A License Plate Image Enhancement Method in Low Illumination Using BEMD

Wensi Cao
North China Institute of Water Conservancy and Hydroelectric Power, Zhengzhou, 450011, China
Email: eegscaows@ncwu.edu.cn

Jingbo Liu
School of electrical engineering, Southwest Jiaotong University, Chengdu, 610031, China
Email: ljb79@126.com

Abstract—Recognizing vehicle license plate image captured in low illumination place is a difficult problem. To solve the problem, this paper proposes a new license plate image enhancement method using bidimensional empirical mode decomposition (BEMD) technique. BEMD is a 2D data-driven adaptive nonlinear signal decomposition approach derived from the 1D empirical mode decomposition (EMD). In the proposed algorithm, the main procedures are designed as the following: first, the license plate image is denoised by the use of alpha-trimmed mean filter and transformed from RGB color space into HSV color space, then, extract the V component to form intensity image for enhancement; second, with BEMD method, the intensity image is decomposed into a number of intrinsic mode functions (IMF) as well as a residual image; last, the brightness of residual image is adjusted using Retinex theory, and fused with the IMF images to achieve enhancement of license plate image. Experimental results show the proposed method provides superior performance over traditional schemes for license plate image enhancement in low illumination.

Index Terms—image processing, license plate image enhancement, bidimensional empirical mode decomposition, low illumination, brightness adjust

I. INTRODUCTION

With the rapid development of intelligent transportation systems, the applications of license plate recognition (LPR) are widely used [1], such as the monitoring of unsupervised park, traffic law enforcement, and so on. In practical LPR systems, the source image is not always ideal for recognition for noise causes the significant degradation of image quality, especially in a low illumination environment. The requirement for a clean source license plate image such as adequate lighting conditions, expensive camera, and high quality video capture systems is impractical for most locations.

Many image enhancement schemes are to improve the visual quality of images. Among them, contrast enhancement is a popular approach and has been widely used in many display related fields, such as digital camera, medical analysis, and so on. It is well-known that an image with wider histogram dynamic range generally has better contrast. Consequently, to enhance the contrast in an image can be achieved by histogram equalization which expands image’s histogram distribution. Besides traditional histogram equalization, other approaches are proposed to improve quality of the license plate image. Lin et al. [2] propose a nonuniform interpolation method which was adopted to reconstruct license plate image from a series of low resolution vehicle license plate images. Abolghasemi and Ahmadyfard [3] improve the work of Zheng et al. [4] by enhancing the low quality image, extracting the vertical edges, and constituting some regions as plate regions using morphological filtering. Nevertheless, these algorithms cannot meet the requirements for they process the whole image and be easily interference by noise as traditional image enhancement methods.

As image features often correspond to variations in spatial frequencies, Fourier based methods are often employed for image enhancement powerfully. Nevertheless, they rely on a projection onto a linear set of predefined bases. This limits the abilities of Fourier methods when processing real world images [5]. To that end, we consider image enhancement via Empirical Mode Decomposition (EMD). It is an efficient and adaptive data driven signal processing method that is originally developed by Huang et al. in [6]. Unlike Fourier methods, the approach is fully adaptive and makes no known prior assumptions of the data. It provides a powerful tool to analysis nonlinear and nonstationary signals by obtaining its local features and time-frequency distribution. Its principle is to decompose adaptively a given signal into frequency components, called intrinsic mode functions (IMF). These components are obtained from the signal by means of an algorithm called sifting process. Different applications as medical signals analysis have showed the effectiveness of EMD. When EMD extended to analyze 2D data, it may be called as bidimensional empirical mode decomposition (BEMD) [7, 8]. Decomposition of an image into intrinsic mode functions (IMFs) can be applied successfully in various image processing problems, for example, texture analysis [9], image fusion [10], and image compression [11]. In practice, the 1D EMD has also been applied to images to obtain IMFs [12],
which process each row and/or each column of the 2D data. However, it has been found that the result of the 1D EMD implementations is poor compared to the standard 2D procedure because of the fact that the former ignores the correlation among the rows and/or columns of a 2D image [13]. So, we adopt the BEMD method to decompose the intensity image in our method.

II. BIDIMENSIONAL EMPIRICAL MODE DECOMPOSITION

A. The 1D Empirical Mode Composition

Intrinsic mode functions (IMF) are obtained from the signal by means of an algorithm called sifting process, which extracts locally for each mode the highest frequency oscillations out of original signal. For a 1D signal \( s(k) \), the decomposition of the signal into IMFs by EMD algorithm is given by:

\[
s(k) = \sum_{j=1}^{n} c_j(k) + r(k),
\]

where, \( r(k) \) is the residual signal which represents an overall trend within the signal is a monotonic function. \( c_j(k) \) consists of the different scale IMF.

