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Invited Paper

Intelligent Imaging Systems for Automotive Applications

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Abstract

In common with many other application areas, visual signals are becoming an increasingly important information source for many automotive applications. For several years CCD cameras have been used as research tools for a range of automotive applications. Infrared cameras, RADAR and LIDAR are other types of imaging sensors that have also been widely investigated for use in cars. This paper will describe work in this field performed in C^2VIP over the last decade – starting with Night Vision Systems and looking at various other Advanced Driver Assistance Systems. Emerging from this experience, we make the following observations which are crucial for 'intelligent' imaging systems:
1. Careful arrangement of sensor array.
2. Dynamic-Self-Calibration.
3. Networking and processing.
4. Fusion with other imaging sensors, both at the image level and the feature level, provides much more flexibility and reliability in complex situations.

We will discuss how these problems can be addressed and what are the outstanding issues.

1. Introduction

In events where complex environments need to be interpreted, visual signals are always desirable because they are rich in the information that is required to describe the relationships among the objects in the environment and indeed the characteristics of the objects themselves. In the automotive area, applications using visual information can be generally classified into those categories,

- Visual enhancement, such as Night Vision.
- Navigation, e.g. Adaptive cruise control (ACC), collision warning (CW).
- Object detection, a topical example in this category is pedestrian protection.

For many years CCD cameras have been used as research tools for a range of automotive applications, however, infrared cameras, RADAR and LIDAR are other types of imaging sensors that are also popularly investigated for use in cars. This paper will describe work in this field performed in C^2VIP over the last decade – starting with our early work in Night Vision Systems and looking at various other Advanced Driver Assistance Systems.

Emerging from this experience is the following question: how can we improve the use of standard imagers in the automotive industry?

The following points seem to be crucial for 'intelligent' sensing systems:
1. Carefully arranged optical construction to give:
    - Special characteristics required to support automotive applications.
    - Appropriate packaging – essential for industrial uptake.

2. Dynamic-Self-Calibration
This is crucial to obtain coherent analysis from a multiple camera system and should include geometrical and temporal aspects.

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3. Networking and processing.
The environment must provide relatively high bandwidth and flexibility. This implies that, in general, multiple processing paths are available and this – of course – raises real-time issues.

4. Fusion with other imaging sensors, both at the image level and the feature level, provides much more flexibility and reliability in complex situations.

It has been realized that there is only limited space in a car for sensors to be installed and limited computing power that in-car power can support to perform data processing and analysis. Consequently, any chosen sensor must be able to provide essential information for as many functions as possible. We believe that the above issues were the key to turn current individual imaging sensors into integrated intelligent sensors.

2. Night Vision System

Near-Infrared based Night Vision Systems (NVS) have been studied by several automotive manufacturers, tier-one suppliers and academic institutions. Our studies were focused on enhanced NVS and its extension to other applications.

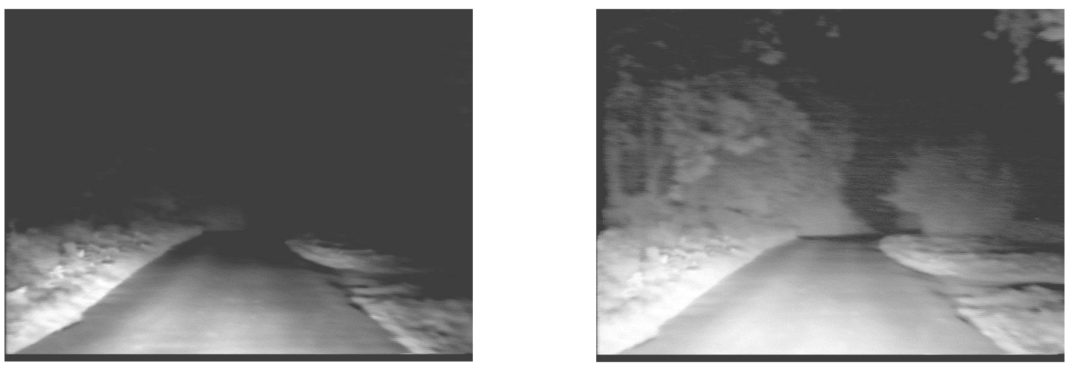


Figure 1 Night Vision System

The above figure shows a typical result of further enhancement of the infrared image obtained from the in-car infrared system. The example demonstrates that affordable optical sensors can have sensitivity and dynamic range which exceed that of the human eye. It was necessary to map the sensor dynamic range to such a brightness range that human being can view it comfortably. In terms of processing techniques, the most difficult one was to enhance the very weak signal (darker part of the image) without introducing uncomfortable visual noise and causing saturation in the bright part of the image.

