MULTI-RESOLUTION-BASED ROAD STATE ESTIMATION

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Abstract:

In this paper, we suggest an accessible and effective approach to the urban road state estimation. The main technical contribution of the proposed method is a novel feature extraction on the basis of the multi-resolution, along with support vector machine for classification. Experimental tests have been carried out to validate our proposed approach which can estimate road state in the sample of a hundred of city road images computational efficiently and effectively .

Keywords:

Road state estimation; Multi-resolution; Support vector machine

1. Introduction

In recent years, there has been tremendous interest in developing automatic vehicle navigation system. In previous work, quantity of methods to extract feature points which separate the road from its surroundings for road area detection have already been demonstrated under real conditions. Based on the result of that, some of the road models are used to fit the road edge, such as quadratic curve model [1], parabola model [2], hyperbolic model [3], spline curves model [4]and so on.

In the urban environment, roads usually are well-structured and the crossroad is the most common form of the road shapes. The road state which includes the right, left and straight road type may provide essential information for localization and navigation. Also, estimating the road state or anticipating the turn in advance gives the direction changing warning, making it possible for the vehicle to slow down ahead. So that the number of accidents could fall, improving the traffic safety level. Road state could be estimated by calculating the derivative or using other mathematically calculations of the functional equations of those road models just mentioned. However, it is obvious that the estimation is limited by the constant occurrence of over-fitting problems. What's more, on account of complicated computations, we may no longer want to adopt those mathematical functions when we require nothing but the estimation of road state within a short time. In addition, although there have been several road state estimation algorithms available, the feature extraction based on wavelet analysis has not been widely adopted to such task.

Our road state estimation method relies on the multi-resolution analysis and support vector machine. The remainder of this paper is organized as follows. Later in Section 1, the brief descriptions of multi-resolution analysis which is the basis for choosing the feature and support vector machine for classification will be given. The experimental procedure in detail and the analysis of experimental data are then presented in Section 2, showing the efficiency and accuracy of the approach we proposed. In Section 3, the conclusion is drawn and the possible future works are discussed.

1.1. Multi-resolution analysis

Wavelet analysis plays an important role in the signal and image processing [5]. On the one hand, the multi-scale decomposition produced by the wavelet transform has been widely applied into image de-noising, compression, and feature extraction, etc. On the other hand, the sparse representation given by the wavelet decomposition is well-fitted to many recognition or classification problems. The geometrical features of signals or images can be presented by using different kinds of wavelets and different levels to generate feature vectors which are beneficial in classification models [6].

A *multi-resolution analysis* [5] on $L^2(\mathbb{R})$ is a sequence of subspaces $\{V_j\}_{j\in\mathbb{Z}}$ of functions in $L^2(\mathbb{R})$ satisfying the following properties.

(a) For all $j \in \mathbb{Z}$, $V_j \subseteq V_{j+1}$.

(b) $\cup_{j\in\mathbb{Z}} V_j = L^2(\mathbb{R})$.

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(c) $\cap_{j\in\mathbb{Z}} V_j = \{0\}$.

(d) A function $f(x) \in V_0$ if and only if $f(2^j x) \in V_j$.

(e) There exists a function $\phi(x) \in L^2(\mathbb{R})$, called the *scaling function* such that the collection $\{T_n\phi(x) = \phi(x-n)\}_{n\in\mathbb{Z}}$ is an orthonormal basis of the subspace of translates

$$V_0 = \overline{Span}\{T_n\phi(x)\}.$$

In applications, a signal function $f \in L^2(\mathbb{R})$ can be approximated by a linear combination of the translations of the scaling function in a closed subspace V_j, as:

$$f(x) \approx \sum_k a_k T_k(\phi_j)(x) = \sum_k a_k \phi(2^j x - k). \tag{1}$$

What's more, the subspace V_j in the multi-resolution analysis $\{V_j\}_{j\in\mathbb{Z}}$ on $L^2(\mathbb{R})$ can be decomposed orthogonally as:

$$V_j = V_{j+1} \bigoplus W_{j+1}. \tag{2}$$

V_{j+1} contains the low-frequency signal component of V_j and W_{j+1} contains the high-frequency signal component of V_j. According to the wavelet orthonormal decomposition as shown in Eq.(2), V_j is first decomposed orthogonally into a high-frequency subspace V_{j+1} and W_{j+1}. The low-frequency subspace V_{j+1} is further decomposed into V_{j+2} and W_{j+2} and the processes can be iterated until we achieve the pre-defined scale [6].

This notion reminds us of using the decompositions to reconstruct the road area detection's feature points to reduce the interference from the noise in the process of preprocessing.

In the framework of multi-resolution analysis which leads to a fast algorithm of wavelet decomposition, a given signal or image can be represented as linear combination of translations of the scaling function and baby wavelets generated by a mother wavelet.

