Integrated Speed Limit Detection and Recognition from Real-Time Video

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Abstract— **Here we propose a complete system for robust detection and recognition of the current speed sign restrictions from a moving road vehicle. This approach includes the detection and recognition of both numerical limit and national limit (cancellation) signs with the addition of automatic vehicle turn detection. The system utilizes both RANSAC-based colour-shape detection of speed limit signs and neural network based recognition whilst turn analysis relies on an optic flow based method. As primary detection is based on a robust colour and shape detection methodology this results in a real-time algorithm that is invariant to variable road conditions. The integration of both limit, cancellation and vehicle turn detection within the bounds of real-time system performance represents an advance on prior work within this field.**

I. Introduction

RELIABLE traffic-sign detection is currently one of the most important tasks in automotive vision industry. It represents a significant challenge due to common variations in weather and lighting conditions in conjunction with the obvious on-vehicle constraints.

The system proposed here aims to inform the driver of the current speed restriction at any given point in time based on the automatic detection and recognition of roadside restriction signs. Further integration could allow such a system to be employed as part of an adaptive cruise control system or on-board driver information display. Our system was developed in UK and as such follows assumptions based on the UK traffic regulations - namely that an in place speed restriction is cancelled by cancellation sign (also commonly denoted as national speed limit sign) or by the vehicle turning into another road. In addition some experimental data was recorded in Poland where similar signage is present.

II. Related Work

Automatic road sign recognition can be divided into two stages: initial primary detection of candidate signs within the image and secondary recognition (i.e. verification) of the type of sign present. For each of these stages various prior approaches have been proposed.

A. Primary Detection

As such 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, 3] . By contrast Moutarde et al. [1] propose to perform sign detection without prior colour segmentation – relying solely upon shape characteristics.

In this area several shape-based approaches have been proposed: various generalizations of classical Hough transform as in [1,3], template-based matching [4] and even a direct Support Vector Machine based approach [2].

B. Secondary Recognition

Recognition is usually performed by a machine learning based classification algorithm. Commonly this is an Artificial Neural Network (ANN) approach as in [1,3,5] or in some more recent work Support Vector Machines (SVM) [2]. This step of the algorithm may be also divided based upon the classifier input. Torresen et al. [4] propose to extract just single digits from the sign candidate and use just the left one as input in the classification process. By contrast Moutarde et al. [1] propose to recognize multiple extracted digits separately. Although presumably carried out in the interests of real-time performance and generality, we claim that this improvement may be still insufficient for a realistic driving environment. Figure 1 presents example signs (drawn from both UK and Polish roads) that may be classified incorrectly using either of the aforementioned approaches. In contrast Damavandi et al. [3] propose to use the whole sign as the input and achieve 90% recognition using a neural network based approach.

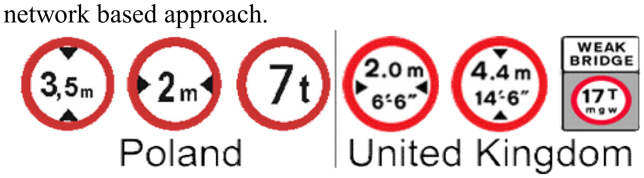

Figure 1. Signs similar to speed restriction signs.

In the system proposed here we couple a similar, whole sign based approach [3], with the robust and efficient shape detection methodology of RANSAC to achieve improved (all weather) performance.

III. Detection and Recognition Algorithm

The outline of our proposed algorithm is initially presented in Figure 2.

