USE OF ADAPTIVE BOOSTING IN FEATURE SELECTION FOR VEHICLE MAKE & MODEL RECOGNITION

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Abstract: Vehicle Make and Model Recognition (Vehicle MMR) systems that are capable of improving the trustworthiness of automatic number plate recognitions systems have received attention of the research community in the recent past. Out of a number of algorithms that have been proposed in literature the use of Scale Invariant Feature Transforms (SIFT) in particular have been able to demonstrate the ability to perform vehicle MMR, invariant to scale, rotation, translation, which forms typical challenges of the application domain. In this paper we propose a novel approach to SIFT based vehicle MMR in which SIFT features are initially investigated for their relevance in representing the uniqueness of the make and model of a given vehicle class based on Adaptive Boosting. We provide experimental results to show that the proposed selection of SIFT features significantly reduces the computational cost associated with classification at negligible loss of the system accuracy. We further prove that the use of more appropriate feature matching algorithms enable significant gains in the accuracy of the algorithm. Experimental results prove that a 91% accuracy rate has been achieved on a publically available database of car frontal views.

1 INTRODUCTION

Several vehicle recognition systems based on correctly recognizing vehicle number plates, are in widespread use at present. However reports by police and media sources have indicated that number-plate cloning, have been recently used to breach the security provided by Automatic Number Plate Recognition (ANPR) techniques. This problem can be addressed by enhancing the reliability of access control systems by the combined use of ANPR and vehicle **M**ake & **M**odel **R**ecognition (MMR) techniques. A match between the vehicle registration number and the make and model will confirm the vehicles authenticity.

Vehicle MMR is a comparatively new research area. A number of techniques that directly relate to vehicle MMR have been proposed in literature. (Petrović and Cootes, 2004) proposed techniques for the recognition of cars, by extracting gradient features from images. (Negri et al., 2006) proposed an oriented-contour point based voting algorithm for multiclass vehicle type recognition. (Zafar, Edirisinghe and Acar, 2008) proposed the use of localised directional feature maps in Contourlet transforms for vehicle MMR. (Dlagnekov 2005; Zafar, Edirisinghe and Acar, 2007; Cheung and Chu, 2008) explored the problem of MMR by using **S**cale **I**nvariant **F**eature **T**ransforms (SIFT) (Lowe, 2004). It is used to identify distinct points of interest in car images, called keypoints, which are subsequently utilized in matching. (Zafar, Edirisinghe and Acar, 2007) proposed a further improvement to this basic approach via restricting the SIFT keypoint detection to only query image and using a SIFT descriptors belonging to all points within a maximum-likelihood area of the candidate images, for matching. (Cheung and Chu, 2008) improved the work of (Dlagnekov, 2005) by introducing improvements to keypoint matching.

Although a number of different approaches have been published in literature for vehicle MMR, the search for a robust, efficient algorithm still remains an open research problem. In this paper we attempt to contribute to the current state-of-the-art in vehicle MMR by addressing the shortcomings of the state-of-the-art techniques in SIFT based vehicle MMR (see Section 2).

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2 RESEARCH MOTIVATION

Vehicle MMR approaches proposed in literature, are based on an initial stage of feature detection, where these detected features are subsequently used in matching. Majority of these methods rely on edge maps, smooth curves/contours as features. However, even the best edge extractor could fail to identify all edges that will be required in uniquely defining make and model of a vehicle in cases where the captured images of the vehicles are not clear, due to adverse lighting effects, occlusion and pose/scale variations etc. The SIFT based car MMR approaches of (Dlagnekov, 2005; Zafar, Edirisinghe and Acar, 2007; Cheung and Chu, 2008), promise to address some of the above mentioned shortcomings of traditional feature based approaches. Specifically SIFT based approaches enable the extraction of invariant features from images that results in more robust feature based matching under occlusion, scale and rotation invariance. Thus SIFT based approaches have been particularly used in object recognition, where the object being searched is immersed in background clutter. The basic SIFT based approach to vehicle MMR (Dlagnekov, 2005) was based on matching the keypoints of a query image to the keypoints of images in a database. One shortcoming of this simple approach is that keypoints from the background (i.e. outliers) of the query and database images may dominate the matching process thereby resulting in wrong matches. As a solution to this problem (Cheung and Chu, 2008) suggested the use of **RAN**dom **SA**mpling **C**onsensus (RANSAC) (Fischler and Bolles, 1981) to separate outliers from inliers. However this approach involved the detection of the vehicle boundary area using edge/contour detectors and then using an iterative algorithm RANSAC. The accuracy of this is highly dependent on the accuracy of the segmentation of the object area and the iterative process makes the approach time consuming.