Figure 2 Day-time view from a near-infrared camera

Another extension of the NVS was to extract road *information* from the real-time image (either nocturnal or diurnal) to use the sensor for many different functions. The image taken by a near-infrared camera was quite different visually from that of normal camera. It was noticeable that there were some good and bad points associated with this type of image in the sense of suitability for further processing. On the plus side, the appearances of road surface and vegetation were greatly simplified, in terms of the textures associated with those areas. On the other hand, the contrast between the objects was reduced. For instance, the two cars immediately in front of the camera were hardly distinguishable – based on their brightness. Obviously, different imaging sensors reveal different physical characteristics of the environment. Practical constraints on cost, space and energy determine that we will almost never have the perfect sensor for the desired application. Some of the information must come from less perfect sensors. This forces us to consider our first topic: a carefully designed sensing system can make the system more capable.

3. Design of optical sensor system

The main concerns regarding the design of an in-vehicle optical system are:

1. The dynamic range of the cameras.
2. The size of the coverage area vs. resolution required to detect objects reliably in the given range.
3. The sensitivity and robustness of the system in terms of object detection.
4. Optimal arrangement for efficient interpretation of the driving environment.

We have chosen stereovision as the basic concept for our camera arrangement mainly due to the fact that a reliable three-dimensional description of the driving environment is required for following purposes:

- Object segmentation.
- Object grouping and classification.
- Wider coverage.
- Better situational analysis.

3.1 Dynamic range tests

Normal CCD cameras were tested against a high dynamic range camera under various lighting conditions. The study revealed critical features associated with different types of objects and the performance of the cameras was judged according to the clarity these features in the captured images. Our research indicates that a dynamic range of 100 dB is needed for our automotive applications.

3.2 Coverage Area and Image Resolution Requirements

An accidentology study was carried out [25]. Combining the evidence from this with our collision model, we are able to define an area of coverage and identify the priorities for each region in the domain according to the degree of urgency.

The 'must-cover' area indicates a region where there is a very high probability of possible collision and no adequate time for either the car driver or pedestrians to react to the threat even if the hazard could be detected. We define this region by considering a typical scenario where a collision between a pedestrian crossing the road and the moving car can occur, see Figure 3.

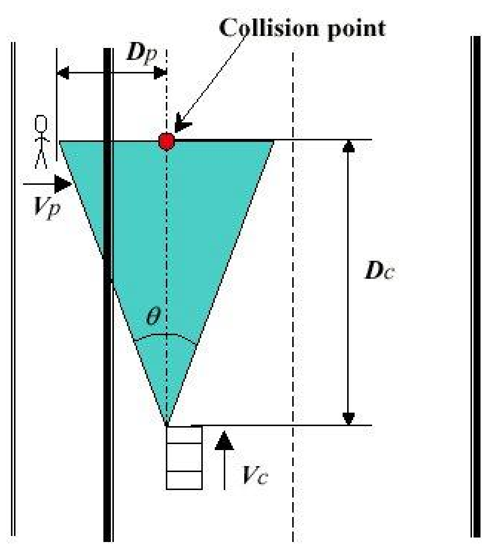


Figure 3. Critical Line for Pedestrian

The angle θ of the 'must-cover' area in front of the car depends on the speed of both car and pedestrian. Based on this angle, we determine the *Critical Line* (CL) of incidents of this type, shown in the angled lines in the figure. Any person who crosses the line will be in danger of colliding with the car. The importance of this line is to define the *Real Critical Area* (RCA) which is intersection between the area defined by the CL line and Zone 2. Zone 2 was defined by the accidentology and project requirements and is basically the area between 10 to 40 metres in front of the car. With this pre-determined area, we are able to design the procedure so as to detect if there are any objects in the RCA and to identify if the object is human being. This allows us to reduce the

amount of classification performed on the image. Since this is the most difficult part of the whole process and takes a long time, it is essential to restrict this stage.
We have: $\theta = 2 \arctan(\frac{Vp}{Vc})$ where *Vc* and *Vp* are the speeds of the car and the pedestrian.

In order for an observed object to be classified our technique (and indeed all the published techniques) requires that the image of the object covers a minimum number of pixels for reliable identification. The requisite spatial resolution (horizontal R_h and vertical R_v), can be calculated from the following formulas;

$$R_h = \frac{2 \cdot N_h \cdot Z_{\max} \cdot tg(\alpha_h / 2)}{W_{\min}} \qquad R_v = \frac{2 \cdot N_v \cdot Z_{\max} \cdot tg(\alpha_v / 2)}{H_{\min}}$$

where W_{min} and H_{min} are the width and height of the smallest object to be detected; Z_{max} is the farthest distance for detection; N_h and N_v are the minimum number of pixels (horizontal and vertical) required for reliable detection of the object.

