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Using a Proactive Sensor-System in the Distributed Environment Model

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Abstract— **In this paper we present the usage of the Distributed Environment Model (DEM) to supply a proactive sensor system. The proactive sensor-system is a novel approach which combines low-resolution range sensors with high-resolution range sensors. Its aim is to achieve a better cost-benefit ratio on getting accurate knowledge about the environment of a car. We describe the main concepts of the DEM and of the proactive sensor system. Furthermore, we show synergistic effects of the DEM environment knowledge base combined with the efficient object classification done by the proactive sensor system. Finally, an evaluation of the DEM and the proactive sensor system in real traffic scenarios is presented.**

I. INTRODUCTION

In the automobile industry, many comfort and safety applications rely on the knowledge about a car's environment. Therefore, environmental sensing plays a fundamental role in this field [19]. This holds in particular for Advanced Driver Assistance Systems (ADASs) which gather environmental information via long range radars and cameras in present-day cars. These sensors produce a huge amount of data which has to be transported by the bus system of the car and processed by electronic control units (ECUs). Managing this data is a non-trivial software engineering task.

In the AUTOSAR consortium [1], leading automotive manufacturers and suppliers are working together to develop and establish an open industry standard for automotive architectures. Common problems like hardware abstraction and real-time communication with the environment are addressed by this standard. Standard software such as operating systems is specified as well. However, fundamental issues like sensor data distribution and the integration of driving situation awareness [11] are not covered in AUTOSAR. To handle these issues in ADASs development and deployment, we propose the Distributed Environment Model (DEM) as an addition to the AUTOSAR specification. DEM meets the requirements of ADASs by a distributed framework, supporting a situation model, situation analysis and thus situation awareness. The DEM provides a uniform driving situation for all ADASs and thus allows the detachment of situation analysis, resulting in reduced ADASs development complexity. Furthermore, the driving situation is used for internal data distribution in DEM, which leads to a more efficient usage of communication resources. In particular, proactive data distribution for the most likely next driving situation, as suggested in this paper, improves the performance of data acquisition from a remote host.

However ADASs development heavily relies on an accurate knowledge about the car's environment to detect other traffic participants and possible threats. One way to gain this knowledge is the use of range sensors such as radars or laser scanners. The latter are often capable of acquiring high-resolution range information, yet it is very time-consuming to obtain a regular set of input data. This would for example require the scene to be scanned line by line. In a dynamic road traffic environment this becomes problematic, as a single 3-D scan of the environment takes as long as 4-12 sec [20]. Our objective is to develop a sensor concept, that provides efficient accquisation of high resolution environment information. In this context, efficiency stands for an optimum cost-benefit-ratio which is the case if an accurate environmental knowledge can be obtained under real-time constraints. We propose the proactive sensor system to fullfill this requirements. The proactive sensor system aims at increasing sensor resource efficiency by allocating control on high-resolution sensors using a saliency driven utility optimisation scheme (see section III).

In this paper we consider the main concepts of DEM and the proactive sensor system and present their synergistic effects. The proactive sensor system profits from information accessible through the DEM. It uses the object trajectories provided by the DEM in order to anticipate the appearance and disappearance of occlusions. As the attempt to observe and classify an occluded object is futile, it decreases sensor resource efficiency. At the same time, the DEM profits from a robust object classification performance because tracking algorithms heavily depend on a good model of object dynamics, governed by vehicle classes.

The remainder of this paper is organized as follows. In section II the DEM architecture is presented. The concept of a proactive sensor system is introduced in section III. Section IV shows evaluation results in real driving scenarios. Summary and conclusion can be found in section V.

II. DISTRIBUTED ENVIRONMENT MODEL (DEM)

The main concepts of the Distributed Environment Model (DEM) have already been presented in [7]. In this section we give a summary on the major parts of the DEM. The focus is the proactive Sensor System described in section III.

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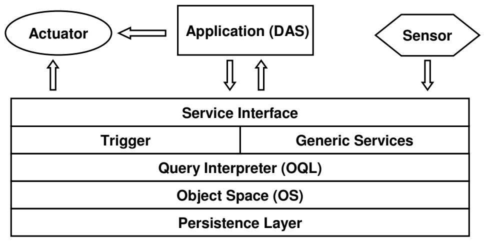


Fig. 1. Layered architecture of DEM

A. DEM Architecture

Real-time middleware is not very much considered in automotive software. More general concepts like RT CORBA and TAO [18] are based on Object Request Broker (ORB) architectures. These architectures are built for remote object calls. They are not suitable for automotive environments because of strict hardware limitations. Data is usually processed on local machines to achieve hard real-time requirements. Data transfer speed can be considered the main requirement for the distributed system. The DEM focuses on real-time situation recognition and subsequent adaptive data distribution.