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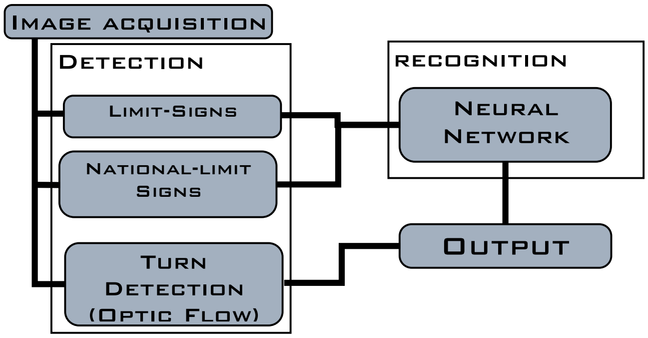

Figure 2. Structure of the algorithm

Overall we propose a two stage process – robust sign detection via colour and shape, then secondary classification of sign type from the trained neural network. Turn detection (discussed separately in Section C) is integrated into the initial detection stage performed on the image to provide a speed limit reset when a significant vehicle turn is detected.

A. Detection Stage

The aim of the detection step is to generate hypothesises – candidate signs for secondary verification. By design this step may produce false positive candidate signs but this over-detection means it will not miss any potential signs.

1) Numerical Speed Limit Detection

All signs from this group are characterised by a circular red boundary (e.g. as per Fig 1).

Firstly, by using the YCrCb colour space, the Cr channel is extracted from the input image (Figure 3(a)), then adaptively thresholded (Figure 3(b)) using two thresholds to provide robust isolation of red scene component. Connected-component analysis is then used to isolate significant components in the remaining red feature space. From these remaining scene components, limit-sign candidates are then selected using RANSAC based circle detection (Figure 3(c)).

The concept of RANdom Sampling And Consensus (RANSAC), proposed by Fischler et al. [6], is very straightforward – given a dataset (i.e. contour), randomly select a sub-set of sample features (i.e. points) and try to fit a geometric shape model (i.e. circle). The model is then compared against the whole feature set. If sufficient number of features from the dataset satisfy the model with a given tolerance, then the feature is determined to exist and RANSAC process is terminated. The number of attempts (trials) to fit a model in a given set of can be estimated using the following formula:

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

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. In our case we use a circle model based on the geometry of three randomly selected feature points within a contour and set the required probability empirically.

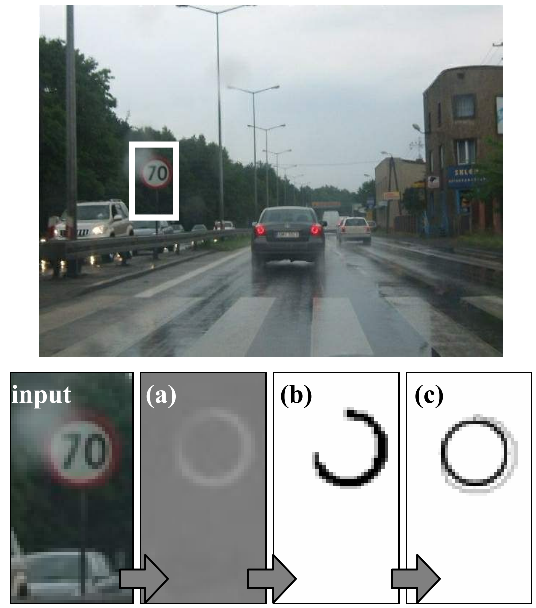

Figure 3: Steps of numerical-limit signs candidates generation algorithm

An example is shown in Figure 3 where we see this algorithm is able to detect the circle even if the original colour segmentation is not perfect due to adverse conditions. This illustrates the robustness of the RANSAC approach to noise and partial occlusion making it highly suitable for the varying road conditions in our detection environment.

