AUGMENTING GPS SPEED LIMIT MONITORING WITH ROAD SIDE VISUAL INFORMATION

M.L. Eichner*, T.P. Breckon †

* Cranfield University, UK, marcin.eichner@cranfield.ac.uk
† Cranfield University, UK, toby.breckon@cranfield.ac.uk

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Abstract

Frequently drivers fail to be aware of the current speed limit at any given moment in time. Present commercial GPS navigation systems have functionality to warn drivers about speeding on the basis of the road type information stored in the map. Unfortunately any temporary restrictions (e.g. caused by road works) are not taken into account. The system we propose here combines advantages of GPS and an optic sensor for reliable current speed limit monitoring. Our solution was initially developed as standalone vision system presented in details in [3], although integrating it together with GPS navigation adds new features and allows correct operation in majority of European countries. Our vision system includes the detection and recognition of both numerical limit and national limit (cancellation) signs. The system utilizes RANSAC-based colour-shape detection of speed limit signs and neural network based recognition.

1 Introduction

According to Robinson et al. [8] exceeding the speed limit or going too fast for current road conditions is the main cause of 15% of accidents in the United Kingdom. However this factor becomes even more significant (26%) when only fatal accidents are considered. Often speeding is caused by unawareness of the current speed limit.
The system we propose here aims to inform the driver of the current speed restriction at any given point in time based on the GPS navigation system augmented with automatic detection and recognition of any temporary speed restriction based on visual processing from onboard camera.

2 Related work

Global Positioning Systems (GPS) together with a vision system have been used for traffic sign inventory as in [6] and [9]. However such integration has not been done for speed limit detection at the present time. Standalone visual road sign recognition have been widely developed in recent years. Automatic signs recognition usually consist of two stages: initial detection of candidate signs within the image and recognition (i.e. verification) of the type of sign. For each of these stages various approaches have been proposed:

The initial detection via colour separation in the Hue, Saturation and Variance (HSV) colour space is usually employed as per Maldonado-Bascón et al. and Damavandi et al [2, 6] . By contrast Moutarde et al. [7] propose to perform sign detection without prior colour segmentation – relying solely upon shape characteristics. Several shape-based detection methods have been proposed: various generalizations of classical Hough transform as in [7,10], template-based matching [5] and even a direct Support Vector Machine based approach [6].
Recognition is usually performed by a machine learning based classification algorithm. Commonly this is an Artificial Neural Network (ANN) approach as in [2,7,10] or in some more recent work Support Vector Machines (SVM) [6].

3 Vision system

Our system is able to successfully detect both numerical and national (cancellation) speed limit signs. Both types of sign are detected using a variation of this well established two stage approach. Firstly colour/shape detection is performed. This stage aims to generate hypothesises (sign candidates). By design some false positives may be produced which are then rejected by the secondary neural network based verification stage. This approach increase robustness and ensures that no sign will be missed.

3.1 Numerical Speed Limit Detection

Numerical speed limit signs are characterised by a circular red boundary. In the first step of our algorithm we segment out red parts of limit signs using adaptive thresholding of the red chroma channel extracted from YCrCb colour space (Figure 1. a,b). Next, the connected-component analysis is used together with RANSAC based circle detection to extract circular shaped components in the remaining red feature space (Figure 1. c).
The RANdom Sampling And Consensus (RANSAC) technique was proposed by Fischler et al. [4]. From a given dataset (i.e. contour) a random sub-set is selected. This sub-set is used to create a geometric shape model (i.e. circle) which is then compared against the whole dataset. If the model is satisfied by a

sufficient number of dataset members (with a given tolerance) then the shape described by the model exists. Number of trials is estimated using probabilities:

$$Trials = \frac{\log(P_{all-f})}{\log(1 - P_1(P_d)^{T-1}}$$

where P_{all-f} is the probability of algorithm failing to detect a model, P_1 is the probability of a data point belonging to a valid model and P_d is the probability of a data point belonging to the same model.