The DEM is a distributed embedded framework for sensor data fusion and interpretation in an automotive environment. As shown in Fig. 1, it has as a layered architecture. The Service Interface is used by applications (e.g. ADASs) to access the internal functionality. Triggers acquire, store, or modify data in the DEM Object Space. The communication with sensors and the wrapping of sensor data to DEM objects is implemented by Generic Services which provide location independent data access. The Object Space is a system wide container for sensor data. Its objects are indexed to allow efficient query operations via the Query Interpreter layer, based on a subset of the Object Query Language (OQL). The Persistent Layer is used for error logging. It enables subsequent error diagnostics and backtracking.

B. Data representation

The DEM uses a multi-level data representation to establish a bottom-up generic sensor data processing. The term generic means that the DEM abstracts sensor data from the producing sensors, a widely used technique in object oriented programming. For example, radar measurements are handled by a C++ class *distance measurements* with an attribute indicating that its data was collected by a radar sensor. So the DEM concepts are independent from specific sensors although more accurate sensors provide more precise information about the car's environment.

As shown in Fig. 2, Sensor Data is processed through Filter algorithms, sensor Data Fusion [24], data Association [3] and a spin-image based Classification [12]. This kind of information processing results in a detailed representation of the environment around the so-called ego vehicle. On level 5 of the DEM data representation, the gathered information is merged into the Situation Model, representing data in both, logical and a spatial scope. Based on this knowledge representation, further strategic operations like Situation Analysis and Proactive Sensor usage (described in section III) can be performed.

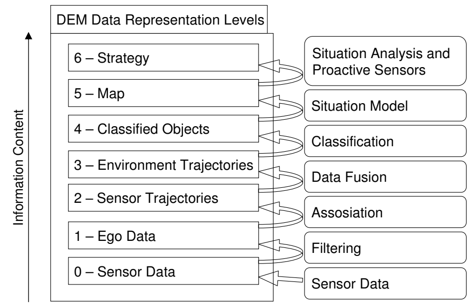


Fig. 2. Data representation levels in DEM [6]

C. Situation representation

To establish situation awareness in automotive applications, we first define the main parts of a common traffic situation. Possible actions and interactions for an artificial copilot are described in [21]. Actions differ from interactions because they can be accomplished without any other traffic participant. In [21], the following nine distinct manoeuvres (MRs) are identified:

MR1 running up	**MR2** follow
MR3 approach	**MR4** pass
MR5 cross	**MR6** lane change
MR7 turning off	**MR8** turning back
MR9 parking	

According to [21], these manoeuvres can be assigned to the manoeuvre groups actions (MG I) and interactions (MG II). The manoeuvres MR2 and MR9 can be assigned to both groups, because they can be interpreted as actions and as interactions. To get distinct sets, MR2 is split into

- **MR21** follow lane as an action and
- **MR22** follow vehicle as an interaction.

The interpretation of MR9 as an interaction can be avoided by considering that a car can be parked while being interacting with other traffic participants. Table I shows the assignment of manoeuvres to manoeuvre groups in the DEM.

Apart from actions and interactions, the behaviour of the driver also depends on the current traffic regulations. The DEM distinguishes traffic regulations in terms of inner city, outer city and of highway specific regulations. So a driving situation in DEM is represented through sets of

- actions,
- interactions, and
- regulations.

Finally, a tuple of sets $\left\langle S_t^a, S_t^i, S_t^r \right\rangle$ represents the current driving situation at a given time t. With S_t^a as the action at time t, S_t^i as the interactions at t and the traffic regulations S_t^a at t. S_t^a contains the actions at t, S_t^i one or more interactions and S_t^r the given traffic regulations.

