# A novel license plate location method based on wavelet transform and EMD analysis 

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#### Abstract

Although various license plate location methods have been proposed in the past decades, their accuracy and ability to deal with different types of license plates still need to be improved. A robust license plate location method can raise the accuracy of the whole license plate recognition procedure. This paper proposes a robust method based on wavelet transform and empirical mode decomposition (EMD) analysis to search for the location of a license plate in an image to deal with some challenging problems in practice such as illumination changes, complex background and perspective change. By applying wavelet transform on a vehicle image and projecting the acquired details of the image, a wave crest that indicates the license plate will be generated. In order to locate the desired wave crest in the nonlinear and non-stationary projection dataset, EMD analysis is applied. Using the reconstructed projection data and the Hilbert transform of intrinsic mode function components, the position of the license plate is detected. Comprehensive experiments show that this method can locate the positions of various types of license plates with a high accuracy of $97.91 \%$ and a relatively short running time.


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## 1. Introduction

Intelligent transportation system (ITS) plays a significant role in city traffic systems problems [1]. As an essential part of ITS, license plate recognition (LPR) is of great importance in numerous applications such as toll collection of expressway, surveillance and management systems of unattended parking lots and traffic law enforcement [2-4]. LPR mainly consists of three parts: license plate location (LPL), character segmentation and character recognition. Among these steps, LPL is a crucial task. An ideal LPL method usually improves the accuracy of the whole system and leads to a quick recognition process. As a classical topic of pattern recognition, more than 20 years have been spent on realization of LPL. Nonetheless, there are few systems can be applied in real situation and accuracy or speed of these systems still need to be improved. This task is challenging due to various factors that can

[^0]lead to low quality images. Some common problems that should be taken into account for practical applications are as follows:
(1) Severe outdoor illumination conditions during image acquisition such as headlight of vehicles and projection or reflection of the sunlight $[5,6]$.
(2) Complex backgrounds, including damaged or unclean license plate, laissez-passer which adheres to the windscreen, nonlicense plate characters printed on the vehicle and so on [7].
(3) Perspective distortion caused by different distance and angles between the viewpoint and the vehicle and blur caused by vehicle motion [8].

Most LPL methods are either vulnerable to factors mentioned above or highly complex, therefore, they work only under restricted conditions such as fixed illumination, limited vehicle speed, designated routes, and stationary backgrounds [9]. Furthermore, many methods can only process one single style of license plate. For example, some systems are only capable of processing license plates with a single line of characters while other systems can only deal with license plates with Arabic numbers and English letters. A capable LPL system must be able to deal with images obtained in severe conditions and different types of license plate.

In order to develop a robust system that can withstand different factors such as variations of the illumination conditions, image resolution, backgrounds, perspective distortion and license plate types, a novel LPL method is presented in this paper. By applying wavelet transform to an image and projecting the acquired detail information, a wave crest that indicates position of a license plate will be generated. In order to search for the desired wave crest, EMD analysis is utilized to deal with the projection data. Compared with traditional methods, the technique presented in this paper is much less restrictive. It can detect the license plate under various conditions such as vehicles of different countries, images taken under different illumination conditions, distorted, blurry or dirty license plates. Extensive experiments demonstrate that the average performance of this method is $97.91 \%$ in terms of detection accuracy and the running time is relatively short.

The organization of this paper is as follows. The major works in this area are briefly reviewed and discussed in Section 2 while Section 3 describes a novel LPL method. In Section 4, based on the characteristics of license plates, we devise the proposed scheme to locate license plate in details. The performance of this scheme is demonstrated and discussed in Section 5. Finally, conclusions are drawn in Section 6.

## 2. Previous work

A useful license plate may usually be accompanied by complex backgrounds. Almost all LPL techniques distinguish a license plate from the backgrounds by analyzing features of license plates. Based on these features, these techniques generate several regions that might be a license plate. Then fake regions will be filtered out by using other features. In [10], the authors use edge information to locate the candidate regions. After applying Sobel edge detection on the whole image, several high gradient averaging calculations are used to generate candidate regions and the final license plate is located according to the geometrical feature of license plate. This approach can solve the low contrast and dynamic-range problems, but only still images can be applied in this method and the size of license plate must be fixed. In [11], Hough transform and contour algorithm are used to detect possible license plates regions. This improved method can achieve a higher accuracy and a faster detection speed than traditional Hough transform based methods. However, this approach cannot extract license plates effectively when the boundary of the license plate is blurry or distorted or the images contain other edges around the license plate region. Neural network [12-14] is also widely used for license plate detection. Pulse coupled neural network, time delay neural network and discrete time cellular neural network are some representative ones. Several candidate license plate regions are extracted from the classification results. Adding new license plate features in neural networks can improve the accuracy. A disadvantage of such methods is that they are usually time consuming. In [15], Marker controlled watershed algorithm is introduced to search for candidates. The authors use top-hat transform and morphological reconstruction to get the local maxima and minima. Despite that this method can eliminate quantization error and over-segmentation caused by local minima from noises, this method is not adaptive enough to deal with multiple styles of license plates. Filter-based methods are applied to car images in $[16,17]$. Localization is accomplished by looking for rectangular regions in images containing maxima of response to line filters. Such a technique shows some robustness in finding different types of car images while it suffers from large computational burden. Other ideas, such as support vector machines [18] and Adaboost [19] are also reported to find candidates regions.