2) National Speed Limit Detection

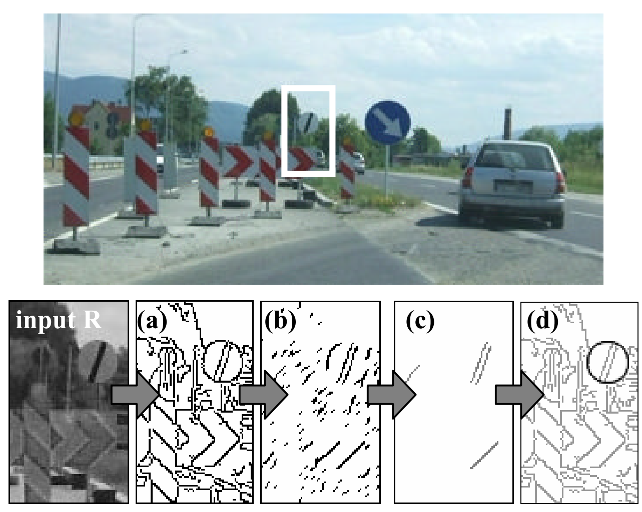

Figure 4. : Steps of national-limit signs candidates generation algorithm

National speed limit (i.e. cancellation) signs are considered as white circles with a left to right diagonal black stripe (Figure 4).

A novel method is proposed for national-speed limit signs detection based on first locating black stripe and then verifying the circular contour around it. Black stripes are located using red channel of RGB input image from which edges are extracted - using canny edge detector (Figure 4(a)). Then morphological opening and closing are applied with appropriate kernels so that only suitably inclined edges remain (Figure 4(b)). Next, their straightness is checked using Principal Component Analysis. Finally, if we detect a pair of remaining parallel edges with a dark interior (Figure 4(c)) we examine it for a surrounding circular contour using RANSAC circle fitting as before (Figure 4(d)). Where a circular contour is successfully detected a candidate national speed limit sign is detected.

B. Recognition Stage

In this step recognition of the candidate limit signs (numerical and national) is performed. Any false positives generated by the earlier detection step are now rejected.

1) Candidates Normalization

The normalization step is an intermediate step before passing sign candidates to the neural network.

In the case of numerical limit-sign candidates this step assures that only white interior of the sign is passed to the neural network. Any remaining red boundary is removed using the prior adaptive thresholding and connected component analysis on the input image converted previously to greyscale.

Figure 5: Removing red boundary from numerical-limit sign candidates

All sign candidates are extracted from the input image to greyscale and thresholded to a binary representation using the average pixel of the candidate interior. This approach gives very good separation of the dark digits from bright background - even in low-light conditions. Some examples of this normalisation process are presented in Figure 6.

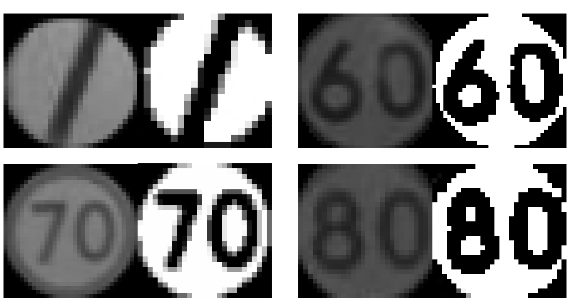

Figure 6: Neural network input normalization

As the last stage of normalization all candidates are scaled to a common size of 20x20 pixels for input to the neural network. 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)

2) Neural Network

A feed-forward multi-layer perceptron network was used in this work [8]. It consists of 400 neurons in the input layer (20x20 normalized pixel sample), 30 neurons in hidden 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 (i.e. not a sign). Each output value is the classification likelihood between 0 and 1 for the corresponding class (i.e. type) of sign.

The size of the hidden layer was set by empirical experimentation. Figure 7 presents performance of the network on the independent testing set of 1050 unseen samples in three configurations (20, 30, 40 neurons in hidden layer) – with 30 giving the best overall performance in terms of the number of correct sign classifications.