	MR1	MR21	MR22	MR3	MR4	MR5	MR6	MR7	MR8	MR9
MG I	X	X				X	X	X	X	X
MG II			X	X	X					

TABLE I

MANOEUVRES ASSOCIATED TO MANOEUVRE GROUPS

D. Situation dependent data distribution

The need for driver assistance depends on the current traffic situation and on the environment around the ego vehicle [8]. Therefore, ADASs are only useful in specific driving situations, e.g. Adaptive Cruise Control [5] on highways. This observation is used by the DEM to establish a situation based data distribution. As shown in [7], a set of tuples $b' = \langle d, e, c \rangle$ describes all subscriptions of a data consumer in corresponding driving situations c, with d representing a unique data type and e an event raised on this data type. So every data consumer register his data needs, consisting of which data at which events in which driving situations is needed, at DEM through a set of tuples $b^{'}$. Depending on the current driving situation, only data required in this situation will be distributed. Thus the aggregated data amount transmitted to a data consumer is reduced by situation dependent data distribution.

Based on the DEM situation analysis, it is possible to predict upcoming driving situations [7]. The situation analysis computes a prediction about the most likely next driving situation, which is then used by the DEM to establish a proactive data distribution. The data requirements of data consumers in the particular driving situations are known by (the concept of) situation based data distribution. The DEM produces a proactive distribution table that contains all data needed by applications in upcoming driving situation. Before a driving situation changes, the DEM distributes this data to the host on which the data is needed after the change, taking the timeliness and the consistency of the data into account. Using this concept of data distribution reduces latency after situation changes and saves computing power as well as network usage during the sensitive period of a driving situation change.

III. Proactive Sensor System in DEM

The proactive sensor system presented in [13], [15] aims at increasing sensor resource efficiency by allocating control on high-resolution sensors using a saliency driven utility optimisation scheme.

This concept can be divided into six processing steps or modules. Each step provides input for the subsequent step:

- low-resolution range image acquisition
- saliency detection and extraction of key points
- selection of key points and regions
- scan pattern generation for 3-D laser scanner
- high-resolution data acquisition (intensity, range)
- classification by matching with 2-D/3-D descriptions

The function of this system during runtime is as follows. A 3-D camera acquires a range image in which several key points are determined, based on a saliency measure. One or more of these key points are then selected to be observed more closely, based on utility theory. The controllable high-resolution sensors acquire range and intensity information of the areas surrounding the key points. This information is then matched with 2-D and 3-D descriptions stored in an object class database, in order to classify the objects in the scene using shape models and spin images [10].

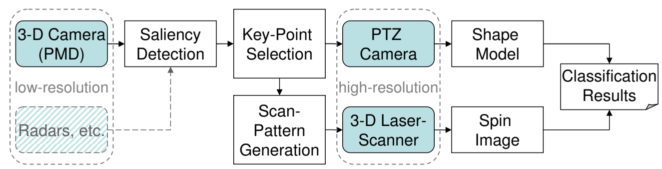


Fig. 3. Block diagram of the proposed sensor system used for object classification. Rounded boxes represent sensor resources or optional sensor resources (hatched) while rectangular boxes represent processing steps.

As shown in Fig. 3, the proposed sensor system receives input from low-resolution sensors such as a 3-D camera [4] which is then used to determine salient regions in the car's environment. Defining the term saliency is difficult because saliency always depends on the actual task and environment. Many publications transfer the definition of saliency from the human visual system, which during its pre-attentive stage considers regions salient that 'pop-out' their surroundings [9]. This definition constitutes a local approach, comparing regions in the image with their surroundings in the same way perceptive fields inside the human eye work. A second definition expects that salient regions are rare, at best unique, in the environment [23]. This definition assumes statistical knowledge about the entire image and is detecting saliency at a global scale.

We propose a combination of these two indicators for salient regions, searching for globally rare combinations of local features. The choice of features is dependent on the used sensors and can not be stated generally. However, for our low-resolution 3-D camera featuring 64×16 pixels resolution, using 2×2 pixels Haar-like feature kernels (cf. [22]) showed to be computationally inexpensive but robust. For dynamic features, a fast translational 3-D motion estimation algorithm has been proposed [14]. Inside salient regions, key points are extracted to serve as oriented points for the generation of spin images.

A key point is then selected to be scanned with a laser scanner or to be observed by a pan-tilt-zoom (PTZ) colour-camera by maximising the utility-to-cost ratio of scanning or observing a certain key point. The utility of scanning a certain key point can be expressed using utility functions describing the key points saliency, current uncertainty, reduction of uncertainty in past scans and observations, distance from other key points, sensor accuracy, and alike.