All the methods mentioned above need to filter out fake candidates according to some specified features of license plates, such as the ratios of width to height [ $9,11,15,17$ ], rectangularity [ 15,17 ], the number of changes from black to white in a horizontal line in a binary image of vehicles [ 10,11 ], vertical projection map [15] and so on. If a method uses many features to generate candidates, it will be time consuming and many fake regions will be generated. Otherwise, the real license plate might not be included in the candidates generated by fewer features.

License plates are also regarded as regions that are composed of some special lines or pixels. Hence, some algorithms are developed to find such candidate lines or pixels to acquire the license plate. In [20], horizontal and vertical details are found first and then details beyond a threshold are filtered out. After scanning the remaining details, lines that might belong to a license plate are found, and then the license plate, which is a combination of those lines, is located. A similar approach was introduced in [21] that scans the whole image. Only those pixels whose features fit a license plate are kept. However, this method involves a large amount of calculation.

There is another kind of approach on how to find the location of license plates. Since a license plate lies in a two dimensional image, if its position is located in each dimension in turn, the final position will be obtained subsequently. In [22], colors of the license plate background and characters on it are regarded as a unique color combination, then this method scans each row of the whole image and finds the positions of the horizontal lines that fit the selected color combination pattern as the possible vertical positions (noted as $Y$ position in this paper) of the license plate. And the possible horizontal positions (noted as $X$ position in this paper) of the license plate are obtained with the same method. Though color-based methods show better performance, they still have difficulties in locating the license plate in a natural scene, since color is not stable and sometimes there are regions whose colors are similar to the license plate. In [6], based on the fact that characters on a license plate have high distinctive intensities in their backgrounds, a wavelet transform based method is used for extracting important contrast features to detect the desired license plates. The extracted contrast features are projected to two directions to generate several possible $X$ and $Y$ positions of the license plate. However, this paper did not provide a standard to determine which possible $X$ and $Y$ positions are the real positions of a license plate.

From the review above we can see that most algorithms only work well in special application conditions. For example, the method in [10] can only deal with still images while the method in [15] can only detect limited styles of license plates. Otherwise, methods show higher accuracies are usually complicated and time consuming [12-14].

## 3. A novel LPL method

In this section, features of license plates are discussed first. Based on these features, our proposed LPL method is presented.

### 3.1. License plate features

In order to detect a license plate, one should learn about what a license plate is like first. In [23], the authors categorized the factors that can decide the types of plate styles into 'internal' and 'external' ones. These factors, such as rotation angle, number of character lines, character types and formats can strongly change the style of license plates.

Take a typical Chinese license plate as an example, license plates fixed in the front and back of a car have a uniform format,
i.e., they share the same width of 440 mm and height of 140 mm . There are 7 or 8 characters arranged in one line on each license plate. From left to right, the first character is a Chinese character and the second character is a capital English letter which is followed by a dot. The rest of the characters are a combination of Arabic numbers and capital English letters. Every single character has a height of 90 mm which is twice of its width. The total width of a license plate numbers is 409 mm . A typical license plate is shown in Fig. 1.

### 3.2. The proposed LPL method

No matter what method a LPL scheme uses, it usually utilizes one or more robust features of a license plate. It has been shown that a license plate is a region consists of several characters that have high distinctive intensities in their background, and such abundant contrast feature will be used to detect the desired license plates in the proposed scheme. Sometimes preprocesses, including but not limited to, median filtering [10], morphological operation [15] or contrast enhancement [17], need to be implemented first to enhance the features of license plates. In the proposed scheme, histogram equalization and filtering are applied to images if necessary, which will be further discussed in Section 4. There are many methods to gain this contrast feature, such as wavelet transform [6] and Sobel edge detection [10]. When the image is blurry, it may be difficult to find the license plate with traditional methods like Sobel edge detection. A wavelet based method may be more suitable to extract the desired contrast features because it can describe the gradients of an image along different directions.

