Online Learning of Efficient Video based Road Detection using Probabilistic Neural Network

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Abstract: **Road detection is an essential facilitator for the development of the autonomous robot navigation and the driver assistant system. It plays vital tasks in intelligent transportation systems and various applications. The main goal of this paper is to detect the driveable road region from the other entire region. Also this paper focuses on investigating the suitability of probability neural network for video based road detection. Through PNN boundary and non-boundary regions are differentiated efficiently. The proposed method is finally evaluated on the several videos.**

Keywords: Machine learning, Autonomous navigation, Road detection, probability neural network (PNN).

1. INTRODUCTION

In recent years, injuries due to traffic became an important problem for public. This in turn causes increase in death rate which is due to the driver's inattention and tiredness. To prevent the people from accidents, the capacity of transportation system can be increased by increasing the number of lane miles and on-board automotive driver assistance systems. Driver Assistance System (DAS) [1, 4] is developed and equipped to serve as an autonomous reminder and guidance for the drivers. Road detection is the fundamental technique that enables DAS, because it is the initial step for a vehicle to become moveable and many intelligent maneuvers are based on it. Due to range of environmental conditions like day, night, rain, shadow, sunshine, fog, autonomous road detection becomes challenging. Vision-based road detection algorithms can be classified into three main classes: feature-based technique, model-based technique and region-based technique. One of the effective approaches is region-based technique which involves machine learning.

In this paper, we address the problem of video-based road detection by using an online strategy. The major focus is on inspecting the structural information of the input data through the probability neural network. Also, the learned model is updated online to adapt to the change in the environment.

2. EXISTING ROAD DETECTION ALGORITHMS

In general, similarity based road detection method consists of following steps:

- Sampling input image into regions.
- Retrieving most similar samples of known surfaces from the database.
- Processing the retrieved information from the similarity database and estimate that the sample from input image contains road or non road region.

*Road detection can be divided into three groups: model-based, feature-based, and learning-based.

Model-based method considers the assumption of road shape, which is actually taken as road model. Then finding the fittest parameters [5-7] under the model assumption is the aim of this method. Several approaches of model fitting are used to get the road model. Although Model-based methods can accurately determine the road region for a proper road model, changes in the road shape may became invalid due to the vehicle moving. Therefore, it is tough to find an appropriate model for unstructured roads within constant conditions.

Feature-based method depends on the extraction of image features to the detect road boundaries and road region. To measure local neighbourhoods the features such as colour, gradient and texture are commonly used and a likelihood function is formulated by feature clustering, threshold segmentation [8, 9] or region growing approach to obtain the road region. The main advantages of the feature-based method are that it is unresponsive to the shape of roads and little previous knowledge is required. But it is susceptible to shadows and other illumination changes.

Learning-based method generally makes use of a trained neural network or classifier to differentiate between the road region and non-road region. Such methods are independent of special road markings and are capable of dealing with non-homogeneous road appearance, only if the characteristics of road or non-road regions are properly represented by the feature space. For learning-based method, although less prior knowledge is needed, it heavily relies on the training sets and training strategies. But unfortunately, most of the classifier and neural network are trained once, it is unable to adapt to the changes in the environment. The road detection problem can be successfully interpreted using a variant of the above three approaches or a combination of them. The proposed method belongs to the learning based prototype, while taking advantages of advanced features and road boundary fitting.

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3. PROPOSED METHODOLOGY

In the existing system LBP, BRISK methods were used for the feature extraction and SSVM classifier is used for the classification. In the proposed methodology, SURF and HOG methods are used for the feature extraction and using PNN classifier classification has been done.

We focus on the drivable road detection, aiming at inferring the road region in a video collected by a camera mounted ahead of a vehicle or robot.In particular, the road region is inferred from the road boundary, which is not restricted to only structural roads with distinguished lanes or curbs.