The selection of a metric to asses the expected utility is a central point in this resource allocation problem [2]. To optimise overall utility, methods such as maximising the Nash product of all key points' utilities [16] are used.

Once a key point is selected to be scanned by a laser scanner, a scan-pattern for that key point is generated, again maximising a cost-benefit function of acquisition cost and expected classification rate. A method to generate efficient scan-patterns is presented in [12].

The spin images calculated from the acquired laser scanner data as well as the shapes observed by a PTZ camera can then be matched against an object model database in order to classify the objects in road traffic scenes.

A. Enhancing the Proactive Sensor-System using DEM

By supplying the proactive sensor systems with object tracks from the DEM, the resource efficiency can be increased further. This is mainly due to prior knowledge about object occlusions.

There are two main cases in which the DEM can help to anticipate occlusion effects. First, occlusion occurrence after which it is futile to try to observe the occluded region, and second, occlusion disappearance where a lot of information can be gained observing the newly visible region.

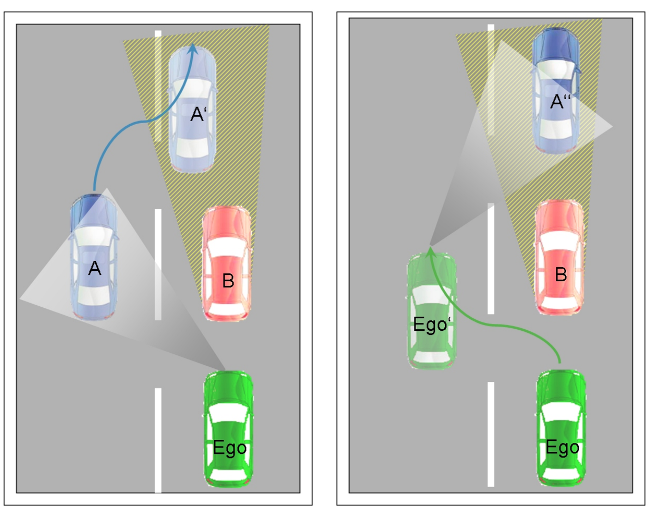


Fig. 4. Appearance and disappearance of object occlusion due to manoeuvres.

Fig. 4 shows a common traffic scenario, illustrating both cases. Our own vehicle – labled *Ego* – has a good view at vehicle *A*, which is currently passing *B*. Our vehicle's sensors can now start to acquire data in order to classify vehicle *A*, but not for long, since *A's* trajectory inside our DEM points towards the area occluded by *B*. It is efficient to stop acquiring information about vehicle *A* before it enters the occluded area (hatched), whereas the trajectory of *A'* should ideally be maintained as it now influences *B's* trajectory.

Now it may turn out that driver *B* is rather unhasty, and we might decide to pass *B* as well. At this point, it is still futile trying to acquire data about *A"*. This changes when we have reached position *Ego'*, from where we have a good view at *A"* again or on whatever there might be at that time.

The advanced knowledge of the appearance and disappearance of object occlusion, provided by the DEM, thus improves sensor resource efficiency by reducing the time spent on scanning or observing occluded objects and by delaying the investigation of an occluded area until it becomes visible.

B. Enhancing DEM using a Proactive Sensor-System

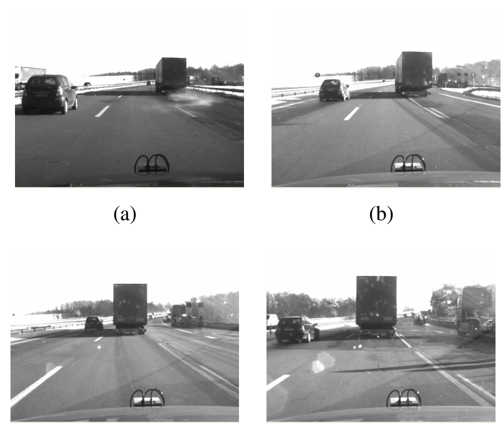
The proposed proactive sensor system is more efficient than conventional sensor systems in the sense that it reduces the amount of raw sensor data. This reduction is desirable for two reasons. First, less data is transmitted from one DEM instance to another. Second the computational cost to process the acquired data is reduced.