3.3 The sensitivity and reliability of the system in terms of object detection

In stereovision, the length of the base-line generally determines the sensitivity of the distance measurement. Of course, the optical axes of each camera are not necessarily parallel to each other. This allows us to increase the total viewing angle and achieve coverage of the Real Critical Area.

Given the minimum depth resolution required for our application, we have calculated the minimum size of the base-line.

The above discussing was based on the assumption that an optical sensing system was going to be used. The authors were not in any intension to suggest that optical system is better than the other sensing system. We used the optical system as an example and believed that there are equivalent issues with other sensing system.

4. Dynamic-Self-Calibration

So far not only in automotive applications, the calibration procedure for the sensing system was carried off-line. For some other applications, off-line calibrations are acceptable because the system carriers in those applications are generally riding very smoothly with less intrusion from their environment. For automotive applications, however, it is important to notice that the vehicles are not always in a smooth ride and for safety issues the body of a vehicle was designed to have certain degree of flexibility to absorbing the external intrusion. Consequently, for a multi-sensor in-car system, the physical relationships among these sensors were not as rigid as they were expected.

It was identified from our research experience that it was great challenge to mount imaging devices into a car with very strict constraints from both packaging and optical stability points of view. We have been carrying out studies on the stability of the camera system, for both single and multiple cameras. Focus on the following issues:

- The relationship between vehicle movement and camera movement.
- How the mount mechanism could affect the above relationship.
- Design concerns for increasing the stability of the camera system.
- Developing algorithms to compensate camera motion.

However, it was realised that it almost impossible to control or constraint the movement of the imaging devices. The realistic approach to solving this issue is to carry our run-time dynamic-self-calibration (DSC) process. The main difference and indeed challenges for doing DSC was the following,

- There is no pre-designed calibration target.
- It has to done very quickly.

Theoretically, the calibration of the whole system can be decomposed into calibration of each individual component in the system. Again, a camera system was taken as an example of this issue. The figure 4 shows a co-ordinate system for describing the general movement of a camera in space.

Let *x*, *y* be the image co-ordinates of the projection of the real world point *P*(*X, Y, Z*), C_X, C_Y, C_Z be the original camera position, expressed in some world-centred frame, and $\varnothing_X$, $\varnothing_Y$, $\varnothing_Z$ the original camera orientation. If (*X′ Y′ Z′*) denotes the position of *P* expressed in the camera co-ordinate frame, then

$$[X'Y'Z'1]^T = T\,[X\,Y\,Z\,1]^T \tag{1}$$

where

$$T = \begin{bmatrix} R_{11} & R_{12} & R_{13} & C_x \\ R_{21} & R_{22} & R_{23} & C_y \\ R_{31} & R_{32} & R_{33} & C_y \\ 0 & 0 & 0 & 1 \end{bmatrix} = \begin{bmatrix} R & C \\ 0^T & 1 \end{bmatrix}$$

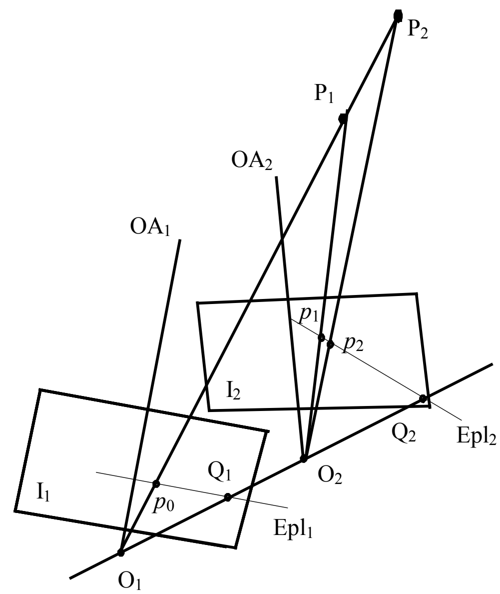


Figure 4 General camera movements

we obtain

$$\begin{bmatrix} dx \\ dy \end{bmatrix} = \left(\begin{bmatrix} yd\phi_x - \left(x + \frac{1}{x}\right) d\phi_y & d\phi_z \\ -d\phi_z & \left(y + \frac{1}{y}\right) d\phi_x - xd\phi_y \end{bmatrix} + \frac{1}{Z} \begin{bmatrix} -dC_z & \frac{1}{y} dC_x \\ \frac{1}{x} dC_y & -dC_z \end{bmatrix} \right) \begin{bmatrix} x \\ y \end{bmatrix} = \left(dR' + \frac{1}{Z} dC' \right) \begin{bmatrix} x \\ y \end{bmatrix} \tag{2}$$

in which the camera rotation is expressed by *dR′* and its translation by *dC′*/*Z*.