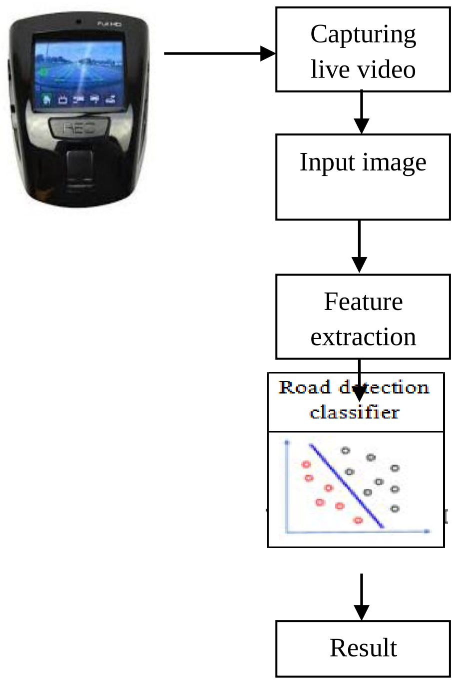

Fig.1. Video based Road Detection Architecture

Depending on the basic theory and problem analysis, we developed a new method for road detection with sustainable modifications and reliable improvements: firstly, sky removal. It is possible to determine the horizon line of the images directly if the camera is well calibrated.

4. VIDEO BASED ROAD DETECTION

The main components of the proposed methodology are Segmentation, Feature extraction, Classification.

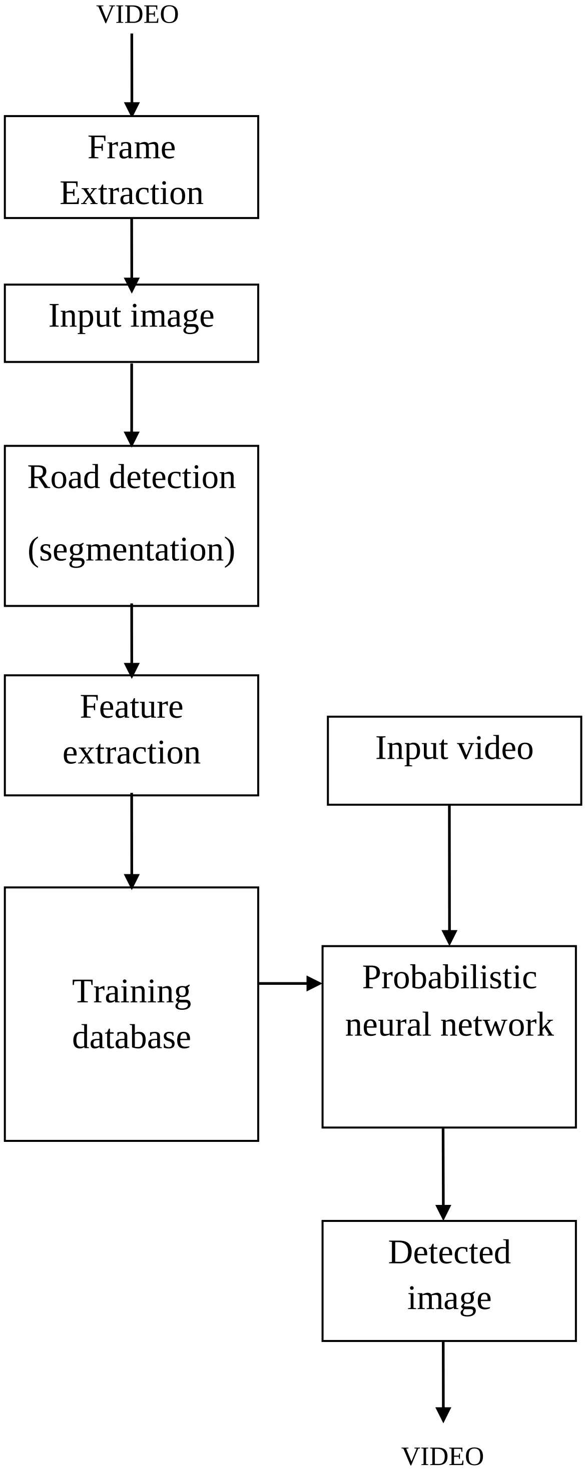

Fig 2 Flow diagram of the proposed system

4.1. Segmentation:

In road detection, image contains both the road and other parts and three segmentation methods used for the discrimination of road region from non-road region which are active contour method, cropping the ROI and template matching.

The idea behind active contours or deformable models is quite simple for image segmentation. The user specifies an initial guess for the contour, which is then moved by image driven forces to the boundaries of the desired objects.