The process of a two dimensional wavelet transformation to an image is shown in Fig. 2. $G$ stands for a low pass filter while $H$ is a high pass filter. When the input image $A_{j}$ undergoes a wavelet transform, the resulting image will have 4 components, i.e., approximation image $A_{j-1}$, horizontal details $H_{j-1}$, vertical details $V_{j-1}$ and diagonal details $D_{j-1}$. Take $H_{j-1}$ as an example, the input image is first dealt by a low pass filter, leading to a result that low frequencies in the vertical direction are mainly kept. Then the processed image undergoes a high pass filter which allows high frequencies in the horizontal direction retain. As a consequence, horizontal details are enhanced and vertical details are smoothed. The vertical details are generated in a similar way. Wavelet transform can decompose complex information and patterns imbedded in the vehicle pictures into details at different scales and orientations. It can separate the detail information of the license plate from


Fig. 1. A typical Chinese license plate.


| $2 \downarrow 1$ | Resample line, keep even lines |
| :---: | :---: |
| $1 \downarrow 2$ | Resample row, keep even rows |

Fig. 2. Wavelet transform of images.
the whole vehicle images without losing the main information related to the license plate. In addition, fast wavelet transform has been implemented and realized. Based on the good and fast performance of extracting horizontal and vertical details separately, wavelet transform is used in our scheme.

As described in Section 3.1, a license plate comprises several characters which are organized in one or two lines and wavelet transform may extract the significant horizontal and vertical details of those characters. Take the vertical details as an example, in the $V_{j-1}$ sub-image, details are marked with higher values, thus when projecting the vertical details onto the $Y$ axis, there should be a wave crest generated by the character details since all the characters lie in a same horizontal line (image distortion will be discussed in Section 4.4). If such a wave crest in the projection dataset can be located, the $Y$ position of the license plate will be easily detected.

However, most vehicle images are taken under natural scene. There may be other vertical and horizontal details in the images, so there might be other wave crests in the projection dataset. In addition, the position and distinctness of these details are not predictable. Moreover, a change of the sensor placement with respect to vehicles can change the size and clearance of the license plate. As a result, the width, height and position of both the target wave crest and the other wave crests may be different and the target wave crest may even be imbedded in a wider wave crest if there are other details around the license plate. Therefore, the position of the desired wave crest is unpredictable.

In a real world, contrast in an image is unpredictable and could occur in any position of each line. If we think of the pixel values of each line as a finite discrete time series in the $V_{j-1}$ sub-image, then each line is nonlinear and non-stationary, just like the data from other natural phenomena. The projection of the vertical details onto the $Y$ axis is a linear combination of the values of each row. Thus, the projection is also a finite nonlinear and non-stationary discrete time series. If we want to locate the license plate from the projection dataset, a self-adaptive method is needed. Traditional methods such as Fourier transform and Wagner-Ville which are based on linear or stationary assumptions and need a priori basis may not locate the wave crest well. To analyze nonlinear and nonstationary data, Huang et al. [24] developed an adaptive method, named the Hilbert-Huang transform (HHT) that comprises EMD and Hilbert spectral analysis. Beyond time-frequency analysis, EMD is of great usage in that it can adaptively decompose a dataset into different scales. So EMD is applied in our scheme to find the target wave crest from the projection data.

EMD is a data-driven time-frequency technique that adaptively decomposes a signal into a finite set of components called intrinsic mode functions (IMFs). It is found to be a useful tool in extracting physically meaningful information. For one dimensional data, a complicated dataset can be adaptively decomposed into a finite number of components which represent the local different oscillation modes embedded in the original dataset. IMFs can be obtained from an iterative sifting process that continues until the number of extrema reaches a stop criterion [24]. Its good performance of being adaptive to nonlinear and non-stationary data has been verified in many fields. Hence, it is well-suited for analyzing the nonlinear and non-stationary projection data of the extracted details. The EMD algorithm decomposes the signal $x(t)$ as
$x(t)=\sum_{j=1}^{n} c_{j}(t)+r_{n}(t)$
where $c_{j}(t)$ represents the IMFs and $r_{n}(t)$ is the residual. The sifting process algorithm is as follows:
(1) Let $r_{0}(t)=x(t)$ and $j=1$.
(2) Extract the $j$ th IMF component
(i) Let $h_{0}(t)=r_{j-1}(t)$ and $i=1$.
(ii) Identify all local maxima and minima of $h_{i-1}(t)$.
(iii) Find the upper $e_{\max }(t)$ and lower envelopes $e_{\min }(t)$ that interpolate all the maxima and minima respectively.
(iv) Calculate the envelope mean $m_{i-1}(t)=1 / 2\left[e_{\max }(t)+\right.$ $\left.e_{\text {min }}(t)\right]$.
(v) $h_{i}(t)=h_{i-1}(t)-m_{i-1}(t), i=i+1$.
(vi) Repeat (ii-v) until $h_{i}(t)$ becomes an IMF. Then let $c_{j}(t)=h_{i}(t)$.
(3) $r_{j}(t)=r_{j-1}(t)-c_{j}(t), j=j+1$.
(4) Repeat (2-3) until $r_{j}(t)$ matches the stopping criterion [25].