[dC_x, dC_y, dC_z, $d\phi_x$, $d\phi_y$, $d\phi_z$] describes the camera motion during an unit time period, the [*dx dy*] is the average velocity of the image motion during that time period. The calibration task became to chose reliable reference points, establish a set equations involving those reference points and solving the equation set for the motion parameters.

It is clear that the above mentioned calculation is very much demanding on the computing power. In the following sections, we will be discussing how we addressed this issue.

5. Networking and processing.

The data processing demands great computing power, so does the communication for collecting information from ever increasing sensor array. The computing environment must provide relatively high bandwidth and flexibility. This implies that, in general, multiple processing paths are available and this – of course raises real time issues.

5.1 Networking

Our approach was to establish a in-car network to deal with this issue. Our study started from the analysis of the requirement of the processing functionalities.

Applications	Function required	Elementary information	Sensors
NightVision	Road Geometry	Road edges	Cameras
LDW (Lane Departure Warning)	Host car trajectory	object detection	Infra-red sensor
WAP utilization	other stationary objects	object classification	Laser device
FCW	other dynamic objects	object tracking	radar
…	Weather	host car position	audio sensors
	...	...	GPS, GIS
			...

Figure 5 Application cascade

It was interesting to notice when the application list was increased,

- The elementary information required was actually very stable in size.
- The required information can actually from different sensors.

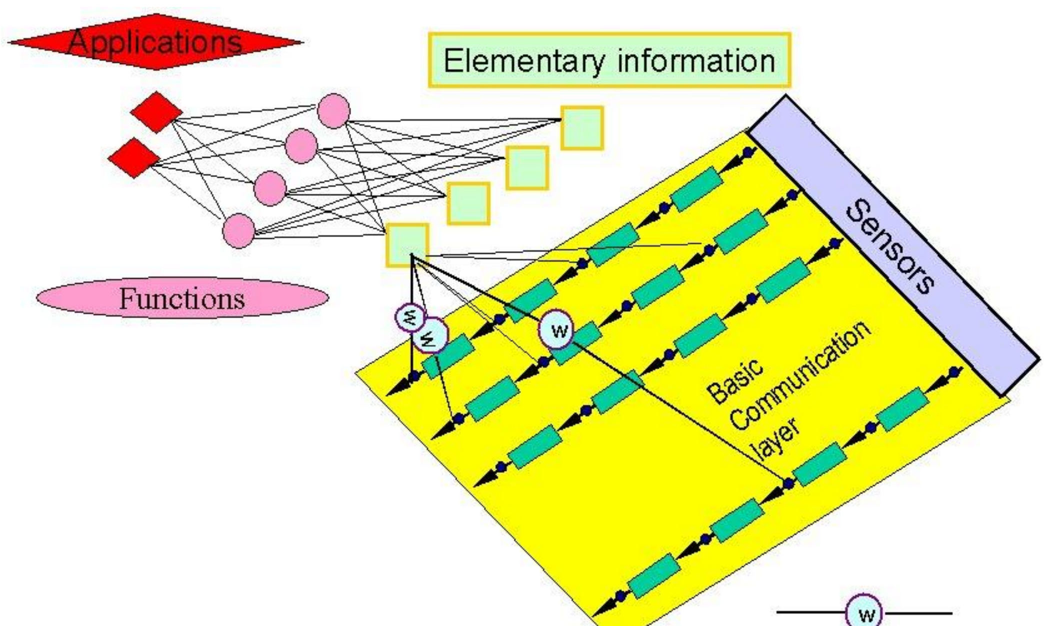


Figure 6. Logical schematic of the network

It follows that it will be great helpful to have network in which applications can obtain information not only from it dedicated sensor but also from other sensor and exchange intermediate results with other applications.

A multiple-layer network was proposed. The logical schematic of the network was shown in the figure 6. in the network, the applications were sitting on the very top layer, whilst the sensor array was on the very base layer. Between the application and sensor array, there were elementary information layer and function layer. The most processing and calculations were to carried out on the basic communication layer and main tasks for the higher layers were to do organisation.