Template matching method of segmentation is done by calculating the pixel values of the road region and segmenting that region by colouring the other entire region. Similarly the region of interest can be segmented by cropping the image into two, upper part and the lower part. This lower part contains the road region which is the area of interest. The input image is cropped to the area of interest determined by the rectangle of required width and height.

4.2. Feature extraction approach:

For the determination of road region, the feature selection is a critical factor. This includes features like local gradient and texture and they are significantly manifest for road boundary. We have used two methods. They are as follows.

HOG feature: HOG feature was first proposed for the problem of human detection. Ever since then, numerous experiments have proved the strength of HOG, because it is invariant to changes in lighting, small malformation, etc. In this work, we also take HOG features to detect the boundary. Similar to SIFT, the original HOG computes a histogram of gradient orientations in each block. In our experiments, sampling instances are considered as a block and each block would generate one column feature vector. The dimension of the HOG descriptor can be adjusted by changing the sampling distance of the histogram. The magnitude of the gradient is

$$|G| = \sqrt{I_X^2 + I_Y^2} \longrightarrow \quad (1)$$

The orientation of the gradient is given by

$$\theta = arctan\frac{I_Y}{I_X} \longrightarrow \quad (2)$$

SURF feature: It is a local feature detector that can be used for various tasks such as object recognition , registration, classification or 3D reconstruction. SURF is very faster than SIFT and claimed by its authors to be more robust against different image transformations than SIFT.

To detect interest points, SURF uses an integer approximation of the determinant of Hessian blob detector, which can be computed with 3 integer operations using a pre computed integral image. It can be represented as

$$\mathrm{H(X,}\sigma) = \begin{bmatrix} L_{xx}(X,\sigma) & L_{xy}(X,\sigma) \\ L_{xy}(X,\sigma) & L_{yy}(X,\sigma) \end{bmatrix} \longrightarrow (3)$$

where $L_{xx}(X,\sigma)=I(X) * \frac{\partial^2}{\partial x^2}\, g(\sigma)$

$$L_{xy}(X,\sigma)=I(X) * \frac{\partial^2}{\partial xy}\, g(\sigma)$$

$L_{xx}(x,\ \sigma)$ in equation 3 is the convolution of the image with the second derivative of the Gaussian. Its feature descriptor is based on the sum of the Haar wavelet response around the point of interest.

4.3. Probability neural network:

With the obtained feature vectors, a PNN classifier is adopted to make a decision of boundary/non-boundary. The instances belonging to the same class may have the same data structure distribution in the feature space, this structure constraint can obviously eliminate the outliers. The classifier is learned in the first frame and is updated in every following frame.

A probabilistic neural network is predominantly a classifier It develops the probability density functions within a pattern layers using a supervised training set.

All PNN networks have four layers:

1. Input layer: There is one neuron in the input layer for each predictor variable. For the case of categorical variables *N*-1 neurons are used where *N* is the number of categories. Input neurons (or processing before the input layer) standardizes the range of the values by subtracting the median and dividing by the inter quartile range. Then input neurons feed the values to each of the neurons in the hidden layer.

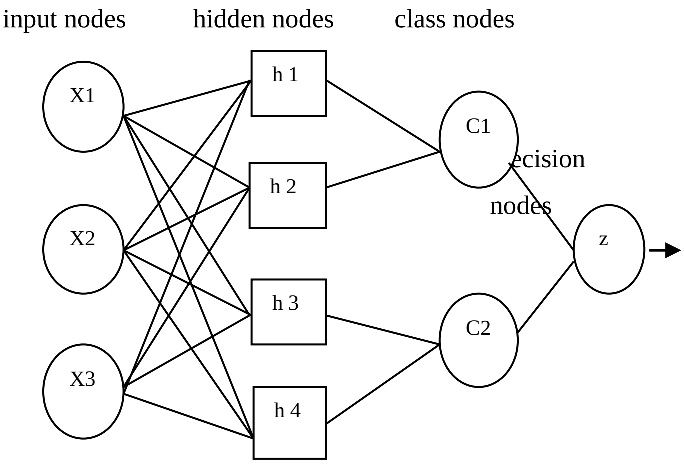

Fig.3. Architecture of PNN

2. Hidden layer: This layer has one neuron for each case in the training data set. Neuron stores the values of the predictor variables along with the target value for the case. When presented with the *x* vector of input values from the input layer, the Euclidean distance of the test case from the neuron"s center point is computed by hidden neuron and then using the sigma value(s) apply the RBF kernel function. Resulting value is passed to the neurons in the pattern layer.