The computational efficiency is furthermore increased by constraining object classification algorithms to key points. This leads to a higher chance for successful classified compared to an exhaustive search in the environment.

The DEM also profits from a correctly classified object because in this case it is able to adapt the dynamics model for the respective track according to the object class. Correctly classified traffic participants will lead to better tracking results, since algorithms such as Kalman filters heavily depend on a good model of object dynamics.

IV. Evaluation of the DEM and Proactive Sensors

In this section we present evaluation results of the DEM and of the proactive sensor system in real driving situations on German highways.



(a) (b)

(c) (d)

Fig. 5. Sequence of a DEM evaluation scenario which shows a critical highway scenario with a truck cutting in the ego vehicles lane and other traffic participants preventing a lane change to left.

Fig. 5(a)-5(d) show video frames of a test-drive on a highway. To get repeatable scenarios, all taken sensor data, including radar measurements, video data and laser scanner measurements was recorded through the Automotive Data- and Time-Triggered Framework (ADTF) [17]. Fig. 6 displays

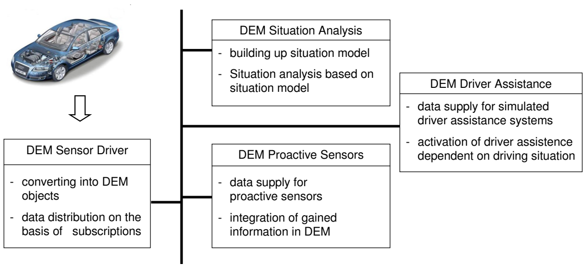


Fig. 6. Setting of the DEM evaluation

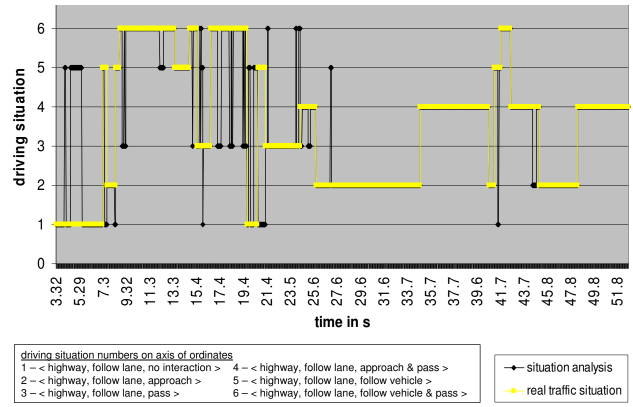


Fig. 7. Driving Situation Recognition

the basic setting of our evaluation. Through the ADTF interface, we were able to access the data of the integrated long-range radars, short-range radars, the laser scanner and the camera. All this data was converted to DEM objects to enable further processing according to the DEM data representation (cf. section II-B). In the *DEM Situation Analysis*, the current driving situation was broken down and upcoming driving situations were predicted. According to the current driving situation, the simulated ADAS components Adaptive Cruise Control and Lane Change Assistant on *DEM Driver Assistance* were activated or deactivated. If an ADAS was inactive in the current driving situation, none of the subscriptions of this ADAS were computed, and so no specific data of these ADAS were distributed. *DEM Proactive Sensors* hosts the proactive sensor system explained in section III.

Based on this setting, several test-drives have been made. The results of the evaluation are shown in the following subsections.

A. Situation dependent data distribution

We showed in [7] that, using driving situation dependent data distribution, the transferred data volume can be decreased significantly. Now, as a second step, an evaluation of the situation dependent data distribution and of the situation analysis in real road traffic scenarios was done.

At initialisation state of the evaluation scenario, the subscriptions of ADASs and the proactive sensor-system were processed by the DEM to build specific distribution tables for every driving situation (cf. section II). During the evaluation scenario, the amount of data to be distributed to data consumers was determined. In addition, a data logging of recognised driving situations and predictions of upcoming driving situations was done.

We compared the data volume using situation dependent data distribution with the data volume not using this concept. Furthermore, the recognised driving situations were compared with the driving situations we identified by hand, and the quality of the given predictions was determined.