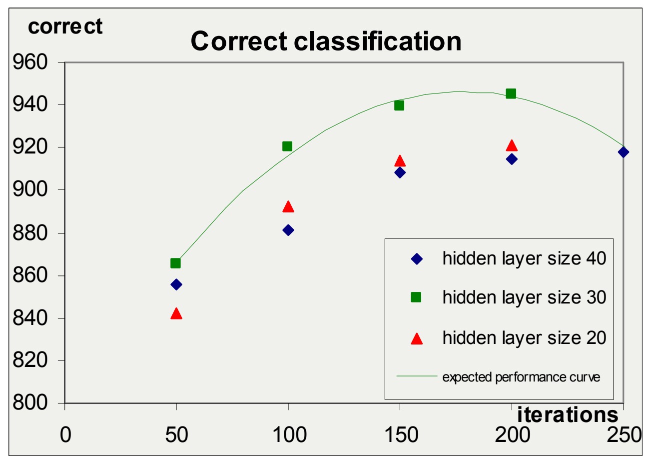

Figure 7. Neural Network training results

Analyzing the expected performance curve (Figure 7) we have decide to use 150 iteration as a termination condition for final training. This value assures good performance and at the same time prevents over-fitting of the classifier.
A given sign is considered as successfully classified by the network if the difference between the highest and the second highest classification likelihood returned in the output layer (of the 12 outputs) is greater than 0.5. Cases where we do not achieve this level of class separation in the classification output (i.e. multiple classes occur within the 0.5 uncertainty bound) are not classified.

C. Automatic Turn Detection

The final part of the system is the integration of optic flow based vehicle turn detection.

Turn detection calculation is restricted only to the situations when turn indicator is activated by a driver to avoid turn detection when following a (non-junction) turn in the road. Optic flow is then calculated between successive video image frames using the pyramidal implementation of the Lucas and Kanade work presented in [1].

In general, optic flow is a vector between corresponding points on image I and J that minimizes the residual function defined as:

$$\varepsilon(d) = \varepsilon(d_x, d_y) = \sum_{x=u_x-w_x}^{u_x+w_x} \sum_{Y=u_Y-w_Y}^{u_Y+w_Y} (I(x,y) - J(x+d_x, y+d_y))^2$$

where w_x and w_y are the size of the image neighbourhood over which the localised flow is calculated. As it is a computationally expensive process, we calculate it only for the a sub-sampled grid of points spread over the image (Figure 8). This approach allows us to accurately detect the turn whilst significantly reducing the computational requirement of the process and hence maintain real-time performance. The white lines in Figure 8 represent the optic flow vectors for potential vehicle turn scenarios.

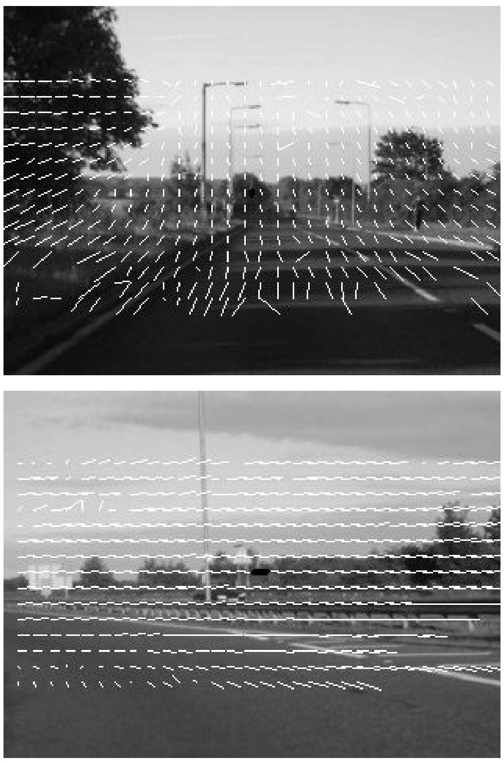

Figure 8. Optic flow on straight road (top) and while turning (bottom)

One can observe that on a regular section of road (Figure 8 top) the resultant mean flow vector over this grid is close to 0, whilst during the turn (Figure 8 bottom) it is greater then 0 (bias one direction). To additionally reduce the influence of the noise present in homogeneous regions of the image (e.g. sky, road), we limit our calculations to only include flow vectors deflected less than 45 degrees from horizontal axis in the mean flow calculation.

Turn is confirmed when the average value of these mean flow vectors over the past fifteen video frames is above certain threshold. This threshold was tuned to avoid overtaking manoeuvre being detected as turn. Two examples of the real road situations are presented as graphs in Figure 9 with the mean flow per 15-frames as the y-axis and time in number of frames on x-axis. Introducing a common flow threshold, (Figure 9) combined with the earlier deflection constraint, allows the robust determination of vehicle turns with as minimal computation as possible.