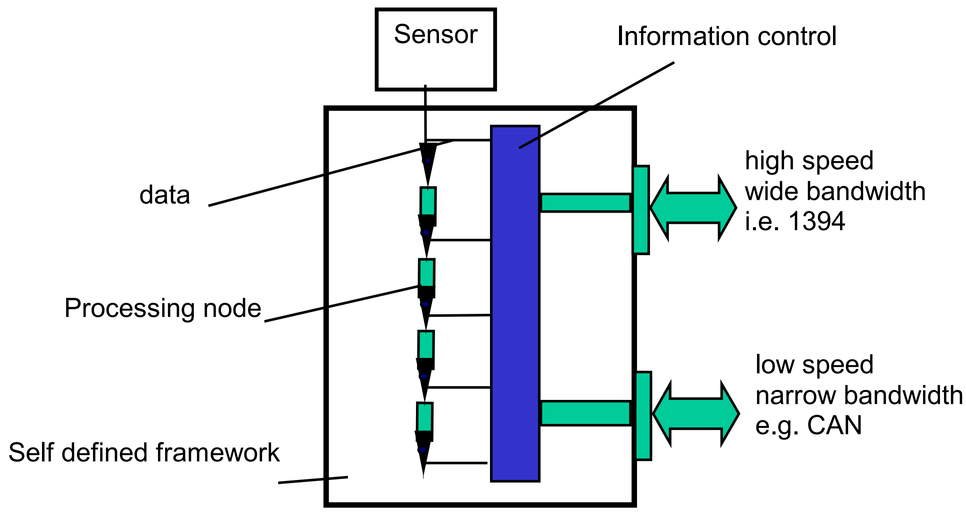


Figure 7. Element of the Network

The physic element of the network was supposed to be a processor and a sensor. The crucial task is to set up a information control for every elements in the network. Within this network, the data was actually floating in a three-dimensional space and utilised much more efficiently.

5.2 Stereovision Algorithm

In general for a stereovision-based system, a significant portion of total processing time is spent on the matching process and this has been one of the major obstacles preventing stereovision systems from being used in real-time automotive applications.

A new feature-indexed, correlation-based stereo-matching approach has been developed to achieve fast and high quality matching. The basic concepts of the technique are:

- Feature points are selected on both images as an index to the candidates of the corresponding points.
- The matching constraint is the intensity profile in the neighbourhood of feature points.
- The calculation of the cross-correlation coefficients only takes place adjacent to the indexed points.

The points with high gradient values, e.g. edge points, are selected as the feature points for our purpose, because they probably indicate the boundaries between objects and have better reliability for cross-correlation calculations.

The stereo-matching procedure is as follows;

Step 1: Select index points on both images according to gradient value.

Step 2: For each index point on the left image, determine the range of candidate corresponding index points on the right image according to the minimum and maximum disparity which can be obtained for given maximum and minimum distance of investigation.

Step 3: Feature-based matching between the index point on the left image and selected index points on the right image to determine corresponding index points.

Step 4: A low aspect ratio rectangular window is then assigned to the index point on the left image and windows of same shape are assigned to the corresponding point and its neighbours on the right image. The normalized cross-correlation coefficients will then be calculated between the pixel array in the window on the left image and those in the windows on the right image. The output at this stage is an array of coefficient values around corresponding index points in the right image.

Step 5: A quadratic fit process is then performed on the coefficient value array obtained in Step 4 to estimate the optimal position where the maximum coefficient value occurs. The position indicates the true location of the correspondence in the right image to the index point on the left image. This position has sub-pixel accuracy and consequently, we will obtain a very precise disparity map for all index points on the left image.

Step 6 Repeat Step1 to Step 5 generating a disparity map which is indexed by the left edge image.

5.3 Three-dimensional Driving Environment Understanding

We were focused on object segmentation and pedestrian recognition. Object segmentation is a major difficulty when we interpret the urban driving environment if only two-dimensional information is available. With three-dimensional information the interpretation on the scene becomes more swift and reliable. The following work is based on the three-dimensionally distributed object points whose positions can be calculated from the disparity map.

5.3.1 Object segmentation

The object segmentation process is divided into two main stages: separate object points that are above the road surface from those on the surface; segment remaining object points into groups each representing a potential object entity.

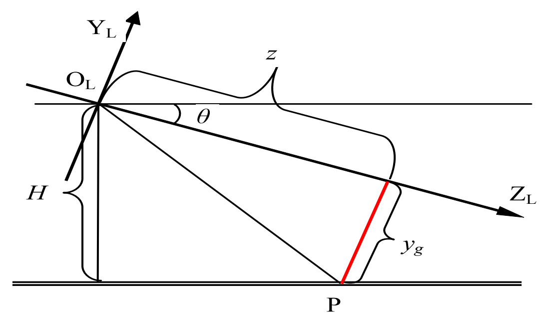


Figure 2 Determination of road surface points

Group Points on Road Surface

We consider all the points that represent road markings and near-surface road furniture, such as kerbs, to be surface points. They are unlikely to be obstacles and relate to road information most of time. We group those surface points together for future use and consequently reduce the complexity of obstacle detection.

