways today - at least not according to known LOS definitions like in [4] and [5]. Moreover, some evaluations in these approaches use hand-annotated training and test data. It is sometimes difficult to manually distinguish especially between two intermediate LOS levels, if more than two levels are used. Reference speed and density data from highly accurate sensors (e.g., inductive loops or triple-tech sensors) are seldom used, although often available on motorways and highly useful. And finally, the presented approaches mainly do not come up with performance figures which enable an estimation of how many camera live streams can be analyzed in parallel on a common server host. This is of great importance for our work since we aim at being able to analyze hundreds of camera live streams from the Austrian motorways in parallel.

This contribution describes two definitions of LOS, takes one of them as reference, and proposes a model for estimating the prevailing LOS in the compressed MPEG4 video domain within a defined region of interest (ROI). The estimations are based on a set of four statistical features of selected motion vectors in the ROI, observed within an observation period of one minute. The feature set includes:

F_1: average region area covered (*ARAC*)
F_2: average region object count (*AROC*)
F_3: average region vector length (*ARVL*)
F_4: average region object vector length (*AROVL*)

Features F_1 and F_2 estimate the density of the traffic stream, features F_3 and F_4 both the density and the speed. All calculations are based on a previous motion vector clustering step to detect objects within the ROI. The computed features as well as ground truth LOS data obtained from triple-tech reference sensors are finally fed into a Gaussian radial basis function network (GRBFN) to train and classify the LOS. Evaluations on a 10 hours training and 1 hour test set covering numerous examples of all four LOS levels have shown an average classification accuracy of 78.2% on the training set using cross-validation and 86.7% on the test set, for all four LOS levels.

The remainder of this work is organized as follows. Section II discusses related work in the area of vision-based vehicle speed and density estimation in the compressed and uncompressed video domains. Section III presents our LOS classification method for the compressed MPEG4 domain including details about our feature set. In section IV, experimental results on a comprehensive real-world training and test set are presented. Finally, section V concludes this paper and presents potential future work.

II. Related Work

In principle, level of service (LOS) classification based on computer vision involves two types of features: features that relate to the vehicles speed and features that relate to the traffic density. For the uncompressed domain, the detection of the traffic state has been extensively studied over the past decades using background modeling [6], [7], vehicle detection [8], [9], [10], or feature-based tracking [11], [12], [1] algorithms. In [2], a new LOS classification method for the uncompressed domain is presented. The method uses a Gaussian radial basis function network to classify the traffic state from optical flow-based motion features and edge-based density features. The proposed method is designed to run in real-time on smart cameras and achieves an average classification accuracy of 86.2% for all LOS levels.

A comprehensive study about compressed-domain features used for content analysis and indexing is provided in [13]. Several publications deal with speed estimation in the compressed domain. In [14], a method for estimating the mean vehicle speed from MPEG4 motion vectors using a calibrated camera is described. Motion segmentation is applied to cluster the motion vectors and track the moving vehicles. By estimating the speed from the length of the motion vectors, the method achieves an accuracy of 85% to 92%. A similar approach is shown in [15]. Road markers are used for auto calibration of a static surveillance camera. The mean speed is estimated from the length of motion vectors for a segmented road region or region of interest. In [3], Porikli et al. present an unsupervised congestion estimation approach for the compressed domain. The method utilizes a Gaussian Mixture Hidden Markov Model to classify the traffic condition from motion vectors and DCT features.

Table I
Abnormal traffic classification of DATEX II.

Level	Velocity	
	(% of free-flow level)	(km/h @ 130 km/h ref.)
stationary	[0,10)	[0,13)
queuing	[10,25)	[13,32.5)
slow	[25,75)	[32.5,97.5)
heavy	[75,90)	[97.5,117)

Experimental results indicate an accuracy of around 91% for four different traffic states.

In this paper we present a new method for video-based LOS detection in the compressed domain. It uses a similar classification method as [2], however it does not use features based on KLT optical flow. Instead it utilizes only motion vectors of compressed MPEG4 streams to calculate both speed and traffic density features. In order to perform real-world, real-time tests, the proposed method is implemented for MPEG4 encoded video elementary streams in simple profile in accordance with the surveillance cameras of ASFINAG - our national operator of motorways and expressways.