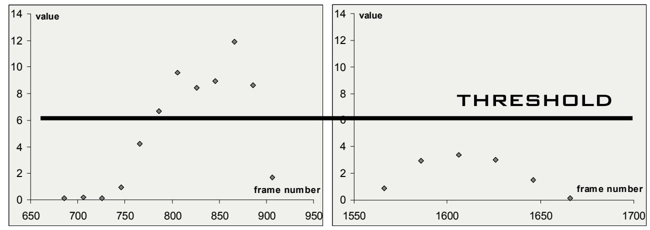

Figure 9. Mean optic flow over 15 frames.

Turning (left) versus overtaking (right)

IV. RESULTS

Our detection and recognition method achieves 27 fps processing speed (1.6GHz single-core Intel CPU) which is reduced to 12 fps when turn detection is active due to the required optic flow calculation. Even at this reduced frame rate, processing every second frame, we note that real-time performance is achieved and does not decrease the overall detection/recognition performance of the system.

The capabilities of the system were tested on footage gathered from camera mounted behind windscreen recorded in UK and Poland and cover various weather conditions (Figure 10). Results are summarized in Table 1 where we see a high rate of successful recognition. On average 13 correct recognitions per sign in Poland and 6 recognitions per sign in UK over the 101 total sign instances passing the host vehicle. This difference is due to the fact that signs in UK are very often smaller than those found in Poland.

SAMPLES TESTED			RESULTS			
Limit Sign by limit 20 30 40 50 60 70 80 90 100	Cancellation Signs	Total	Missed Signs	Valid signs **recognitions** Correct	Wrong	Signs candidates **detections**
2 6 16 6 10 33 11 2 3	12	101	3	1155	3	3498

Table1. Detection and Classification Results

During the experiment just 3 signs were missed from 101 signs instances encountered, which gives an overall 97% of the signs detected. The system then made only 3 misclassifications against the 1155 correct recognitions (of these 101 instances occurring over multiple frames). This means that misclassification ratio of the system is less than 1% (0.2%). However, this consideration does not take into account instances lost in the uncertainty bound (due to lack of separation between classes).

Some examples of system operation are presented on the Figure 10 where we see the correct classification of speed restriction signs under a number of different weather conditions.