Since the oscillation modes of details of a license plate characters are embedded in the projection dataset and EMD is an adaptive multi-scale decomposition, we have a good reason to assume that, among all the narrow band components decomposed by EMD analysis, one or more components may contain the variation information of the character details. In order to test this assumption, an experiment is conducted in Section 4.2. From the experiment, we find a strong correlation between IMF2 and IMF3 of the projection dataset and variation of details of the characters. In order to locate a license plate from IMF2 and IMF3, we assume that there are fast variations around the license plate because of the characters' details. So we calculate the instantaneous frequency of each point to find the detailed dynamics of IMF2 and IMF3. Now the extracted components are mono-components and Hilbert transform is an ideal tool to calculate instantaneous frequency, then we will have no difficulty in applying it to each IMF separately. For a time series $X(t)$, its Hilbert transform $Y(t)$ is defined as
$Y(t)=1 / \pi P V \int_{-\infty}^{+\infty} X(\tau) /(t-\tau) d \tau$
where PV stands for Cauchy Principal Value. The Hilbert transform $Y(t)$ is a convolution of signal $X(t)$ with the reciprocal of time $t$ emphasizing the local properties of $X(t)$.

Ever since HHT was introduced, many researchers have expanded this method to two dimensional dataset applications. A two dimensional EMD is quite similar to one dimensional EMD. The only difference is that two dimensional EMD has to find the local extrema in a two dimensional dataset in the sifting process. Thus two dimensional EMD is time consuming and may not be acceptable in LPL. In addition, even when the IMFs related to the variation of the license plate are detected, we still need to use traditional methods to locate the license plate in two dimensional IMFs. Hence, in this paper, we employ one dimensional EMD to decompose the one dimensional projection dataset, although some methods [26] have been developed to improve the sifting speed of two dimensional EMD.

The framework of the proposed LPL method is shown in Fig. 3.

## 4. Steps of the proposed scheme

### 4.1. Preprocessing

A LPL method can often be decomposed into several procedures and the subsequent steps' accuracies depend on the preceding ones. For example, according to the discussion in Section 2, some algorithms first find several candidate regions and then filter out fake regions. It requires that the real license plate must be included in the procedure of finding possible license plate regions; if not, no license plates will be detected in the following procedures. When the error rate increases with increment of the amount of calculation, such errors are called accumulative error.


Fig. 3. Framework of the proposed LPL method.
With the purpose of reducing accumulative errors, some preprocessing is needed.

In the proposed scheme, vertical and horizontal details are applied to locate a license plate. Preprocessing is mainly used to reinforce the contrast in an image and reduce the noise, which is composed of the following two steps.
(1) Gaussian filtering: Images taken from cameras may suffer from noise interference, and many filters can be used to solve this problem, e.g., Gaussian filter, median filter, etc. Since Gaussian filter has rotational symmetry, it can filter noise in every direction. Hence, in our work, the Gaussian filter is adopted to remove noises. Gaussian filter is described by the following equation:
$h[i, j]=\frac{1}{\sqrt{i=0} \sum_{j=0}^{1-1} g[i .,]}(f[i, j] \times g[i, j])$
where $f[i, j]$ and $g[i, j]$ denote the original image and the Gaussian kernel, respectively, and $h[i, j]$ is the result image.
(2) Histogram equalization: Since illumination conditions vary a lot in real world, the luminance plane will be equalized by the following equation if no license plate is detected:
$f\left(L_{i}\right)=\left(L_{i}-L_{\text {min }}\right) /\left(L_{\text {max }}-L_{\text {min }}\right) \times 255$
where $L_{i}$ is the original luminance value, and $L_{\max }$ and $L_{\min }$ correspond to the maximum and minimum luminance values, respectively.

Nonetheless, Gaussian filtering also blurs the image a little bit and both filtering and histogram equalization will increase the calculation time. Hence, preprocessing is exploited only when no license plate is detected.


Fig. 4. Car images.


Fig. 5. Projection of vertical details onto the $Y$ axis.