In order to resolve these problems we propose a novel approach to SIFT based vehicle MMR. The idea is based on the fact that humans are able to identify a given vehicle's make-model based on a mental matching of each model's unique features, such as the shape of the grill, badge, shape of lights etc. We show that after the keypoints have been found, AdaBoost (Freund and Schapire, 1997) can be used to *select features* that are most representative of a given make-model enabling its use in vehicle MMR. We provide experimental results to prove the effectiveness of the proposed algorithm.

For clarity of presentation, this paper is divided into five sections. Apart from this section which introduces the reader to the problem domain and highlights open research issues in vehicle MMR, section 2 introduces the fundamental theoretical concepts required to support the introduction of proposed methodology in section 3. Section 4, provides results of a number of experiments performed to prove the effectiveness of the proposed approach. Finally section 5 concludes with an insight to future improvements.

2.1 Theoretical Background

The proposed approach uses SIFT as the feature detector (Lowe, 2004) and 'AdaBoost' for feature selection. A summary of AdaBoost can be presented as follows.

2.1.1 Adaptive Boosting (AdaBoost)

AdaBoost is an algorithm first introduced by (Freund and Schapire, 1997). It is an adaptive algorithm that can boost a sequence of classifiers. It gradually improves the accuracy of a learning algorithm by concentrating on the "hardest" examples (those most often misclassified) over each round and combine these weak prediction rules in to a single strong prediction rule by taking the (weighted) majority vote of these weak prediction rules.

The AdaBoost Algorithm: According to (Freund and Schapire, 1997; Freund and Schapire, 1999), pseudo code for boosting is:

- Given: Training set of $(x_1, y_1),...,(x_m, y_m)$ where $x_i \in X$ are the instances of some domain X, and $y_i \in Y = \{+1,-1\}$ are labels of the instances.
- Initially all training samples are given equal weights i.e.

$$w_i^{\,1} = D_1(i) = 1/m \text{ for i=1,…,m} \tag{1}$$

- For $t = 1,...,T$:
  - o Set $D_t = \dfrac{w^t}{\sum_{i=1}^{m} w_i^{\,t}}$ (2)
  - o Train weak learner on distribution D_t .

- Find a weak hypothesis/classifier $h_t : X \rightarrow \{+1,-1\}$ with small error

$$\in_t = \sum_{i=1}^{m} D_t(i) \,|\, h_t(x_i) - y_i \,| \tag{3}$$

- Select $\alpha_t = \frac{1}{2}\ln\left(\frac{1-\in_t}{\in_t}\right)$ (4)

- Update

$$D_{t+1}(i) = \frac{D_t(i)}{Z_t} \times \begin{cases} e^{-\alpha_t} & if \quad h_t(x_i) = y_i \\ e^{\alpha_t} & if \quad h_{t(x_i)} \neq y_i \end{cases}$$

$$= \frac{D_t(i)\exp(-\alpha_t y_i h_t(x_i))}{Z_t} \tag{5}$$

where, Z_t is a normalization factor.