3. Pattern layer / Summation layer: The next layer in the network is different for PNN. For PNN networks for each category of the target variable there is one pattern neuron. The actual target category of each training case is stored with each hidden neuron; the weighted value coming out of a hidden neuron is fed only to the pattern neuron that corresponds to the hidden neuron"s type. Pattern neurons add the values for the class they represent (hence, it is a weighted vote for that category). .

4. Decision layer: For PNN networks the decision layer compares the weighted votes for each target category accumulated in the pattern layer and uses the largest vote to predict the target category.

PNN is pattern classification algorithm which falls into the broad class of "nearest-neighbor-like" algorithms [6]. Although the implementation is very different, PNN are conceptually similar to *K-Nearest Neighbor* (k-NN) models. Basic idea is that a predicted target value of an item is likely to be about the same as other items that have close values of the predictor variables.

Advantages of PNN networks:

1) It is usually much faster to train a PNN network than multilayer perceptron network.
2) PNN networks often are more accurate than multilayer perceptron networks.
3) PNN networks are relatively insensitive to outliers (wild points).
4) PNN networks create or generate accurate predicted target probability scores.
5) PNN networks approach Bayes optimal classification.

5. PERFORMANCE EVALUATION

5.1 Experimental set up:

In this section, experiments are conducted to verify the effectiveness of the proposed method. Then the experimental settings are described and the parameter selection is done. A data set of different kinds of road videos has been collected for validation. The videos are RGB image sequences and the acquisition rate is 25fps. In our framework, the size of video frames is normalized into 256*256.

5.2 Performance analysis:

Many qualitative experiments were conducted to measure the performance of the algorithm used. The extracted regions were compared with ground truth regions in each frame of a video sequence.

It was seen that the proposed method was able to detect more than 95% of road area in the input images. Sensitivity and specificity of the proposed method gained 90% and 100% respectively.

$$\text{Accuracy}=\frac{TP+TN}{TP+FP+TN+FN} \longrightarrow (5)$$

$$\text{Sensitivity} =\frac{TP}{TP+FN} \longrightarrow (6)$$

$$\text{Specificity} =\frac{TN}{TN+FP} \longrightarrow (7)$$

This method provides good results in the presence of shadowing effect. Further this work can be extended for unstructured roads as well.

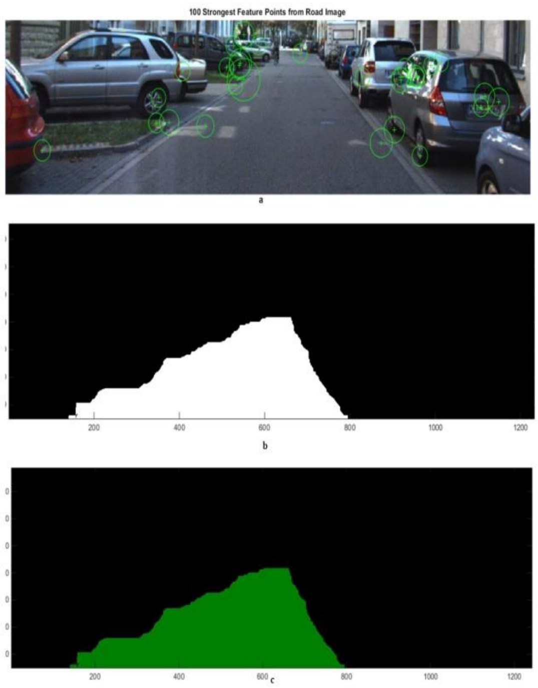

Fig.4 Typical road boundary inference results

Fig 5 Typical road detection results of the proposed method

VI.CONCLUSION AND FUTURE WORK

In this paper, we present an online-learning method for *efficiently extracting the drivable road region in a video sequence. Firstly, the features are extracted and the feature vectors are given as input to a probability neural network classifier to determine the boundary and non-boundary region. Finally, the road area is acquired from the boundary and the learned classifier is updated online.

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