III. LOS classification method

A. LOS definition and motion vectors domain

Level of service (LOS) is a qualitative measure to describe the operational conditions of a traffic stream. In theory, two types of LOS definitions exist: those which take into account only the speed of the vehicles (further referred as *LOS-1*) , and those which consider the vehicles speed as well as their density (further referred as *LOS-2*). *DATEX II*[4], the upcoming European standard for exchanging traffic related information between suppliers and consumers, is a representant of definition type LOS-1. DATEX II defines the LOS with reference to the free-flow level, i.e. the currently allowed maximum speed at a certain road location. Based on this reference, it defines the four abnormal traffic levels *stationary*, *queuing*, *slow*, and *heavy* as shown in Table I.

In this table, the first column values define the relative ranges of speed levels (in percent) with respect to the free-flow speed. The second column values show the respective speed range for a free-flow reference speed of 130 km/h, with is the maximum allowed speed on motorways in Austria. The table also shows that the level *free-flow* is not included, since DATEX II is designed to only signal abnormal traffic conditions. Nevertheless, it is questionable, whether it is justified to consider the level *free-flow* as normal traffic stream condition, since in heavy congested areas *free-flow* may be the non-regular and hence “abnormal” service level.

Computing the LOS based on LOS-1 definitions like in DATEX II has the additional disadvantage that the density is not considered at all. However, the density may have an important impact on the change of the LOS from one time instance to another, since the more dense the traffic becomes

Table II
LOS CLASSIFICATION FOR A SINGLE LANE ACCORDING TO [5].

Level	1 Lane	
	Velocity (km/h)	Density (vehicles/km)
1 (free flow)	[80,∞)	[0,20]
2 (heavy)	[80,∞)	(20,50]
3 (queuing)	[30,80)	[0,50]
4 (stationary)	[0,30)	(50,∞)

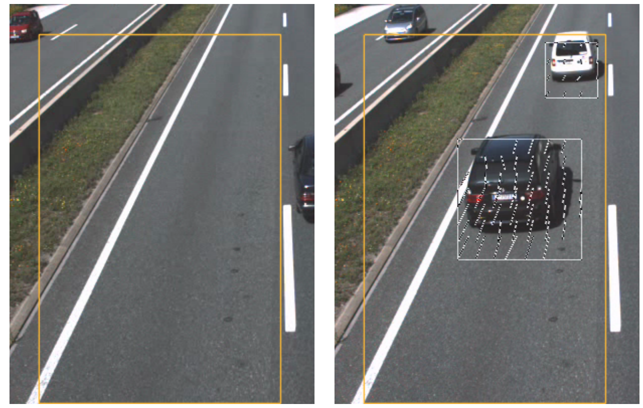
the more likely the LOS will decrease. Motorway operators like ASFINAG in Austria therefore typically use LOS-2 definitions for traffic state estimations on their roads. As proposed in [5], the Austrian motorways operator's service book considers four classes of LOS: *free-flow* (level 1), *heavy* (level 2), *queuing* (level 3), and *stationary traffic* (level 4). These levels are computed in dependence of the average vehicle speed and density for each individual lane. Table II illustrates the conditions for computing the service level on a single lane on Austrian motorways. In this table, the velocities are given in km/h and the densities in vehicles/km.

The investigated LOS classification method in this work is based on the LOS-2 definition and utilizes the LOS classes of Table II. It is designed to operate on a large set of parallel video streams of static, *uncalibrated* surveillance cameras in real-time. The Austrian motorways operator currently maintains more than 4000 surveillance cameras, whose video streams are encoded as MPEG4 video elementary streams (following the MPEG4 Visual standard [16]), in simple profile. Therefore, the proposed method performs efficient motion vector analysis in the compressed MPEG4 domain and is evaluated with live camera streams in real-world, real-time settings. However, our method is not limited to MPEG4. It can be easily adopted to support H.264, which is the upcoming standard also being used in the road surveillance area.

B. Feature extraction and motion segmentation

Our method uses only motion vectors of the MPEG4 encoded camera video stream to calculate the feature set, which is finally fed into a Gaussian radial basis function network (GRBFN) to estimate the level of service. In contrary to most vision-based detectors, this method neither relies on vehicle tracking, nor does it decode the video stream to apply edge or texture-based computations of the traffic density. It just utilizes the available motion vectors in the encoded frames to estimate both the speed and the density of the vehicles. This is accomplished within a rectangular analysis area denoted as *region of interest* (ROI), as illustrated in Figure 1(a). Due to this ROI restriction, the calculated motion features are local features which can be computed very fast.