### 4.2. Detect the $Y$ position of a license plate

As shown in Fig. 4, there are four images ( $640 \times 480$ pixels each) taken from different angles and distances. It has been discussed that wavelet transform is used to extract the horizontal and vertical details of an image. In order to reduce the calculation time, the simplest Haar wavelet basis is applied to obtain the vertical and horizontal details, and our experiments show that one level wavelet transform can extract enough details. In Fig. 5, curves $\mathrm{a}, \mathrm{b}, \mathrm{c}, \mathrm{d}$ are the projections of the vertical details of the images shown in Fig. 4 onto the $Y$ axis, respectively. The abscissa in Fig. 5 refers to the $Y$ position of a detail image (whose value is half of the real position in the original image, since the width/length of the detail image decomposed by wavelet transform is half of the original one) and the projection value is used as ordinate. The red part indicates the real $Y$ position of the license plates. As we can see, thanks to different distances between the viewpoint and the cars, the desired wave crest could be in any position in the projection dataset. And due to complicated backgrounds, the desired crest could be either higher or lower than peripheral crests in different images. Furthermore, stochastic noises in the images may lead to a result that the desired crests are hidden in numerous burrs. Hence, it may be difficult to locate the desired wave crest in the original projection line. EMD analysis is further applied to accomplish this task.

Take Fig. 4(a) as an example, the original image is decomposed by one level Haar wavelet transform. The horizontal and vertical subbands are shown in Figs. 6(a) and (b), respectively. After getting the projection of the values of all the pixels in Fig. 6 (b) onto the $Y$ axis, the EMD analysis of the projection is shown in Fig. 7. In this case, the original dataset is decomposed into six IMF components. Clearly, the projection is decomposed into different frequency bands from high to low. IMF1 shows the highest
frequency component. At the same time, the amplitude and the standard deviation of the amplitude of IMF1 is the lowest. It implies that the stochastic noise may be contained in IMF1. Similarly, the rest IMFs may contain other higher frequency details, respectively. Since the Hilbert transform can emphasize the local properties and the region of license plate contains abundant local properties, i.e., the extracted contrast features, the Hilbert transform of some IMFs may emphasize the region of the license plate. For the sake of enlarging the emphasis, the square of the Hilbert transform, as shown in Fig. 8, is calculated. Here, in order to distinguish IMF from the square of the Hilbert transform of IMF, the latter is named shIMF.

As we can see from Fig. 8, the positions of the maxima in the first several shIMFs may have a correlation to the $Y$ position of a license plate. To study the relation between the positions of these maxima and the $Y$ positions of a license plate, one hundred randomly selected images from an online database [27] are used for a test, using the maxima of the first four shIMF components. Extensive experiments show that increasing the number of maxima used in the test will increase the calculation time, thus only the first three maximal maxima are used to study the correlation. The result is shown in Fig. 9. Respectively, $A, B, C$ stand for the number of the positions of the maximal maximum, the second maximal maximum and the third maximal maximum that lie in the interval of the wave crest which stands for the $Y$ position of a license plate. Sometimes, the maximal, second or third maximal maximum may all appear in the position of a license plate. $D$ stands for the number of images that the position of license plates cannot be located using the positions of the first three maximal maxima by this test.

A LPL system should reduce its calculation time as much as possible, thus it is desired that the position of the license plate can be detected with as few maxima as possible. Fig. 9 shows that the maximal maxima on shIMF2 and shIMF3 have the biggest correlation with the positions of license plates. In other words, details of license plates (or other regions that have similar details) are mainly contained in IMF2 and IMF3. One more test result shows that the maximal maximum on shIMF2 added by shIMF3 has a higher correlation with the positions of the license plates. Hence, IMF2 and IMF3 are used in the proposed LPL method. For the example image (Fig. 4(a)), the shIMF of IMF2 added by IMF3 is shown in Fig. 10. Respectively, the $Y$ positions of the first three maxima are 169, 138 and 183.

If we ignore the first several ( $n / 2$ or $n / 2+1, n$ is the number of the IMFs) higher frequency components of the decomposed IMFs, the projection can be reconstructed by the rest IMFs and the contour of the projection will be kept. The reconstructed projection of Fig. 4(a) is shown in Fig. 11 and the $Y$ position of the license plate is between about 158 and 191. As shown in Figs. 10 and 11, both the $Y$ positions of the maximal maximum and the third maximal maximum lie in the interval of the $Y$ position of the license plate. If the position of the maximal maximum is located, the position of the wave crest which indicates a license plate will


Fig. 6. Result of wavelet transform: (a) horizontal details and (b) vertical details.