The scaling function and mother wavelet function can be obtained by solving the following two scale equations:

$$\phi(x) = \sum_k p_k \phi(2x - k), \tag{3}$$

and

$$\psi(x) = \sum_k q_k \phi(2x - k). \tag{4}$$

Then ϕ is called the scaling function, ψ is called the mother wavelet.

In short, in the theory of wavelet analysis, the core idea behind it is to process data according to different scales or resolutions. If we further choose the fixed wavelet basis, not only could the data itself be sparsely represented and studied with the varying resolutions, but also the feature of it could be extracted by the way of finding out the features of the corresponding wavelet coefficients.

Since generating feature vectors at different levels are beneficial in classification models, multi-resolution analysis provides an insight into our following research for the feature extraction of the road state.

1.2. Support Vector Machine with Cross Validation

In 1995, Support Vector Machine (SVM) was proposed by Vapnik as a new classification technique based on the statistical learning theory [7]. Working as a non-linear classification which involves making an optimal separation among the complex-structure data, support vector machine adopts kernel by mapping input data into higher dimensional feature spaces. It has been applied in many different realms because of its robustness, high accuracy and efficiency.

Cross validation is a statistical method of evaluating and comparing learning algorithms [8]. At present, it has been widely used in support vector machine.

The fundamental idea of cross validation is to split the data set instead of using the entire one during the training, which means that before the training begins, part of the data are removed until the training period ends. After the training period, the removed data will be utilized again to test the performance of the trained system.

The basic form of cross validation is k-fold cross validation. As taken literally, the whole data set is divided into k subsets. To be more precise, one of the subsets acts as a test set, while the rest of them (k-1 subsets) perform as the training set. Correspondingly, each data needs to be in a test set once and to be in a training set k-1 times. In this case, cross validation makes sure that all of the data can be involved, which makes the best of the limited data and improves the whole performance.

The 5-fold cross validation is selected in our experiment which will be discussed in more detail in the following section.

2. Road State Estimation

Our road state estimation includes four steps: Acquisition, Preprocessing, Feature extraction and Classification & Estimation. The flow is shown in Figure 1.

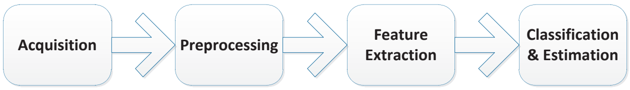


FIGURE 1. Block diagram of the proposed approach.

2.1. Acquisition

In our proposed approach, we use a series of pictures, in total of one hundred, which are grouped into three categories, including the right, left and straight lane of continuous driving in the city environment, with 64, 26 and 10 images respectively for experiment. A sequence of pictures of different typical road states are shown in the following three pictures. All of the images are labelled for the three different states.

(a) (b) (c)

FIGURE 2. Different types of road state. (a) Right State. (b) Left State. (c) Straight State.

2.2. Preprocessing

We base our road state estimation on the result of the road area detection's feature points by taking advantage of stereo vision technology which could be implemented relatively well [9]. Although it is one of the most advanced methods to extract the feature points at present, noise still cannot be voided at times, as one straight sample illustrated in Figure 3. So, our first priority is to exclude a certain degree of noisy interference to get the relatively precise data. Otherwise, the estimated state is not guaranteed to be correct due to the noise.

As stated in the previous section, one advantage of the approximation coefficient based on the wavelet decomposition structure is its capability to deal with noisy data. It's important to note that in order to control other variables at a standard level, the entire system ought to adopt the fixed wavelet basis. Here, we select the Symlet wavelet which is a symmetrical wavelet and widely applied due to its superior performance [6]. An example of straight road with 26 feature points which corresponds to Figure 3 is under the test of several dimensions of Symlet wavelet multi-resolution decompositions and reconstructions for approximating, the results are organized in the order of five levels in Figure 4.

FIGURE 3. Feature points of one straight sample.

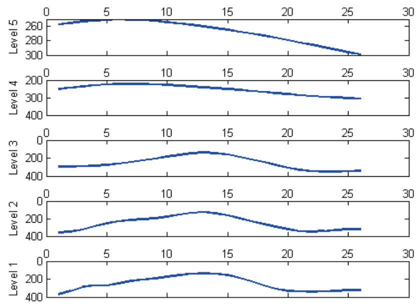


FIGURE 4. Approximations at different levels.

The intuitive understanding of the diagram above is that approximating at the first, the second and the third level are more close to the real situation. In order to compare their superiorities with the purpose of improving the quality of the feature, we make these approximation signals at different levels act as three feature vectors and then put them into the support vector machine respectively to estimate the road states. We eventually choose the first level data according to the test results, as presented in Table 1, so that our estimation approach can be guaranteed to perform well under noisy environment.