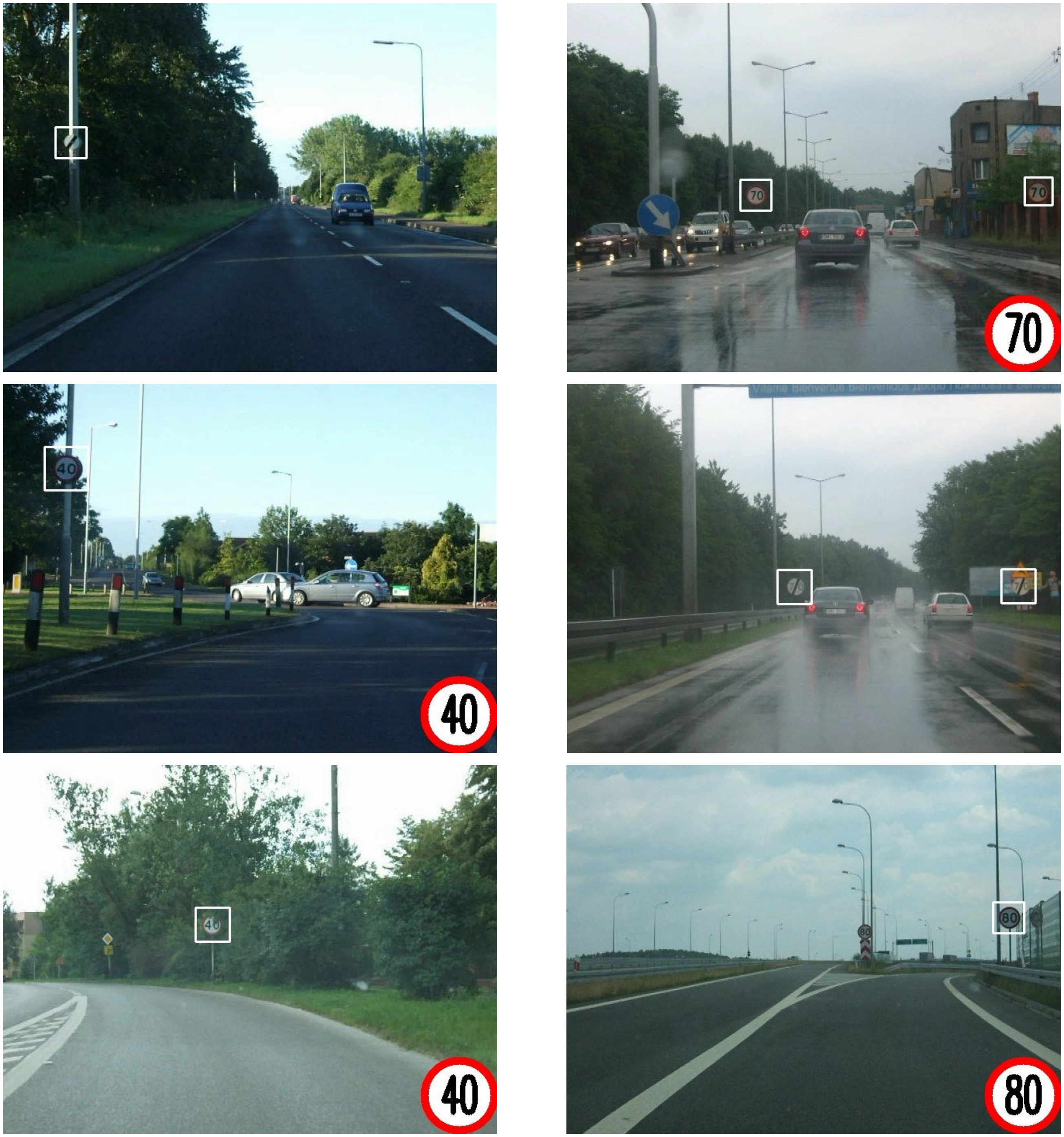

Figure 10. Examples of successful speed sign detection (numerical & cancellation) in varying road conditions and environments.

In Figure 11 two example signs extracted from the misclassified samples are presented. Even for a human viewer it is confusing to classify these examples with the first corresponding either to 50 or 90 (Figure 11, left) and the second being 80 or 30 (Figure 11, right). It is noted that fortunately such misclassification occurs very rarely and is characterised when sign is distant from the host car. A constraint of the size of the sign in the image as part of the initial detection stage would resolve this problem but due to varying national signage standards is left as an area for future work.

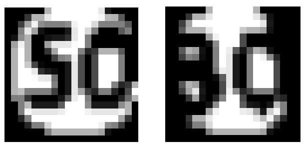

Figure 11. Misclassified samples

I. Further work

Parallel implementation would allow real-time operation whilst processing every frame during turn detection which may further improve the overall global sign detection ratio. Additional work investigating the temporal clustering of approaching sign recognitions would also help improve performance.

Whilst the system has been developed to meet UK road regulations developing a specific junction detector could extend its application to other countries in which this instance cancels current speed restriction.

II. Conclusion

We present a novel system, that integrates both numerical speed limit signs recognition, robust cancellation-sign detection and automatic turn detection within the bounds of real-time performance. This advances the current state of the art with regard to sign recognition approaches [1,2,3,4,5] and uniquely integrates optic flow based turn detection. It may be used for on-vehicle continuous current speed restriction awareness or for integrated speeding prevention. The system has been successfully tested under various daylight weather conditions with good performance. Night time operation, the use of temporal clustering and road feature detection are left as areas for further investigation.

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