The first IMF contains the highest local frequencies of oscillation or the highest local spatial scales; the final IMF contains the lowest local frequencies of oscillation. Furthermore, each IMF needs to satisfy two conditions: (a) in the whole data sets, the number of pole and the zero-crossing should be equal or differ at most by one; (b) at any point, the mean of the two envelopes associated with the local maxima and local minima are approximately zero. The decomposition structure of EMD is shown in Fig.2. To illustrate the EMD, we show an EEG signal decomposed in 8 IMF’s in Fig. 3 (from top to bottom).

The focusing algorithm for 2D is shown as follows [7]:

1. Initialize: \( r_0 = s \) (the residual) and \( j = 1 \) (index number of IMF),
2. Extract the \( j \)th IMF:
3. (a) Initialize \( h_0 = r_{j-1}, i = 1 \),
   (b) Extract local minima/maxima of \( h_{j-1} \),
   (c) Compute upper envelope and lower envelope functions \( x_{j-1} \) and \( y_{j-1} \) by interpolating, respectively, local minima and local maxima of \( h_{j-1} \),
   (d) Compute \( m_{j-1} = (x_{j-1} + y_{j-1}) / 2 \) (mean envelope),
   (e) Update \( h_j := h_{j-1} - m_{j-1} \) and \( i := i + 1 \),
(f) Calculate stopping criterion (standard deviation $SD_{ji}$),
where,
\[
\sum_{k=1}^{K} \left[ \frac{(h_{ji(k)}(k) - h_{ji-1}(k))^2}{h_{ji-1}^2(k)} \right] \leq SD
\]
h_{ji-1}(k) and $h_{ji}(k)$ represent two successive sifting iterates. The SD value is usually set to 0.2-0.3.

(g) Repeat steps (b) to (f) until $SD_{ij} \leq SD_{MAX}$ and put then $s_j = h_i$ (ith IMF).

4. Update residual $r_j = r_{j-1} - s_j$,
5. Repeat steps 2 to 4 with $j := j + 1$ until the number of extrema in $r_j$ is less than 2.

\[\text{Fig.3. Illustration of the Empirical Mode Decomposition: 1st until the 8 modes (from top to bottom)}\]

Once the first set of ‘siftings’ results in an IMF, define $c_1 = h_{j1}$. $c_1$ contains the finest spatial scale in the signal. Generate the residue $r_1$, $r_1 = I - c_1$. $r_1$ contains information about larger scales. Repeat sifting to find additional components $r_2 = r_1 - c_2$, ..., $r_n = r_{n-1} - c_n$.

The superposition of all the IMF reconstructs the data: $I = \sum_{j=1}^{n} (c_j) + r_n$.

B. BEMD

BEMD is two-dimensional extensions of EMD. In two dimensions, BEMD has its unique priorities for adaptively extracting the different frequency components of signals. When used to process the image, first it needs to find the locally extreme interpolation surface. Every mode (IMF) contains information of a specific scale, which is conveniently separated. IMFs represent the high and low frequency components of the original image. Spatial information is retained within the mode. Let $x(m,n)$ be the image to be processed, the sifting processing to find the IMFs of an image may be briefly summarized as the following steps [15]:

1. Find all the amplitudes and positions of the local minima and maxima in the image space:
\[\text{in}\_k = x(m,n),\]
where $l = 1 \cdots L$ denotes the IMF number, and $k = 1 \cdots K$ is the iteration number, in the sifting.

2. Generate the upper and lower envelopes by using appropriate surface fitting techniques. We use the Fast RBF [13] interpolation technique. Denote the upper and lower envelopes as $e_{upper}(m,n)$, $e_{lower}(m,n)$ respectively.

3. For each location $(m,n)$, calculate the mean envelope $e_{mean}(m,n)$ of the upper and lower envelopes:
\[e_{mean}(m,n) = \frac{1}{2}(e_{upper}(m,n) + e_{lower}(m,n)),\]

4. Determine the first estimate of an IMF by subtracting the mean surface from the input signal:
\[h_{lk}(m,n) = \text{in}\_k (m,n) - e_{mean}(m,n),\]

5. Check if the mean signal $e_{mean}(m,n)$ in step 4 is closed enough to zero or not. The process stops when the mean envelope is close enough to zero.
\[|e_{mean}(m,n)| < \varepsilon, \quad \forall(m,n)\]
The IMF is defined as the last result of step 4.

\[c_l(m,n) = h_{lk}(m,n),\]

If not, take the resulting signal from step 4 as input signal and repeat the process from step 1 for a sufficient number of times.