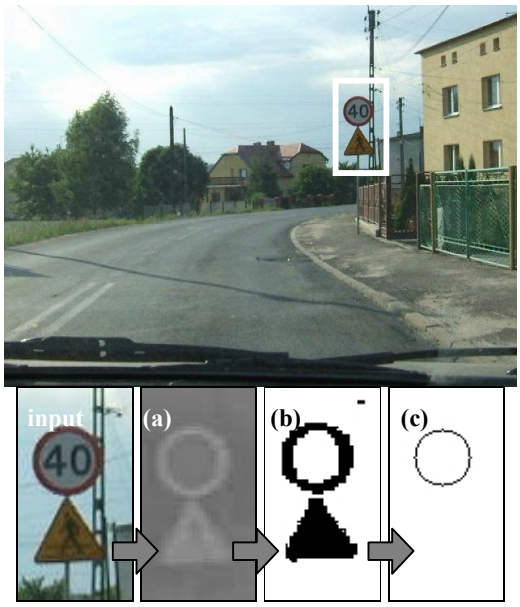

Figure 1: Numerical-limit signs candidates generation algorithm

The presented algorithm detects candidate signs even if the original colour segmentation is not perfect due to noise (occlusion, adverse conditions). In figure 2, a partially occluded detection example is presented, illustrating RANSAC suitability for varying road conditions.

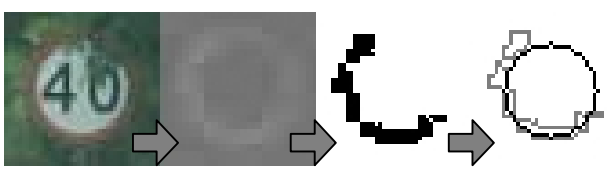

Figure 2: detection of partially occluded numerical-limit sign

In the final step, each circle corresponding to the sign candidate may be slightly shifted and resized so that it covers only the white interior of the sign. This is done using adaptive thresholding and connected component analysis on the greyscale conversion of the input image. Such normalization assures low variation in relative size of the digits present on the sign and helps during recognition stage.

3.2 National Speed Limit Detection

National speed limit (i.e. cancellation) signs are considered as white circles with a left to right diagonal black stripe (Figure 2), additionally grey colour numerical limit may be present.

In [3] we have proposed a novel method for national-speed limit signs detection based on first locating black stripe and then verifying the circular contour around it.

Black stripes are located by finding inclined parallel lines in the image and examining the interior between them. To obtain these lines, PCA is performed on the edge segments, retrieved by applying canny edge detector and morphological operations to the red channel of the RGB input image (Figure 3(a)).

If a black stripe is located we examine its surrounding for a circular contour using RANSAC circle fitting as before Figure 2(c). National speed limit sign candidates are extracted if such a circular contour around black stripe is detected.

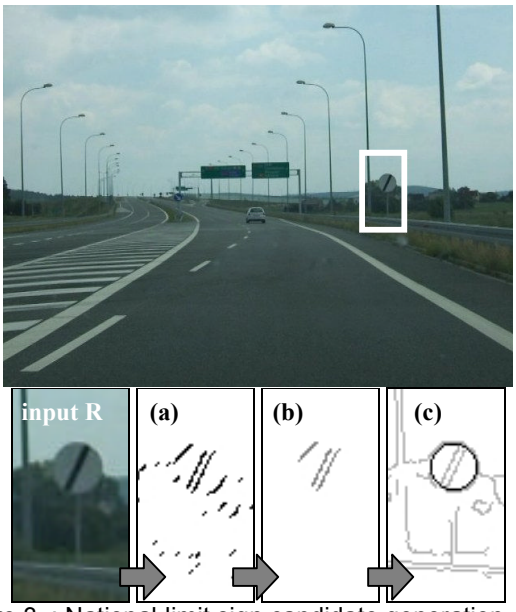

Figure 3. : National-limit sign candidate generation algorithm

3.3 Recognition Stage

In this step any false positives generated by the earlier detection step are rejected.

Every sign candidate is extracted from the input image to greyscale and thresholded using its average pixel value. This approach gives very good separation of the dark digits from bright background - even in low-light conditions. Finally, all signs are scaled to the size of 20x20 pixels. This is required to normalize the spatial distribution of the sign sub-image to a common number of neural network inputs (i.e. 20x20, 400 inputs). Examples of sign candidates pre-processing are presented in Figure 4.