Fig. 7 shows the recognized driving situations in the evaluation scenario (black line) and the expected driving situations (yellow line). Total there were 1543 driving situations to recognize which lead to 20 driving situation changes. DEM detects 1377 driving situations that is a recognition rate of 89,24 % (see also table II). As Fig. 7 shows the missed driving situations are usually short-term outlier, which are the results of bad sensor readings or the switching between situations with nearly the same possibility. Both problems can be solved by adding additionally sensor to improve the precision of the situation model. In the second case, also corrections on the situation analysis algorithm are leading towards the common aim. Further research has to be done to evaluate the behavior of the situation analysis in the near 50:50 case.

Table II summarizes the results of the driving situation recognition, shows the prediction rates of upcoming driving situations and the decrease of the transported data volume by using situation dependent data distribution. The transported data volume to data consumers like ADASs and proactive sensor-system could be reduced by 17,36 %. 89,24 % of the driving situations and 90 % of the driving situation changes in our scenario could be recognized. Also the given prediction of the upcoming driving situation were accurate in 30 % of the considered cases.

Recognised driving situations	89,24 % (1377 of 1543)
driving situation changes	90 % (18 of 20)
Predicted driving situation change	30 % (6 of 20)
Reduction of data volume	17,36 %

TABLE II

EVALUATION OF SITUATION DEPENDENT DATA DISTRIBUTION AND SITUATION ANALYSIS

B. Proactive Sensors

The use of a PTZ camera that is able to observe a variable – but preferably small – region in the environment is tested using full video frames of a road traffic scene. The PTZ camera is emulated by clipping regions from the original video frame and inserting them over an originally black background[1]. As time progresses, the inserted intensity images fade to the background colour, thus representing the decreasing relevance of past observations. The cropped frames are also passed to a trained classifier in order to recognise and classify traffic participants inside the focussed region (cf. Fig 8, [15]).

[1]Demonstration footage: http://www.matzka.net/ptzCameraEmulation.mpg

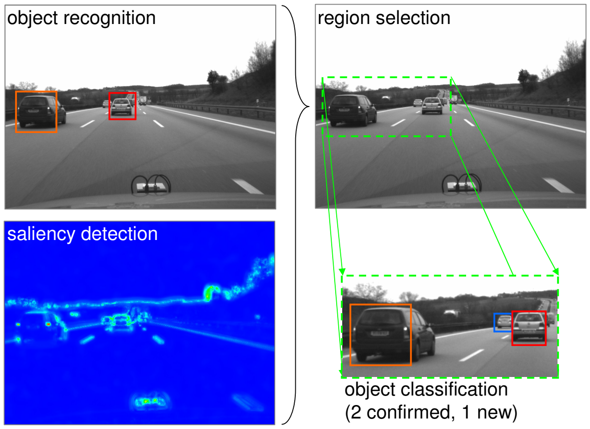


Fig. 8. Regions of interest are selected from a full video frame of a road traffic scene using our utility driven gaze control algorithm. The selective vision of a PTZ camera is emulated by extracting a 256×120 pixel image region from a 640×480 pixel video frame.

It can be seen from both Fig. 8 and the demonstration footage[1] that relevant regions in the scene are determined and traffic participants are correctly classified using our utility driven gaze control algorithm. At the same time, only $\frac{256px \times 120px}{640px \times 480px} = 10\%$ of the total area is observed at any given moment. This results in a highly reduced amount of raw data, while retaining enough information to classify traffic participants using trained classifier cascade [15], [22].

V. Conclusion and Future Work

In section IV we showed that the concepts of situation dependent data distribution and of proactive sensor-system can be implemented in an automotive environment.

The concepts of the DEM and the situation dependent data distribution were presented. They reduce complexity in ADASs development and decrease bus loads in automotive environment. In the case of situation dependent data distribution, the transmitted data volume is reduced significantly. However, this concept highly depends on the quality of situation analysis as a prediction of upcoming driving situation. As shown in section IV we obtain good results in recognition of driving situation but the prediction of upcoming driving situations is still a problem. Therefore, future research on the DEM architecture and functionality will focus on situation analysis and prediction.

The concept of a proactive sensor system has been presented. Its aim is to increase sensor resource efficiency and also to reduce the amount of sensor raw data to be processed. It has been shown that a proactive sensor system is able to reduce video data to 10% and less while retaining the ability to classify traffic participants in the environment. Future work will include the quantitative evaluation of the presented sensor system, with an emphasis on proving the concept's potential to increase sensor resource efficiency and its ability to perform object classification in dynamic road traffic scenes under real-time constraints using current hardware.

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