We group these points by verifying their distance to the road surface. There are two methods that we can obtain the road surface. The first one is to model the road surface based on camera calibration.

$$y_g = (z \cdot \sin(\theta) - H)/\cos(\theta)$$

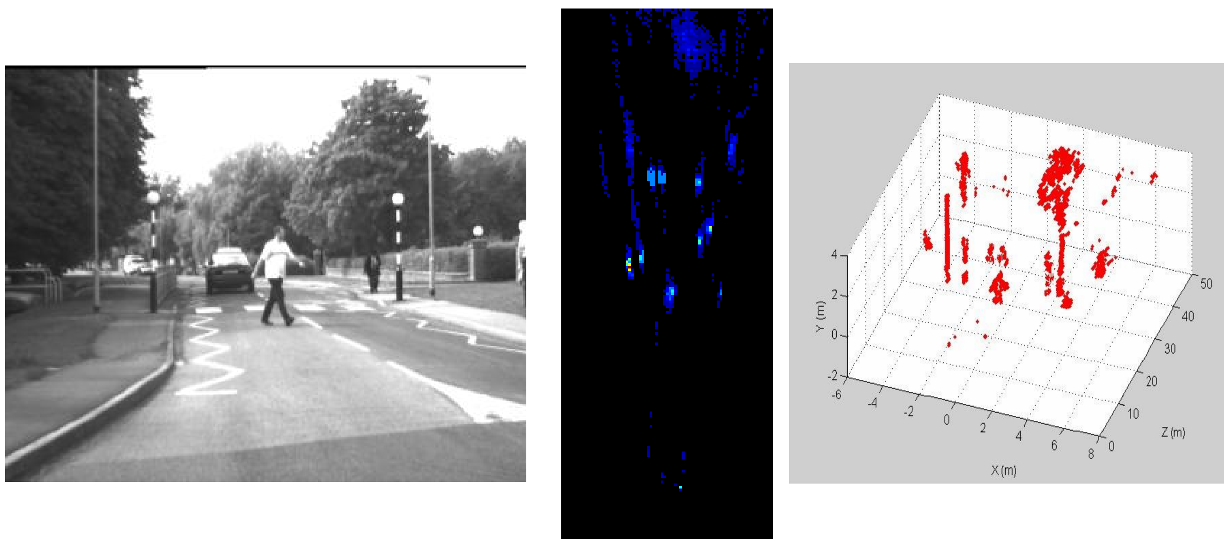
where H is the camera height, θ is the tilt angle towards the road plane.

Alternatively, we can dynamically determine the lower envelop of detected object points. The results are similar but the first method is faster.

Object Grouping

The second stage of grouping is to segment all the object points that are above the road surface into groups each representing one object entity. The segmentation is performed on a depth map.

It was observed that the distribution of points that belong to an object is irregular and discrete, to a certain degree. However, the distribution centre is clearly detectable. Our segmentation procedure first filters the range map using a Gaussian-based kernel to estimate the centre of gravity for every object. The shape of the kernel depends on the object for which we are looking. For example, a size equivalent to 1m by 1m is good to isolate human objects. A boundary condition can then be easily established to encapsulate the object. Figure 3 was a typical complex scenario involving a pedestrian. Note the clarity of the three-dimensional map.



(a) raw image (b) Range map (c) 3D representation of objects

Figure 3. Dynamic tests: typical example of driving environment within a short range.

5.3.2 Hierarchical Object identification

Object identification was carried out in different stages. Firstly, the aspect ratios were used to detect objects that could be human targets. Note that in the object grouping stage, the aspect ratio between the depth and width has already been applied. The aspect ratio between height and width is checked at this stage to complete the first level of identification.

Identification based on aspect ratio alone would pick up all human targets, however, the false positive rate is relatively high. Two model-based techniques were studied giving more precise identification. They were a Fourier descriptor-based model and a point distribution model which can be considered a multi-dimension aspect ratio model.

The quality of the model is critical. The procedure we have used is summarised as follows:

- Based on the aspect ratio of the object, we collect a space of samples which are mainly human targets. The typical defects of those samples could be: non-human targets, incomplete encapsulation, inclusion of incorrect points that do not belong to the same object.