Figure 1(b) shows a motion vector segmentation result of the applied motion vector clustering algorithms (cp. Algorithm 1 and Algorithm 2). The algorithm starts with the elimination of vector outliers not belonging to the main traffic stream direction. The resulting set of motion vectors is then used to perform a *region growing* approach for clustering all vectors in the 8 neighborhood of each vector. This approach is repeated recursively until no more valid vectors are in the neighborhood or all macroblocks of the ROI have been processed. Finally, detected clusters which bound to each other are merged together. Figure 2 illustrates this region growing-based clustering algorithm. In the feature set described below, the terms *cluster* and *object* are used synonymously.



(a) Region of interest specification. (b) Motion vector clustering.

Figure 1. Feature extraction using MPEG4-based optical flow in an analysis area.

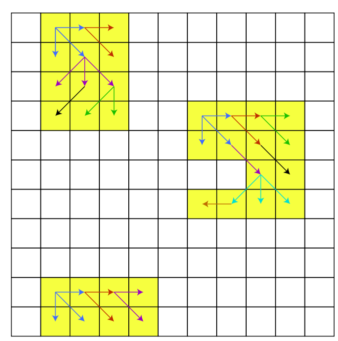


Figure 2. Region growing-based motion vector clustering.

C. Feature set specification

After the application of the region growing algorithm to determine the objects within the ROI, four motion-based features are calculated for a defined observation period of frames N. In our evaluations, N is typically set to 1500 (i.e., an observation period of one minute at a frame rate of 25 fps). In all equations of the subsequent feature specifications, k denotes the k^{th} observation period within the stream. ROI_i denotes the ROI of the i^{th} frame.

1) F_1 - Average region area covered (ARAC): The *ARAC* feature determines the average number of occupied mac-

Algorithm 1 ClusterMotionVectors

Input: MB_{ROI} {set of macro blocks in ROI}
Input: MV_{ROI} {set of macro blocks with motion vector}
Output: $Clusters_M$ {field of macro block cluster indexes}
  $cl_{idx} \leftarrow 0$
  $MVO_{ROI} \leftarrow EliminateOutliers(MV_{ROI})$
  for all $mb \in MB_{ROI}$ **do**
    if $mb \in MVO_{ROI} \wedge Clusters_M[mb_{idx}] =$ undef **then**
      $cl_{idx} \leftarrow cl_{idx} + 1$
      $AddBlock(Clusters_M, cl_{idx}, mb_{idx})$
    end if
  end for
  $Clusters_M \leftarrow MergeClusters(Clusters_M)$

Algorithm 2 AddBlock

Input: $Clusters$ {field of macro block cluster indexes}
Input: cl_{idx} {current cluster index}
Input: mb_{idx} {current macro block index}
Output: $Clusters$ {computed field of mb cluster indexes}
  if $mb_{idx} < |Clusters| \wedge Clusters[mb_{idx}] =$ undef **then**
    if $hasValidDirection(Clusters, mb_{idx}) \wedge hasValidLength(Clusters, mb_{idx})$ **then**
      $Clusters[mb_{idx}] \leftarrow cl_{idx}$
      for all $nmb_{idx} \in getNeighbours8(mb_{idx})$ **do**
        $AddBlock(Clusters, cl_{idx}, nmb_{idx})$ {recursive region growing}
      end for
    end if
  end if

roblocks in the ROI for observation period k. A macroblock is said to be occupied, if there is a motion vector for this block in the respective frame. This feature is used to learn the average density of the traffic stream. Equation 1 specifies the calculation of the ARAC feature.

$$\begin{aligned} ARAC_k &= \frac{1}{N} \cdot \sum_{i=k\cdot N}^{(k+1)\cdot N-1} OCC_i \\ OCC_i &= \frac{\text{\#occupied macroblocks in ROI}_i}{\text{\#macroblocks in ROI}_i} \end{aligned} \quad (1)$$

2) F_2 - Average region object count (AROC): The average number of detected objects in the ROIs of observation period k is determined by the feature *AROC*. This feature is also used to learn the average density of the traffic stream. The calculation of this feature is given in Equation 2.

$$\begin{aligned} AROC_k &= \frac{1}{N} \cdot \sum_{i=k\cdot N}^{(k+1)\cdot N-1} NOR_i \\ NOR_i &= \text{\#objects in ROI}_i \end{aligned} \quad (2)$$

