Improvement to Neural Network License Plate Recognition by Setting the *Lowest Strong Feature* as Plate Area: Experiment and Results

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Abstract – This report presents results of experiment with a new feature-selection algorithm that we have shown to improve the effectiveness of our license plate recognition system. Empirical evidence suggests that we have raised our system effectiveness from approximately 92.70% to 93.93% correct identifications.

Introduction

Our previous experiments with the '31Aug06' image set have successfully recognised 1435 of 1748 candidate images analysed; a success rate of 82.09%.

Of the images that have failed to have the licence plates correctly analysed we observe, by human inspection, several distinct categories of image that continue to appear as failed results, and present here some possible underlying causes for recognition failure:

1. Mislabelled 'correct' plate name.
2. Multiple plates appear in image; the system is analysing the plate that is not labelled.
3. The system has given a non-plate feature such as painted text, vehicle grille, or headlights a higher value for likely plate area than the actual plate.

We estimate that approximately 200 of the candidate images from the '31Aug06' set are in fact mislabelled. Assuming that this is true, then our previous experiments have an actual success rate of approximately 1435 of 1548 images or 92.70%.

Where multiple plates appear in one image, we intend to, in future works, identify and recognise *both* plates. We will therefore ignore this problem for now.

It must be noted, however, that algorithm that we have devised for this experiment may have upset the 'correct' (as far as our statistical system is concerned) identification of these multiple plate images, and we can therefore expect the statistics produced by this experiment to be not absolutely in agreement with previous statistics concerning 'correct' identification.

The category of false-identifications that we are interested in improving by this experiment is the third listed cause; where non-plate features have been assigned higher values as they are analysed by the system as being more likely to be plate features than the plate itself. We will henceforth refer to this category as *Type*-3 images. Figures 1 and 2 illustrate an example of this problem.

Figure 1: Example of Incorrect Plate Area Identification

Figure 2: Feature Map of likely plate areas for the image in Figure 1.

Analysis of Feature Map Problem

Figure 2 illustrates a Feature Map of zones from the original image that the system has identified as highly likely to be vehicle number plates. Note, with reference to Figure 1, that the correct number plate area has, in fact, been identified and indicated on the Feature Map as being a strong candidate.

The system was previously configured to always choose the strongest feature as plate area. We can see that, in this case illustrated in Figures 1 and 2, the strongest feature was not the plate, but the text painted onto the vehicle. However, we can note, with reference to Figure 2, as we can from inspection of other examples of this type, that the actual plate feature:

- Is relatively strong
- Is vertically lower than the other features

We have experimented with a system variant that always selects the vertically *lowest* feature (regardless of strength) from the Feature Map as plate area, and found that whilst we were then able to correctly classify most of our *Type-3* plates, images of vehicles that have small features below the actual plate feature (such as low headlights) as relatively common, and the overall effect of this system variant was significantly worse; with only 1348 correct identifications from the '31Aug06' image set.

We have therefore developed a simple algorithm that will choose the *lowest strong feature* as the plate area. Refer to Algorithm 1.

Algorithm 1: Lowest Strong Feature

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1. Find from the Feature Map and store in an array the 8 features with the highest strength values .
2. For each of the features in the array:
   - IF feature height < maximum-strength feature height AND feature strength > strength threshold THEN plate area = feature area

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Method of Lowest Strong Feature Experiment

In order to determine just how *strong* our relative strength threshold needed to be, we conducted an experiment; testing a run of the system over the '31Aug06' image set with a range of threshold proportions; from 0.1 to 1.0 the strength value of the highest-strength feature.

Because we are storing the largest features in an array for later comparison, we also considered the effect a threshold supplying a minimum feature separation distance in pixels, might have on the system, with the aim of reducing the number of separated parts of the same features being stored in separate array positions. We have repeated each run of the experiment with each of the test values for pixel separation {1,2,3,4,5,67}.

The combined results of our 2-independent variable experiment are presented in Table 1.

Conclusions

Enforcing a feature pixel separation threshold had no significant effect on the correct classification of results by our system on analysis of the '31Aug06' input image set.

We can see in the graph of results in Figure 3 that we were able to alter the effectiveness of the system by providing differing relative strength thresholds.

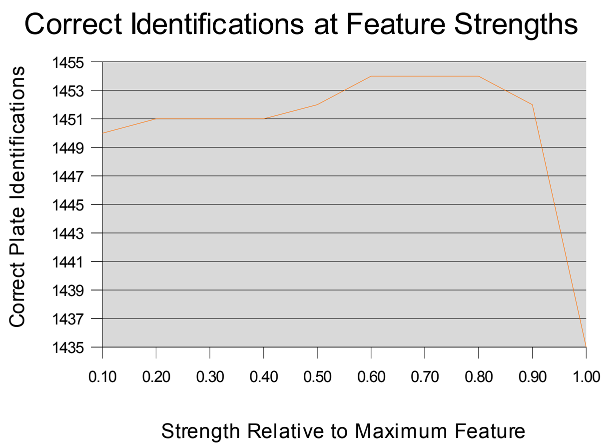

Figure 3: Experiment Results at relative feature strengths.

Our system effectiveness peaked across the 0.6 to 0.8 threshold range; probably because we are successfully identifying *all* of the Type-3 images. A more extensive input image set might allow us to determine a more specific optimal range.

As a result of this experiment we are able to correctly identify 19 more plates from the '30Aug06' image set; 83.18% (a 1.1% improvement).

If we consider our earlier assumption that there are 200 mislabelled plates being analysed, then we have made an improvement from approximately 92.70% to 93.93% correct identifications.