- The tolerance is required to compensate for the imperfections in the training set. Bayesian methods were applied to establish a tolerance on each vector to determine the quality of the samples.
- A neural network was then applied to induce the models.

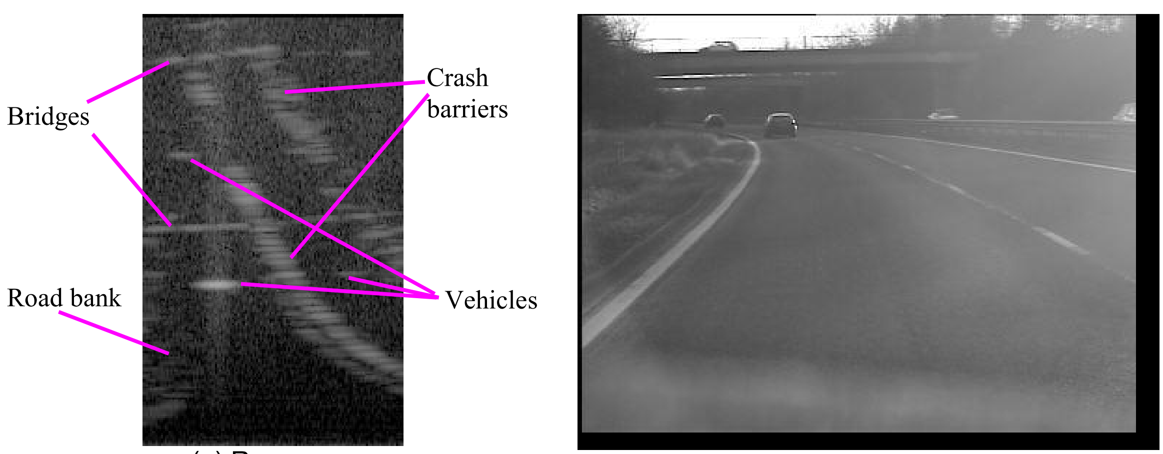
6. Working with other imaging sensors

6.1 Millimetre Radar

The use of millimetre wavelength radar has been increasing for a range of applications in the automotive industry. Radar-based based systems, in general, can be operated over a range of 150 meters ahead in all weather conditions, even when fog or rain is heavy enough to cut the driver's visibility down to 10 meters (Jones, 2001). At present, the most common application is *Adaptive Cruise Control* (ACC), although there is increasing interest in such applications as automatic *Stop and Go*, *Collision Warning* and *Collision Avoidance*. In those applications, radar information is required to determine the positions and speed of the vehicles ahead, as well as the road geometry.

Radar-based systems employ a variety of sensing and processing methods to organise the information about the road ahead. The styles of information representation may be different from one device to another, however, they generally start with producing range maps giving the strength and variation of the reflected electromagnetic wave within the view of the sensor. The image below (Figure 1) shows a typical example of the range map produced with an example of this class of radar. The brightness of the map indicates the strength of the reflected signal.

The interpretation of radar range maps is not intuitive due to the major differences between imaging radar range maps and ordinary optical imaging. The strength of the reflecting signal depends on the material of the observed objects and their surface orientation. The appearance of the road surface is much darker than that of the objects with "right " material and reflecting surface. This is because the road surface is not properly oriented to reflect electromagnetic waves back towards the radar, although tarmac is, in general, a reasonably good reflecting material for millimetre radar.



(a) Range map (b) Camera view

Figure 4 – Road view represented by radar range map and optical camera

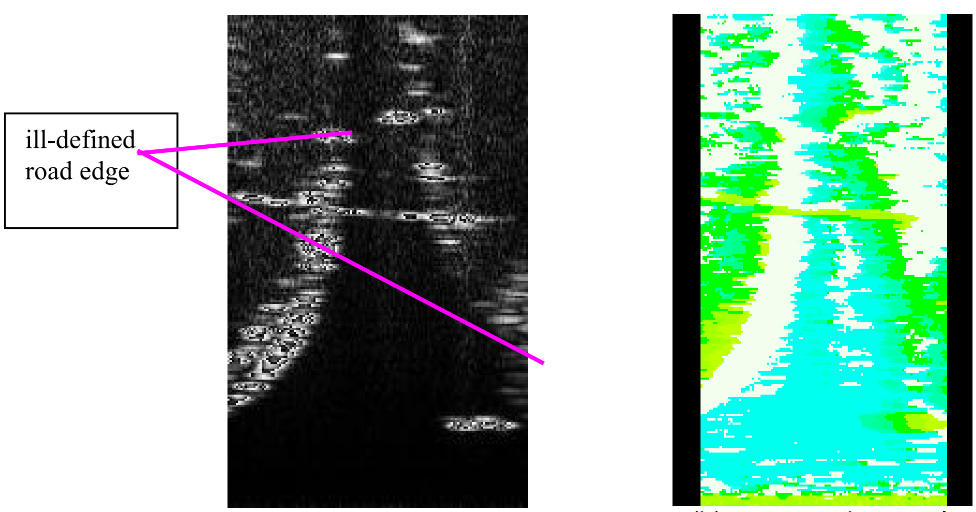
Normally, radar makers would provide radar user (car manufactories) with system which can produce run-time range maps, and more complicated automotive application will be carried based on the analysis of the maps. Our earlier work (see References 4, 5) focussed on determining the road geometry and the position of vehicles from the strong radar returns present in the scene. The clutter, mainly weak back-scatter from those surfaces that their orientation are not favourable of returning radar signal back to device, was simply regarded as noise to be eliminated in the pre-processing steps.