- Output the final hypothesis which is a weighted majority vote of the T weak hypothesis.

$$H(x) = sign\left(\sum_{t=1}^{T} \alpha_t h_t(x)\right) \tag{6}$$

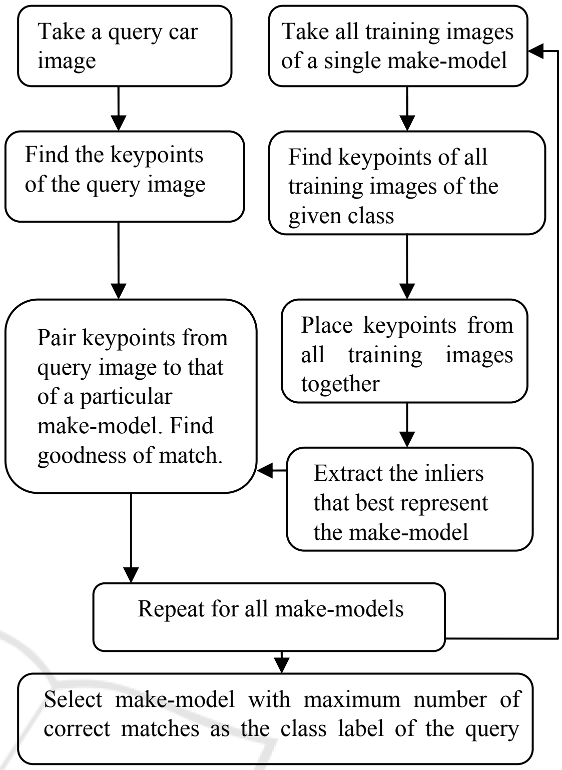

Figure 1: Proposed System. overview.

3 PROPOSED APPROACH

Figure 1 illustrates the block diagram of the proposed approach to vehicle MMR. The basic idea is to match the keypoints of a query image against selection of unique and most representative feature set selected from each make-model.

The stages involved can be detailed as follows:

3.1 Dataset Preparation

Two sets of training images are collected. In the first set, images from the training and test sets are cropped to include only the front grill, lights and bumper area of all cars using the cropping approach proposed in (Petrović and Cootes, 2004). Second set consists of frontal views of cars that include background clutter such as other cars, parking slot markings, tarred surfaces, lamp posts etc. The test/query images consist of cropped frontal views of images of cars without background.

3.2 Feature Detection

As the first step of the proposed processing algorithm, we investigated the use of interest point detection technique: Scale-Invariant Feature Transform (SIFT) (Lowe, 2004). SIFT defines interest points as minima and maxima of the difference of Gaussians that occur at multiple scales, allowing a consistent detection of features on images of cars.

In the proposed application of SIFT, keypoints from all training images of a make-model are pooled together. Similarly we detect keypoints for the test images. Figure 2 illustrates the detected SIFT features from two individual training images(Audi A4) and the projection of all keypoints from all training images on an image of a selected image of an Audi A4 car. It shows that the keypoints concentrate near the grill, lights, badge and front bumper areas.

3.3 Feature Selection

Images of cars in practical situations are assumed to be taken on streets or in parking lots. This presents the problem of having a background scene in the image that can greatly affect the relevance of interest points that are detected. Within our present research context, the method proposed to eliminate

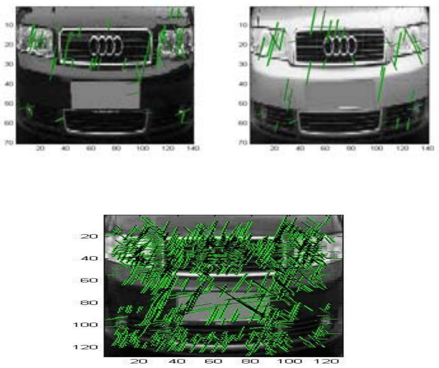

Figure 2: Detected SIFT features of individual images (top row) and projected keypoints of a particular make-model on a sample image

outliers, i.e. the interest points not associated with a car, is to use AdaBoost (Freund and Schapire, 1997; Freund and Schapire, 1999)

According to (Freund and Schapire, 1999), a useful property of AdaBoost is its ability to identify examples that are either mislabelled in the training data or which are inherently ambiguous and hard to categorize. These are thus called 'hard' points, whereas robust points are called 'easy' points. As AdaBoost focuses its weight on the hardest examples, the examples with the highest weights often turn out to be outliers. Further according to (Caprile, 2002), Entropy (Information Entropy, 2008) is used as a measure for separating 'easy points' from 'hard' points based on weight values. Exploiting this, we have proposed the use of feature selection based on weight values attached to the keypoints of the training images of a particular make-model.