Fig. 7. IMFs and residual of the projection of the vertical details of Fig. 4(a) onto the $Y$ axis.


Fig. 8. Square of the Hilbert transform of each IMF.
be located. In order to get the vertical boundaries of a license plate in the reconstructed projection, one has to find the two minima in the reconstructed projection beside the $Y$ position of the located maximum, which indicates the upper and lower boundaries of a license plate. In our method, the position of the maximal, second and third maximal maximum is used in turn to indicate the possible position of the license plate until one license plate is found. If they all fail to detect the license plate, we will consider that no license plate exists in the processed image. The final located $Y$ position of the license plate is shown in Fig. 12.


Fig. 9. Relations between the poison of the maxima and the license plate.


Fig. 10. shIMF of IMF2 + IMF3.

### 4.3. Detect the $X$ position of a license plate

After the $Y$ position of the license plate is acquired, the projection of the horizontal details onto the $X$ axis will be decomposed by EMD analysis and the $X$ position of a license plate is detected in a similar way. The result of EMD analysis and the reconstructed projection is shown in Figs. 13 and 14, respectively. The final located license plate is shown in Fig. 15.

In Fig. 14, there seems to be two wave crests (100-225) that cover the horizontal location of the license plate. In such a case, the right wave crest (175-225) is considered as a gentle hump on


Fig. 11. The original projection of the vertical details onto the $Y$ axis and the reconstructed projection.


Fig. 12. $Y$ Position of license plate.


Fig. 13. IMFs of the projection of the horizontal details onto the $X$ axis.
the right slope of a wider wave crest (100-225). When a maximum is located, the scheme will calculate the differences in value between the maximum and the two minima beside it. If the ratio of the two differences is beyond a selected threshold, it is believed that there might be a hump on the desired wave crest and thus the next (prior) minimum will be used as the detected boundary of the license plate.

The whole license plate location steps are indicated in Table 1.

### 4.4. Influence of distortion of image

In Section 3.2, it is assumed that all the characters are in a same horizontal line. Sometimes, a change of the relative placement between a viewpoint and a vehicle will change the shape of a license plate, which is called perspective distortion. The performance of the proposed scheme under this situation will be discussed in this part.


Fig. 14. Reconstructed projection of the horizontal details onto the $X$ axis.


Fig. 15. Final located license plate.

The proposed approach utilizes the significant detail information of the characters on the license plate to accomplish the location task. Those characters, e.g., Chinese characters, capital English letters and Arabic numbers, consist of not only horizontal and vertical lines, but other direction lines. In another word, when perspective distortion of the license plate in an image occurs, the characters on the plate still consist of horizontal and vertical details which can be extracted by wavelet transform. Thus, when projecting the vertical details onto the $Y$ axis, there still will be a wave crest that indicates the $Y$ position of a license plate.

In order to illustrate this issue, a picture taken from reference [28] is used as the background of a license plate. This image contains pattern structures of different scales. As shown in Fig. 16, a horizontal and distorted line of characters are added to the picture using Adobe Photoshop CS4.

The projections of the vertical details of the license plates in Fig. 16 onto the $Y$ axis are shown in Fig. 17. In Fig. 17, the blue line stands for original projection and the red one stands for reconstructed projection. As illustrated in Fig. 17, both the projection of the normal license plate and the distorted plate has a wave crest that indicates the position of the license plate. However, thanks to the distortion, the wave crest's width of the distorted plate is wider than the normal one. Thus in this case, the final located license plate will contain some non-license plate region as shown in Fig. 18.

## 5. Experimental setup and results

### 5.1. License plate location result

In our experiment, altogether 765 images, including 16 images taken at night, are used to examine the feasibility of the proposed scheme. Among all the images, 580 of them can be found in an online image database [27] and 153 Chinese images are taken from

Table 1
Steps of license plate location.
Input image I

1. Preprocessing (if necessary)
(1) Gaussian filtering
(2) Histogram equalization
2. One level Haar wavelet transform
3. Get the projection $p_{1}$ of the HL subband onto the $Y$ axis
4. Apply EMD analysis to $p_{1}$, get n IMFs
(1) Use the latter $n / 2-1$ (or $n / 2$ if the reconstruction is too rough) IMFs to reconstruct $p_{1}$
(2) Apply Hilbert transform to IMF2 + IMF3, get shIMF
5. According to the first three maximal maxima of shIMF to locate the $Y$ position $Y_{1}$ of the license plate 6. Get the accurate location $Y_{2}$ of the $Y$ position
6. Get the projection $p_{2}$ of $Y_{2}$ in the LH subband onto the $X$ axis
7. Apply EMD analysis to $p_{2}$ and get the horizontal location $X_{1}$ of the license plate
8. Get the accurate location of the final license plate


Fig. 16. (a) A normal license plate and (b) a distorted license plate.