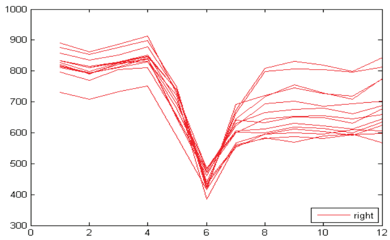
2.3. Feature Extraction

It might seem that using the entire one level of approximation signals as the extracted feature has helped us to obtain a

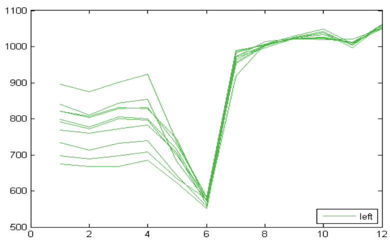
TABLE 1. The prediction accuracy at different levels

Level	Prediction accuracy
1	95%
2	90%
3	92%

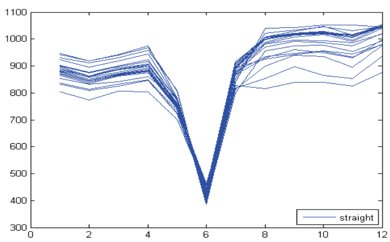
good classifier already. But taking future practical application into consideration, we may come across different situations, for instance, different numbers of feature points for road area detection obtained by varying measures. To address this shortcoming and also to reduce the number of the feature vector's dimensions, the next step for us is to figure out a way to search for the global fixed-number characteristic to distinguish road state, regardless of what kind of the methods to obtain the feature points, instead of using the de-noised data directly as well.



(a)



(b)



(c)

FIGURE 5. Approximation coefficients at the third level. (a) Right State. (b) Left State. (c) Straight State.

According to the introduced concept of wavelet above, we naturally associate the possible solution with the wavelet coefficient. Since the fixed wavelet is adopted, we compute the approximation coefficients of the de-noised signals which have been acquired in the previous step. Theoretically, under the same state, the changes of the wavelet coefficients ought to remain nearly consistent. As we known, curves can be used to describe the changes in data. Therefore, the corresponding points are connected to observe the relationship among them. Some of the samples' approximation coefficients at third level are selectively shown in Figure 5.

By the comparison of these figures, the apparent distinctions of different types can be distinguished easily. Each of the road state types has the limited and unique curve trend, for instance, the single peak or single valley usually appears in the middle of the picture. One simplest way to describe the different tendency of them is to fix some of abscissa values and then to compare their corresponding ordinate values. It is worth mentioning that compared to straight road, turning is much more complicated since it may be the joint of two completely different straight roads. So that in the selection of the large sample data's training set, we might consider whether any particular type of the road has different wavelet coefficients or not, that is to say, the full range of features of the exact type should be considered. Here, an example of right state is given in Figure 6. And we take both of these conditions into consideration during the selection.

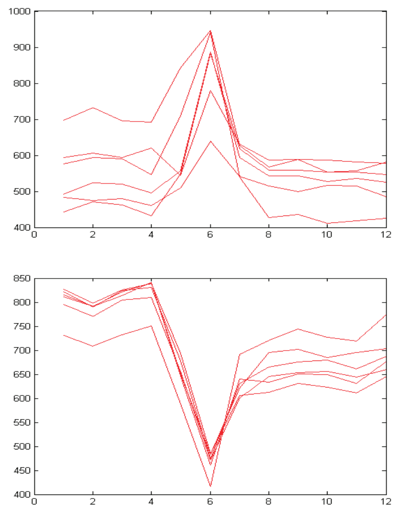


FIGURE 6. Different approximation coefficients of right state.

Through a great deal of tests with several combinations, we select the signals' quarter, one-third, half, two-third and three-quarter values on the horizontal axis to achieve their corresponding ordinate values at three levels as the feature vector. The advantage of this is that compared to the exact amount of the feature points gotten in our previous experiment by using the whole approximation signal which is 26, vector dimension decreases and is fixed at 15 with no harm to classification performance which will be verified later. At the same time, with the reduction of the amount of the computation, it helps to save time.

2.4. Classification & Estimation

The city road images mentioned above are divided into two parts in this part: the training set and the test set. In the training set, 16 images which have the distinguishing feature of the three basic road states are carefully selected, leaving the other 84 images to be the test set. A 5-fold cross validation method of support vector machine, a supervised classification technique, for training and testing is introduced.

The experimental result illustrates that after using the proposed methods, the trained system can successfully estimate the state of the road with 98% accuracy which is really high. Besides using 26 feature points, we also adopt other number of feature points, such as 40 and 60. The stability and general applicability of our approach are demonstrated by the high prediction accuracy of them (all greater than 95%) as well.

3. Conclusions

This paper presents a new approach based on the wavelet analysis and support vector machine to estimate road state. Initially, wavelet is used for preprocessing the data, along with feature extraction. Next, support vector machine is adopted jointly to classify a sequence of urban road images. Experimental results indicate that the proposed method is able to successfully estimate the road states in structured roads, which compared to other methods, reduces the computational complexity and improves the accuracy at the same time.

However, the limitation is obvious that it is not a general case to some degree. For further work, more experiments will be carried out in urban environments and we will extend the approach to the more complex road environment as well.

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