Figure 4: NN input pre-processing (original=greyscale, left; normalized = binary, right)

Neural Network

Encouraged by results obtained by Damavandi et al. in [2], we have decided to use feed-forward multi-layer perceptron neural network as the classifier. Our network consists of 400 neurons (20x20 pixel sample) in the input layer, and 12 neuron outputs corresponding to the following signs types (UK/Poland): 10, 20, 30, 40, 50, 60, 70, 80, 90, 100, national-speed limit and false positive. Each output value is the classification likelihood between 0 and 1 for the corresponding class of sign.

Network was trained with few thousand samples and tested on the independent set of 1050 examples. (Figure 5). Configuration with 30 neurons in hidden layer outperforms the others.

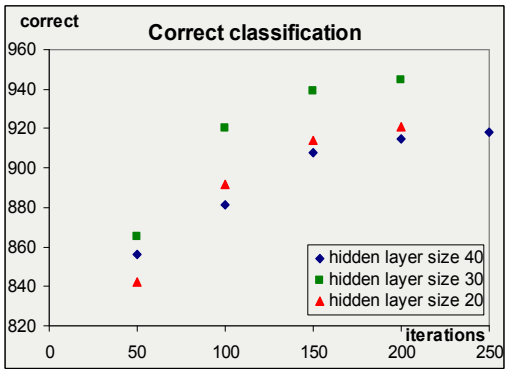

Figure 5. NN training results

A given sample is considered as classified by the network if the difference between the highest and the second highest classification likelihood returned in the output layer is greater than 0.5. Cases when this condition is not true are considered as unclassified. This approach is very reasonable because each sign instance is present in many consecutive frames. To avoid over-fitting a number of iteration during the final training of the classifier was set to 150.

4 GPS Navigation

The navigation system is used as a basic indication of the current speed limit (Figure 5, solid circle), which may be overridden with temporal limit detected by our vision system. When a cancellation sign is encountered, then the displayed limit is set back to the one originating from navigation system. This simple approach allows to take into account all factors effecting maximum allowed speed (i.e. road type, city/country area).

Moreover, some more advanced rules may be developed. Of course these depend on the traffic regulations in the country of use. Unfortunately, even within European Union the road regulations in the area differ widely. In Poland, for example all restriction signs including speed limit are cancelled when next crossroad is encountered. This may be easily overcome by adding to our system new rule for resetting the limit when host car pass through a crossroad, such information can be extracted from the navigation system. In contrast, German law sets a rule that when warning sign is followed by speed limit restriction, this restriction is only valid for the hazard indicated by the warning sign. Unfortunately dealing with overcoming this may be not trivial.

The GPS unit indicates accurately current speed (Figure 5, dashed circle), so warning information or sound may be triggered when the host vehicle exceeds the maximum allowed speed indicated by our combined vision and GPS based system.

Figure 5. Commercial GPS navigation system. Value marked in dashed circle is the vehicle current speed. Solid circle indicates maximum speed allowed at this point on the road according to map.

5 Results

Our system works with 27 fps processing speed (using 1.6GHz single-core Intel CPU). Algorithm testing covered various weather conditions (some results are presented on the Figure 6).

Testing footage contains 101 sign instances, three of them where missed by our algorithm, which gives 97% effectiveness at the detection stage. Our trained classifier made also 3 misclassifications in recognition stage (against the 1155 correct recognitions of these 101 sign instances occurring over multiple frames). This gives misclassification ratio of the system at the recognition stage less than 1% (0.3%). However, this consideration does not take into account instances lost in the uncertainty bound due to lack of separation between classes.

Figure 6. Two real road scenarios are presented in various weather conditions. In both an temporary speed restriction have been encountered.

Scenario 1-1: no temporal restriction – limit according to GPS navigation unit.
Scenario 1-2: encountered temporal speed limit restriction overrides previous limit.
Scenario 1-3: encountered national limit sign cancels temporal speed restriction. limit is set back to the one indicated by GPS navigation unit
Scenario 2 follows similar consideration to scenario 1.

6 Conclusions

We propose here a novel system which offers continuous speed restriction monitoring. It integrates both numerical speed limit signs recognition, robust cancellation sign detection together with GPS navigation for operation in all possible road scenarios (i.e. city, country, highways). It ensures real-time processing speed in all weather condition with good performance. It may be successfully used in most of EU countries, although future work will investigate integration to country specific road regulations. All the measurements and information are gathered by optical sensor and GPS navigation unit so the complete system does not requires any complex integration with the host car.

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