Fig. 17. Projection of a normal license plate and a distorted license plate.


Fig. 18. Location result: (a) normal license plate and (b) distorted license plate.
an expressway toll station. Some blurred, dirty, distorted and shadowed images are also taken into consideration and such images are about two fifths of the total images. Each image has a size of $640 \times 480$ pixels and contains at most one license plate. The proposed method was implemented on a personal computer with an AMD Athlon 2.99 GHz CPU using LabVIEW2011.

The performance of applying the proposed scheme to different types of license plates is shown in Table 2. The original images listed in Table 2 are shown in Fig. 19. As we can see from Table 2 and Fig. 19, this method can process vehicles from different
countries. Fig. 19(a) to (c) represent vehicles from Greece, China and U.S., respectively. The rest pictures in Fig. 19 are all Greek vehicles which represent other kinds of license plates listed in Table 2. The characters of these license plates include Arabic numbers, Chinese characters and English characters. This method can detect the license plate under different illumination conditions, such as images taken in daylight (Fig. 19(a)), night with flash (Fig. 19(d)) and images with shadow in the region of the car or the license plate (Fig. 19(e)). Other conditions, such as perspective distortion (Fig. 19(g)), blurry (Fig. 19(h)), dirty (Fig. 19(f)) and

Table 2
Result for different license plate styles.

| License plate styles | Number of images | Correct rare (\%) | Error rate (\%) | Example images |
| :---: | :---: | :---: | :---: | :---: |
| Greece | 580 | 98.10 | 1.90 |  |
| China | 153 | 98.04 | 1.96 |  |
| U.S. | 32 | 93.75 | 6.25 |  |
| Night | 16 | 87.50 | 12.50 |  |
| With shadow | 74 | 97.30 | 2.70 |  |
| Dirty and with shadow | 160 | 94.38 | 5.62 |  |
| Distortion | 66 | 100 | 0 |  |
| Blurry | 7 | 100 | 0 |  |



Fig. 19. Example images used in the proposed scheme: (a) Greek vehicle (b) Chinese vehicle (c) U.S. vehicle (d) night with flash (e) with shadow (f) dirty and with shadow (g) distortion and (h) blurry image.
different color vehicles (Fig. 19(a) to Fig. 19(d)), are also examined. The average correct rate of the proposed method is $97.91 \%$ and the average runtime of each image is about 0.58 s . When the preprocessing is applied, the average runtime is 0.62 s .

In order to show advantages of the proposed method, Table 3 shows comparisons of our proposed method with several methods mentioned in Section 2. Compared with the other methods listed in Table 3, the accuracy of our method is the highest and the runtime is relatively short at the same time. In our future work, the proposed algorithm will be further improved to achieve a shorter runtime.

### 5.2. Discussion

When we review the test results, we find that some of the acquired license plates, such as the images shown in Fig. 20, are not satisfying. The located license plates contain too many nonlicense regions. As described in Section 4, the position of a license plate is obtained according to the position of a wave crest in the projection data. A wider or higher detected license plated region means that a wider wave crest is detected in the projection data. There are mainly three reasons that may cause such unsatisfying results: (1) Similar details like the radiator grilles of a vehicle happen to appear around the license plate region, thus projection of the vertical or horizontal details will have an unsatisfying wave crest which is wider than the crest formed by the license plate. (2) As Fig. 11 shows, the $Y$ position is located according to the projection of the vertical details reconstructed by EMD analysis. If the reconstructed projection contour is too rough, the needed wave crest may merge with the nearby fake wave crest and thus the located license plate will merge with the nearby non-license plate region. (3) Perspective distortion discussed in Section 4.4 may be another reason. If an unsatisfying location is caused by the second reason, we can add a higher frequency IMF component to reconstruct a more accurate projection contour. In addition, few unsatisfying locations are caused by the first reason. In this case, traditional method such as the vertical projection map method mentioned in [15] may be used to solve this problem.

Of the 765 images, 16 of them failed to be located. After analyzing the 16 images, we find that most of them contain other similar details, such as other characters on the car. As a consequence, the EMD analysis will mistakenly detect the wave crest that indicates the region containing the similar contrast features instead of the true wave crest. To be specific, it is even harder to
locate the license plate when the license plate region is blurred or other similar contrast features exist at the same time. Fig. 21 shows an example image that cannot be detected by the proposed method. In Fig. 21(a), a circuit diagram whose details are similar to the license plate characters' is painted on the hood. In Fig. 21(c), the red part indicates the position of the license plate and the green part is the wave crest found by the proposed scheme. From Fig. 21(c) we can see that the circuit diagram painted on the hood is detected as the license plate.