3) F_3 - Average region vector length (ARVL): Feature *ARVL* determines, within a given observation period k, the averaged motion vector length of detected objects in the ROI over N frames. Equation 3 illustrates the computation of this feature. Here, $\mathcal{V}_{i,j}$ denotes the set of all motion vectors belonging to object j in ROI i, and $\|\vec{m}_{i,j}\|$ the Euclidean norm of a vector in this set. Variable NOR_i is the same as in Equation 2 of feature AROC. In contrary to F_4, discussed in section III-C4, F_3 is not only correlated to the average motion vector length, but also depends on the traffic density. For instance, for a constant average motion vector length, a decreasing traffic density (i.e., less motion vectors) causes a decrease of F_3. Therefore, the main purpose of feature F_3 is to discriminate situations in a robust way, where the number of motion vectors is low.

$$\begin{aligned} ARVL_k &= \frac{1}{N} \cdot \sum_{i=k\cdot N}^{(k+1)\cdot N-1} RVL_i \\ RVL_i &= \begin{cases} \frac{1}{NOR_i} \cdot \sum_{j=1}^{NOR_i} OVL_{i,j} & \text{if } NOR_i > 0 \\ 0 & \text{else} \end{cases} \\ OVL_{i,j} &= \frac{1}{|\mathcal{V}_{i,j}|} \cdot \sum_{\forall \vec{m}_{i,j} \in \mathcal{V}_{i,j}} \|\vec{m}_{i,j}\| \end{aligned} \quad (3)$$

4) F_4 - Average region object vector length (AROVL): Unlike *ARVL*, *AROVL* depends on the average motion length with respect to the total number of detected objects in period k. Therefore, the feature F_4 is primarily correlated to the average speed of objects. However, especially for a low number of motion vectors the *AROVL* feature is more susceptible to outliers than *ARVL*. Equation 4 illustrates the computation of this feature. Variable RVL_i has the same meaning as in Equation 3.

$$\begin{aligned} AROVL_k &= \begin{cases} \frac{\sum_{i=k\cdot N}^{(k+1)\cdot N-1} RVL_i}{NOP_k} & \text{if } NOP_k > 0 \\ 0 & \text{else} \end{cases} \\ NOP_k &= \sum_{i=k\cdot N}^{(k+1)\cdot N-1} NOR_i \end{aligned} \quad (4)$$

D. Training and classifying the LOS

The computed features *ARAC*, *AROC*, *ARVL*, and *AROVL* for each observation period k are fed into a Gaussian radial basis function network (GRBFN)[17] to classify the average traffic stream service level for this period. For modeling and feeding a GRBFN we use the data mining workbench Weka[18]. Several tests with all provided network models in this workbench have shown that GRBFN achieves the best results for classifying the LOS.

For training the network we use as ground truth LOS data from highly accurate triple-tech sensors which utilize a combination of Doppler radar, ultrasound, and passive

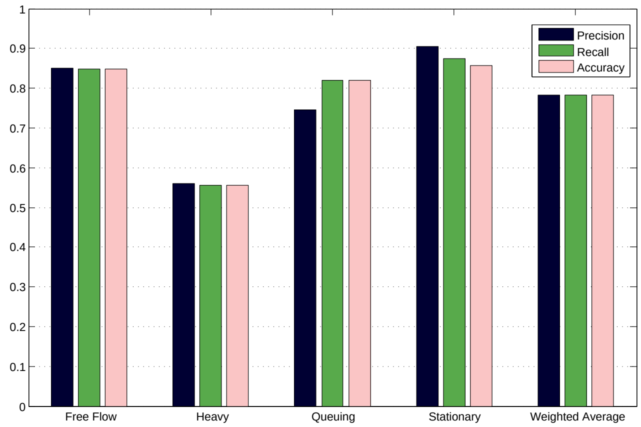


Figure 3. Precision, recall, and accuracy of the GRBFN classifier.

infrared sensor technologies to determine vehicle speed and road area occupancy. Training is accomplished with a camera video stream over several hours, extracting our described feature set for the ROI, and feeding the computed features together with the LOS ground truth of the same road location into the GRBFN.

IV. Experimental results

A. Data set and evaluation setup

The proposed LOS classification method was evaluated with an 11 hours MPEG4 video elementary stream recorded from a surveillance camera on an Austrian motorway. 10 hours of the video were used as training data, 1 hour was used as test data. The video captures the traffic stream during daylight and contains multiple occurrences of all four LOS levels according to Table II. The encoding properties include a CIF resolution (352x288) and frame rate of 25 fps. The reference LOS provided by the triple-tech sensor at the same location as the stream's source camera was obtained from the Austrian motorway authority. The reference vehicle speeds, vehicle densities, and LOS values are averaged values over a one minute observation period. Therefore, we set $N = 1500$ in the feature formulas above during the evaluation.