6. The next IMF is found by starting over from step 1; now treat the residue as the input signal.
\[\text{in}\_k+1 (m,n) = h_{lk}(m,n),\]

After the IMF $c_l(m,n)$ is found, define the residue $r_l(m,n)$ as:
\[r_l(m,n) = \text{in}\_k (m,n) - c_l(m,n),\]

6. The next IMF is found by starting over from step 1; now treat the residue as the input signal.
\[\text{in}\_k+1 (m,n) = r_l(m,n),\]

7. Steps 1–6 can be repeated for all subsequent $r_j$. The BEMD is finished when the residue does not contain any extreme points. The image can be expressed as the sum of the IMFs and the last residue.

\[I(m,n) = \sum_{j=1}^{l} C_j(m,n) + r_l(m,n),\]
(salt-and-pepper) noise. Poor illumination often causes Gaussian noise arises in an image. Many methods are used to remove the noise, such as mean filtering. As a statistical operator, its effect is to smooth the image more, to remove more detail while giving greater emphasis to the large structures. Another commonly used statistical filter is the median filter. As the median is a pixel value drawn from the pixel neighborhood itself, it can restrain noise as well as protect details of image. The alpha-trimmed filter is one kind of Order-Statistics filters as median filter. In general, the mean filters are well suited for random noise like Gaussian or uniform noise. Median filters are particularly effective in the presence of both bipolar and unipolar impulse noise. The alpha-trimmed filter is useful in situations involving multiple types of noise, such a combination of salt-and-pepper and Gaussian noise [14]. We take this method to remove the noise of license plate image.

In image, suppose that the \( \lfloor \frac{d}{2} \rfloor \) lowest and the \( \lceil \frac{d}{2} \rceil \) highest gray-level values of \( g(s,t) \) in the neighborhood \( S_{st} \) are deleted. Let \( g_{r}(s,t) \) represent the remaining \( mn-d \) pixels. A filter formed by averaging these remaining pixels is called an alpha-trimmed mean filter [14]:

\[
\hat{f}(x,y) = \frac{1}{mn-d} \sum_{(s,t) \in S_{st}} g_{r}(s,t),
\]

(11)

Where the value of \( d \) can range from 0 to \( mn-1 \). The example is shown in Fig.4.

![Fig.4. Denoising by filter](image)

2. HSV transformation

License plate images captured from CCD or digital camera are usually expressed in RGB color space. Enhancement of the low contrast image is mainly concerned about the brightness. In the HSV color space, \( V \) stands for value which describes the extent of the color's brightness. It is defined as the largest component of a color and is independent of the \( H \) (hue) and \( S \) (saturation). So, an HSV transformation is carried out on the color composites of true color image to generate the intensity image \( V \). Due to mainly concerning the brightness, the \( V \) is used only, which is translated by the following formula:

\[
V = \max(R, G, B),
\]

(12)
As observed in the IMFs, the edges are preserved better and are more continuous in the first IMF, which reflect the overall spatial structure of the image in more detail compared to higher order IMFs. This property will be most helpful when the signal is reconstructed for edge enhancement purpose. If the first IMF receives higher weights, an image with more visible edges will be produced after reconstruction. The higher order IMF basically contains low-frequency characteristics and lacks local spatial structure. The method of this paper can decompose the image with such an appropriate pace that the residue contains only the general information of the image after the third level of decomposition.

C. Adjusting Brightness

After decomposition, the residue expresses the lighting component or noise of the image. Since the noise of image has been remove mostly when preprocessing image, then it just needs to take certain transformation to residue component to make the intensity component of the visible image prominent.