During the training phase, keypoints from training images of a particular make-model are compared against rest of the classes. This is repeated for all make-models (Note that we have also introduced a class in training set, which only consists of typical background area). We keep track of weight values attached to all keypoints of particular make-model up to certain number of iterations of boosting. After each iteration weights associated with keypoints are updated in order to focus the algorithms attention on the hard points.

Entropy is then calculated for the stored weights as: The interval [0, 1] is partitioned into L Subintervals of length $1/L$ and the entropy value is computed as:

$$-\sum_{i=1}^{L} f_i \log_2 f_i \qquad (7)$$

Where f_i is the relative frequency of weight values falling in the $i-th$ subinterval ($0\log_2 0$ is set to 0). For our experiments, L was set to 500. These entropy values are first sorted and keypoints with lowest N percent of entropy values are subsequently selected as the valid features for a particular car make-model. These selected features are the best representative features of a class (i.e. car make-model) as they have low uncertainty factor in being classified in the right class.

3.4 Interest Point Matching

We have investigated two different methods for matching interest points. The first is the original SIFT feature matching procedure proposed by (Lowe, 2004).In this approach the keypoints from the test /query image are matched against each of the selected keypoint from a particular model using Euclidean distance as a measure. Pair of interest points that match are considered to be those having the minimum Euclidean distance. The model in the database with highest inliers count will be labelled as being the best matching image to the query image, and the corresponding make-model category will be used to label the query image. Second approach adopted for matching is based on the SIFT matching algorithm proposed in (Zafar, Edirisinghe and Acar, 2007). In this approach SIFT descriptors (Lowe, 2004) of the keypoints of every training image is compared with SIFT descriptors of points within a maximum likelihood area of the test images, centred at the point that corresponds location wise to the keypoint of the training image. It is noted that images are cropped and normalised before the matching method is used.

4 EXPERIMENTAL RESULTS AND ANALYSIS

Two experiments were conducted to evaluate the performance of the proposed algorithm. These experiments were conducted on two datasets.

The first dataset consisted of 50 images of cars (frontal views) belonging to 5 different classes.

These images were cropped at the top (only) to remove the clutter in background due to foreign objects, particularly other cars. However, some background clutter is visible in the sides.

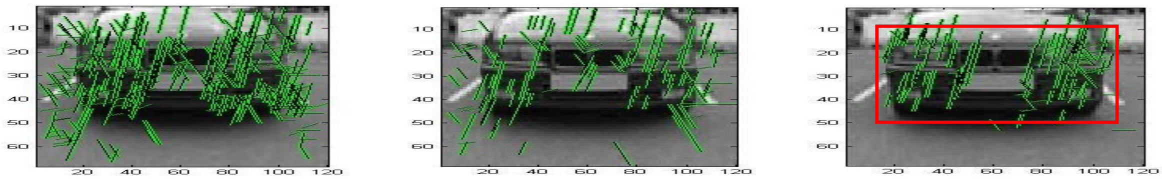

Figure 3: Left to right: First image shows all keypoints from the training set of a class projected onto one selected image. Middle image represent 20% of feature selection based on highest entropy whereas last image represents feature selection with 20% lowest entropy values.

This dataset was collected in order to prove that ada-boosting can be used to identify features unique to a given make-model (see Figure 3) in the presence of other key-points in the training images.

The second dataset consisted of 300 images of cars (frontal views) belonging to 25 different classes. Each training class consisted of at least 8 images of different cars belonging to the same make and model. [Note: the number of cars in each class was not equal]. The images were cropped (Petrović and Cootes, 2004) in all four sides (as appropriate) to remove background clutter.

Initially an experiment was designed and conducted on the second dataset to determine the number of iterations *T*, required for the AdaBoost algorithm to obtain a stable result of classification (discussed in section 2.1.1). In this experiment descriptors of all keypoints of all BMW-3 cars were labelled to be of one class and all other descriptors from all other models were labelled to be of another class. An accurate classification result was noted when either a true positive or a true negative result was obtained. Experiments revealed that after $T = 200$, there is only a negligible decrease in accuracy and the stabilisation accuracy was held constantly at approximately 91%. A similar level of accuracy was obtained for other make-models at similar number of iterations.