Later, we propose a new concept that explains how clutter in the road scene can be generated and thus how clutter information can be used for geometrical analysis from radar range maps. One of the main purposes of scene analysis in our applications is to detect the road path that was previously determined by the road boundaries represented by high reflective roadside objects, such as crash barriers. However, there are many areas where such objects are not found. To study the textural information implicit in the clutter of the range map will provide a novel means of detecting road regions directly from radar returns.

Also it is well known that the price of radar device prevents radar from being widely used. An alternative way to reduce the product price is to get more functionality from the device. If the surface condition of the road ahead could be obtained, together with the information about the road path and motion of the vehicle ahead, by analyse the information from the same radar device, the robustness of a ACC system will be improved. There is no report so far on how to detect the surface condition of road ahead anyway. Following the concept that we are proposing in this paper, it is possible to get some idea about the surface condition from radar clutter.

Having analysed a mathematical model of coherent imaging radar, we showed how such images can be decomposed to give textural information. The model was then used to show how the surface structure affects the radar returns and verify this with images characterising returns from sections of tarmac-covered road and grass verge. However, we have only produced synthetic range maps from two different types of surfaces. One of the characteristics of road scenes is that there is a wide variety of complex images. Examples of this are the range of bridge structures (many of which can give radically different radar returns) and the differing materials and geometries at the boundaries of roads. We have applied Self-Organising Maps (SOMs) to some road scenes to investigate whether texture offered a mechanism for reliable automatic classification of such features. The issue of robustness is obviously crucial.

By colour coding the map derived by a trained SOM, and replacing areas of the image by the colour of the map into which the SOM projects them, it is possible to visualise how the SOM "sees" the textural information in the image. Below is a processed image formed in this way. The original image is also shown, as is the colour-coded map from the trained SOM. The data used to train the SOM was extracted from six images in a short sequence. As can be seen from the processed image the road forms a distinct group in the blue section of the SOM map. Other structures, such as vehicles, crash barriers/kerbs, and the bridge, form groups distinct from the road in the yellow/green and white areas of the map. These results from a neural net trained on a very small data set indicate that the use of textural information is a promising direction to investigate.



(a)original range map (b)segmentation result

Figure 6 – Range segmentation with SOMs

The above results proved that textural information within the range map can be used to distinguish different object areas. One of the strengths of this approach is that a wide range of features (such as intensity, velocity, geometrical location) can easily be combined to give flexible and robust recognition. The example above shows that the clutter analysis is successful in identifying the road even in the bottom right and upper left regions of the road where there are no strong radar returns from the crash barriers.

6.2 Example of Data Fusion

Near Infrared image | Far Infrared Image | Pyramid based fusion

The appearance of active near infrared image appears very much like that from normal CCD camera but with greater range. The passive far infrared image can cover even greater range, however, on the cost of losing surface markings. Fusion of both images will obviously make a good usage of the information in both. Fusion process is very differ from extracting information independently from individual image and then put them together. Two issues were carefully dealt with, geometrical registration and combined presentation of both images.

7 Conclusions

In this paper we have discussed the main issues which have to be resolved before imaging sensors become ‘intelligent’ and multi-functional. We have not considered changing the sensors themselves but considered how a rational network can be formed and the nature of algorithms which will enable this.

The examples we have provided in the paper show that in order to make an intelligent sensing system, we must:

1. Consider all the required application as a whole rather than individual application.
2. Networking is very necessary to deal with:
    - Multiple sensor arrays.
    - High computational demands.
    - Information fusion.

The given examples demonstrated that intelligent imaging system may be achieved which will support multi-functional automotive applications.

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STANDARD DISCLAIMER

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