The Retinex theory proposed by Land and McCann is the first attempts at developing a computational model for human color constancy [16]. Based on it, an image consists of light and reflectivity:

\[ I(x, y) = L(x, y) * R(x, y), \]  

\[ I(x, y) \] is the original pixel value, \( L(x, y) \) is the approximate light distribution pixel value and \( R(x, y) \) is reflectance. After decomposition, we can get a number of IMFs and a residual, residue can be regarded as estimates of the brightness of light, so the image reflectance can use the following formula to estimate:

\[ R(x, y) = I(x, y) / L(x, y), \]  

To increase the brightness in the dark zone and dynamic range compression of image, adjust the light to:

\[ \hat{L}(x, y) = L(x, y)^\gamma, \]  

\( \hat{L}(x, y) \) is the renewed brightness, \( \gamma \) has different parameters for variation image. Then, new residue intensity image can be expressed as:

\[ \hat{I}(x, y) = \hat{L}(x, y)^\gamma * R(x, y), \]  

D. Image Fusion

Image fusion is an image processing technique that can combine multiple images of the same scene with complementary information to generate a new composite image with better quality and more features [17, 18, and 19]. The 2D decomposition by sifting process of an image provides a representation that is easy to interpret. Every mode (IMF) contains information of a specific scale, which is conveniently separated. Spatial information is retained within the mode. When understanding the decomposition process, IMFs can be seen as images. An EMD-based image fusion scheme was described in [20]. It decomposes each channel (RGB) of the original image using EMD to obtain their IMFs. The weighted method is adopted to merge IMFs with different frequency.

BEMD produces a fully two dimensional decomposition of the data, all the IMF images and residue image have the same number of columns and rows as the original image without subsampling. Therefore, the original image may be completely reconstructed without information loss or distortion by adding all the IMF images to the residue image. So, the IMFs of the intensity image are merged with the new residue intensity image \( I'(x, y) \) to get a new intensity image. Let \( I_{IMF} \) and \( I_R \) represent the IMF image and residue image respectively, \( i = 1 \cdots L. \) Then, the fused image can be obtained by:

\[
F = \sum_{i=1}^{L} I_{IMF} + I_R
\]

\[ I_R = I'(x, y) \]  

Transform the new intensity image back to the original RGB space with an inverse HSV transformation then it generates the enhanced license plate image. The results are shown in Fig.9. The enhancement result is compared with by using traditional histogram equalization (HE) and contrast stretch (CS) method.
IV. EXPERIMENTS AND RESULTS

Our method is illustrated on some vehicle license plate images captured in low illumination. And we also enhance the license plate by using traditional histogram equalization and contrast stretch method to compare with our method. The experimental results of second example are shown in Fig.10 respectively. To stop the sifting process, we used the standard deviation (SD). We have used SDMAX between 0.35 and 0.75.

In Fig.10, (a) is the origin image to be processed, which is dim in the picture for captured with poor lighting; the result of noise reduction with alpha-trimmed mean filter is shown in (b); the intensity image composed by the V component of the image in HSV color space is shown in (c); the image (c) is expanded into three layers (mode1–mode 3) and one residue image by using BEMD algorithm, as shown in (d) to (g), it is obvious that the scale is becoming larger and larger from layer1 to layer3, high frequency IMF represents illumination information; last, three pictures on the bottom row give the results enhanced by histogram equalization (HE) method, contrast stretch method and our. The experimental results of another example are shown in the section III, the similar effect is demonstrated.

From these two examples, we can see that license plate image enhancement method based on BEMD technique can make better than the traditional method.

V. CONCLUSIONS

Effect of license plate recognition is bad when the image captured in place where the light is dim. To cope with the problems, this paper uses the BEMD technique to adjust the luminance in the license plate images for increasing license plate recognition accuracy. It is performed to decompose image, IMFs as well as residue are obtained. Then, Retinex theory is used to adjust the brightness of residue image. Finally, the sum of IMFs at different scales and residue image adjusted are taken to construct new image. Our method can suitably adjust both overexposure and over-dark images to enhance the contrast of the license plate images. It is different from general method which merely strengthening and adjusting the places of over-exposure darker. Experiments prove that the proposed method is superior to traditional
enhancement methods for enhancing the license plate image.

ACKNOWLEDGMENT
This work is supported by the Natural Science Foundation of the Education Department of Henan Province (2011A470005)

REFERENCES

Wensi Cao, Kaifeng County, Henan Province, 1978.03. He received his B.Eng. in 2000, in Zhengzhou University, Zhengzhou, China. He received a master’s degree in Zhengzhou University in 2007; he is a teacher at North China Institute of Water Conservancy and Hydroelectric Power, Zhengzhou, China. His major fields of study are in the areas of signal processing, and power electronics.

Jingbo Liu, Zhenping County, Henan Province, 1979.07. He is a Ph.D. student at Southwest Jiaotong University, Chengdu, China. He received his B.Eng. in 2000, in Zhengzhou University, Zhengzhou, China. He was a student member of China Computer Federation (CCF). His major fields of study are in the areas of image processing, pattern recognition, and video surveillance.