A second experiment was designed to determine the effects of applying the proposed technique for feature selection from a pool of features obtained from car images of a particular make-model. To better visualise the effect of applying the proposed technique in feature selection, we first applied the idea on the first dataset. As this dataset consists of areas from the background, it is useful in demonstrating the fact that Adaboost will be able to separate features unique to each make-model from the feature points of the background areas. Further note that the keypoints of a class associated with low entropy measures indicate low uncertainty in classification and are thus best to be used in classification.

Therefore by selecting the keypoints associated with the lowest entropy figures, only the most unique features of a car make-model will be identified. These can be subsequently used in vehicle make-model recognition (see Figure 3).

It is obvious from the results illustrated in Figure 3 that keypoints with lowest entropy values represent the inliers. We have experimented to determine a suitable threshold value for the entropy and found that keeping 25% of lowest entropy gives the best accuracy.

A further experiment was conducted on the second set of data (database of 300 images) to obtain the overall classification accuracies. Keypoints whose entropy values were within the lowest 25% were selected for subsequent processing. Since the second dataset consists of cropped images (from all sides), the feature selection process helps to separate keypoints of the class which are likely to be easily confused with keypoints belonging to other classes. In other words the features selection strategy adopted will be able to identify unique feature points that are distinctive for each make-model.

After the selection of keypoints that are able to best represent unique features of all make-models, the data will be ready for testing. Two methods were used for matching the keypoints of the test image with those of the given make-model classes; the original SIFT keypoint matching algorithm proposed in (Lowe, 2004) and the improved SIFT keypoint matching scheme proposed in (Zafar, Edirisinghe and Acar, 2007). Matching results are based on selected features with lowest 25% entropy are illustrated in Figure 4. Note the high degree of correspondence between the matching keypoint.

The accuracy of classification achieved when the proposed Adaboost based feature selection method was adopted with the original SIFT (Lowe, 2004) keypoint matching scheme, was 82% as compared to 83% when all keypoints were considered in matching.

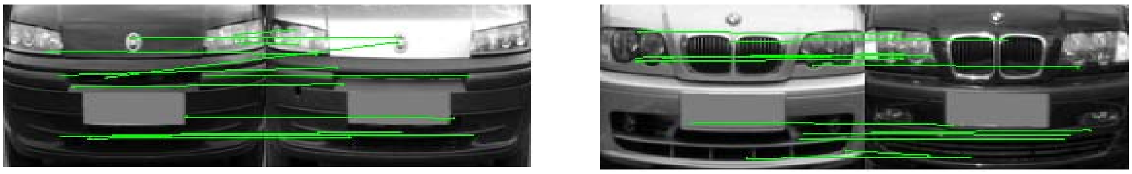

Figure 4: Matching results.

Note that testing was carried out on a random set of 100 images, belonging to all classes. Note that by using Adaboost based feature selection we have been able to reduce the number of feature points used in classification by 75%. Thus we have achieved similar classification accuracy at a significant reduction of computational cost during testing. The matching accuracy can be further improved to 91% by applying the matching scheme of (Zafar, Edirisinghe and Acar, 2007). It is noted that this scheme is more appropriate to be used within the proposed approach as the selected keypoints of the training image set now consists 25% of the most representative keypoints of the model, thus decreasing the use of keypoints from the background and from non-representative areas of the model concerned, in training.

5 CONCLUSIONS

In this paper we have proposed the use of adaptive boosting in selecting the most representative SIFT features of a given car in vehicle MMR. We have shown that the proposed selection of the most appropriate SIFT features allows a significant gain in the computational cost of previous SIFT based approaches to vehicle MMR at negligible cost to the algorithmic accuracy. We have further shown that the adaptation of more relevant feature matching techniques allows significant relative gains in accuracy. The algorithm has been tested on a publically available database of car frontal views to enable easy comparison with existing and future vehicle MMR algorithms.

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