The evaluation was done off-line on a common Intel Core2 Quad server computer. The motion segmentation, feature computation, and LOS classification took about 48 μs per frame on average on the whole test video. This performance result shows that the implemented method is able to potentially process more than 800 camera streams @ 25fps in parallel on one single server node in real-time. In practice, the number of camera streams is typically limited by the maximum transmission rate of the network link.

B. LOS classification

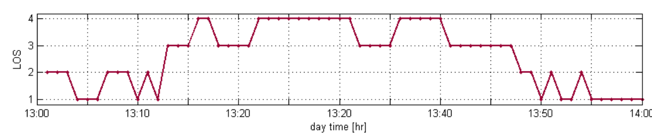
The GRBFN classifier was trained with 10-fold cross-validation with features from a 10 hour training set. Precision, recall, and accuracy for the individual LOS classes

Table III
Distribution of training samples

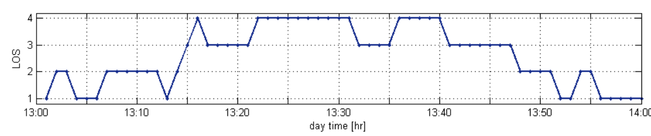
LOS class	number of samples
1 (free flow)	361
2 (heavy)	133
3 (queuing)	50
4 (stationary)	56

are shown in figure 3. It shows an average accuracy of the proposed method of 78.2%. The free-flow and stationary traffic classes show the highest precision and accuracy ($>$ 85%), whereas heavy traffic is harder to discriminate and has a significant lower classification rate. A major reason might be that heavy traffic can only be distinguished from free-flow using density features (cp. II), while the definition of all other LOS levels includes speed and density features.

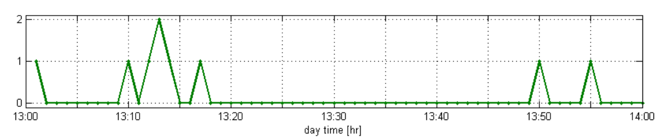
Table III lists the number of training samples used for the different LOS classes. About 60% of the training set are free-flow samples, 22% belong to heavy traffic, 8% are queuing, and about 10% belong to the stationary traffic class.



(a) LOS ground truth



(b) LOS output of the GRBFN classifier



(c) Difference

Figure 4. Classification result for the test set compared to ground truth.

Further, we evaluated our LOS classifier on a one hour test set that contains all 4 LOS classes. Figure 4 shows the classification result of the test set, compared to the ground truth LOS. On the test set, our method achieves an accuracy of 86.7%. It shows that the method performs very well in congestion detection. There is only one incorrectly classified sample (queuing) which differs more than one level from the ground truth (Figure 4(c)).

The proposed method delivers comparable results to related work in the compressed and uncompressed domain. Compared to [2], the classification results on the training set are about 8% lower, but the results on the test set are about 8% higher. With the advantage of being able to theoretically process 800 camera streams at 25 fps in real-time. In comparison to the methods described in [14] and

[15], the classification results on the test set are about 6% lower for free-flow and stationary traffic. However, these methods do not take into account the traffic density and require a time-consuming camera calibration step. Finally, in comparison to [3], the method performance ratio is similar, with the distinction that our method is evaluated using ground truth data from highly accurate sensors on the roads.

V. Conclusions and future work

A novel level of service (LOS) classification method for the compressed MPEG4 video domain was presented. The method utilizes only four statistical features of motion vectors in the encoded streams to estimate both the speed and the density of the traffic stream in the video. Together with ground truth LOS data obtained from triple-tech reference sensors, the obtained features are fed into a Gaussian radial basis function network (GRBFN) to train and estimate the LOS with one minute observation periods. Evaluations on an 10 hours training and 1 hour test data set with a fair occurrence of all LOS levels have shown an average accuracy of 78.2% on the training set using cross-validation and 86.7% on the test set for all four LOS levels. Performance evaluations on a common server computer have shown an average frame processing time of 48 μs.

In future we plan to evaluate our method with non-ideal weather and illumination conditions. A consideration of MPEG4 AVC (also known as H.264) encoded streams is also planned. There the number of macro blocks is higher than in the regular MPEG4, which may improve the classification results considerably.

Acknowledgment

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