In fact, we use details extracted by wavelet transform to locate the license plate in our work. The experimental results show that if the details can be extracted effectively, the performance of the proposed method is satisfying. As Table 3 shows, EMD analysis can well decompose the details generated by Haar wavelet transform and then locate the license plate. Only in some coincidental situations, such as regions contain similar details appear in a car image, our method may mistakenly find a fake region.

On the other hand, in the proposed method, only the maximal maximum (or the second or third maximal maximum) is used to


Fig. 21. A failed example: (a) the original image, (b) the extracted vertical details and (c) projection of the vertical details onto the $Y$ axis.

Table 3
Methods comparison.

| Method | Correct rate (\%) | Error rate (\%) | Execution time per image (s) | Method background, C: CPU, S: image size |
| :---: | :---: | :---: | :---: | :---: |
| Ref. [9] | 97.16 | 2.84 | 0.158 | C: 1.8 GHz S S: $640 \times 480$ |
| Ref. [10] | 97.1 | 2.9 | 0.532 | C: Pentium 4, 3.2 GHz; S: $867 \times 623$ |
| Ref. [18] | 90 | 10 | 1.28 | C: Pentium 3, 800 MHz ; S: $340 \times 240$ |
| Ref. [20] | 97.33 | 2.67 | 0.18 | C: 2.4 GHz ; S: $400 \times 300$ |
| This paper | 97.91 | 2.09 | 0.58-0.62 | C: Athlon, 2.99 GHz ; S: $640 \times 480$ |



Fig. 20. Unsatisfying locations.
find the position of a license plate. In other words, only one possible position of a license plate is located each time and if the possible position is the real position of a license plate, no more calculation is carried on. If none of the three possible positions indicates the region of a license plate, the method will conclude that no license plate exits in the processed image. Therefore, images contain more than one license plates cannot be effectively detected.

In addition, one point that deserves to be mentioned here is that the EMD analysis method itself has some shortcomings, one of which may affect the correct rate of the final result, i.e., the end effects of EMD [25]. This may affect the result when finding the rough position of the wave crest. To solve this problem, many methods have been proposed [29,30,31]. Nevertheless, most license plates lie around the center of the whole image, and we do not use the data around the two ends of the reconstructed projection dataset when finding the location of a license plate in this paper. Only those license plates that lie on the fringe of the whole image and are very small compared to the size of the whole image cannot be located by our method.

The location of the license plate number is uncertain in a vehicle picture which consists of abundant complex non-license plate information. In order to recognize the license plate number, its location must be detected first. In reality, the vehicle picture is taken under unpredictable conditions, leading to a result that the resolution, backgrounds or the types of the license plate of the vehicle pictures are usually different. Moreover, most practical applications need to recognize the license plate number as fast as possible. Hence, a fast and robust LPL approach that can withstand different factors is significant.

## 6. Conclusion

In this paper, a novel method is proposed to locate a license plate in an image. Compared with related license plate location methods, the proposed method is much less restrictive and more robust. The proposed LPL method mainly consists of three steps, i.e., preprocessing, detecting the $Y$ position and the $X$ position by wavelet transform and EMD analysis. Based on Haar wavelet transform, we first get the horizontal and vertical details of an image. After getting the projection of the vertical details onto the $Y$ axis, EMD analysis and Hilbert transform are used to find the $Y$ position of a license plate. After the acquired $Y$ position, another EMD analysis is applied to locate the $X$ position of a license plate.

The major contribution of this paper is that we propose a new and robust approach to detect license plates which combines wavelet transform and EMD analysis. The license plate is detected from a new perspective, i.e., the details of a license plate is regarded as a component of the projection of the details of the whole image and such components can be extracted by EMD analysis. By analyzing the components decomposed by EMD analysis, the position of a license plate is acquired. In contrast to traditional schemes reported in the literature, the proposed method can detect various types of license plates with a high accuracy, including different countries, different colors, different illumination conditions, different character types and perspective distortion, dirty or blurry images. According to the detailed extensive experimental results and comparison with other methods, we may conclude that our method can locate the license plate accurately without ignoring the speed of the whole system. In addition, the correct rate is improved a lot in this model since EMD analysis is highly adaptive to nonlinear and non-stationary dataset. Our procedure can raise the accuracy for the whole license plate recognition process. Nonetheless, our method still has some limitations, which will be studied in the future. One disadvantage
of the proposed method is that only one license plate can be located. In addition, the processing speed also needs to be improved.

## Conflict of interest

None declared.

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