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A TRAFFIC SIGN MOTION RESTORATION MODEL BASED ON BORDER DEFORMATION DETECTION

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***Abstract*--The current technology development in the field of motor vehicle Driver Assistance Systems (DAS) is progressing; in this the safety problems associated with automatic driving have become a hot issue in Intelligent Transportation. The traffic sign is one of the most important tools used to reinforce traffic rules. However, traffic sign image degradation based on computer vision is unavoidable during the vehicle movement process. In order to quickly and accurately recognize traffic signs in motion-blurred images in DAS, a new image restoration algorithm based on border deformation detection in the spatial domain is proposed in this paper. The border of a traffic sign is extracted using color information, and then the width of the border is measured in all directions. According to the width measured and the corresponding direction, both the motion direction and scale of the image can be confirmed, and this information can be used to restore the motion-blurred image. Finally, a gray mean grads (GMG) ratio is presented to evaluate the image restoration quality. Compared to the traditional restoration approach which is based on the blind deconvolution method and Lucy-Richardson method, our method can greatly restore motion blurred images and improve the correct recognition rate.**

I. INTRODUCTION

With the development of urbanization and the popularization of the automobile, problems associated with road traffic congestion, frequent traffic accidents, and the low efficiency level of road transport has become increasingly more serious [1]. In order to alleviate these problems, a Driver Assistance System (DAS) was designed to help or even substitute human drivers to enhance the safety of driving [2,3]. This system films the road information in its natural scene using a camera that is mounted inside the vehicle, and this information is subsequently processed in real time using a relevant circuit system. Then, the system provides information, such as warnings and tips, to the driver. This can greatly reduce driving risks and enhance road traffic and the driver's personal safety. Strictly complying with the traffic rules can improve vehicle safety performance, and it can also effectively reduce traffic accidents. A variety of important traffic signs placed on the road by the traffic department communicates and supports road traffic rules for the driver [4]. Traffic signs are designed to help drivers with piloting tasks while providing information, such as the maximum or minimum speed allowed, the shape of the road, and any forbidden maneuvers. Therefore, recognition of traffic signs is one of the important tasks of the DAS in Intelligent Transportation.

The fast detection and accurate identification of traffic signs hold great significance for automatic vehicles. The ability to project a sharp image is one of the preconditions to correctly recognizing a traffic sign. However, the relative motion between the camera and the natural scene during the exposure time usually causes motion-blurred images, which will severely affect the image's visual quality. It is a challenge to quickly and accurately identify traffic signs in motion-blurred images. There are two main approaches used to solve this problem. First, by improving the performance index of the camera, we can avoid the motion blur from a hardware perspective of image processing. However, there are bottlenecks in technology that affect the camera's performance. The second way is to enhance and restore the motion-blurred images by means of a motion-blurred image restoration algorithm. There are also additional things we can do in this field to enhance image quality.

Nowadays, the recognition of traffic sign has also made great progress. The Hough transformation and a multi-frames validation method were used by Gonzalez and Garrido [6]. A system based on deformable models was studied, and it was immune to lighting changes, occlusions and other forms of image variance and noise [2]. Support vector machines (SVMs) were utilized to detect and recognize traffic signs by Bascon et al [7]. In addition, Khan et al. [8] proposed a method based on image segmentation and joint transform correlation, which also integrated shape analysis. Barnes et al. [9] also presented the radial symmetry detector to detect speed signs in real time.

All of these algorithms that have been used to restore motion-blurred images took place in the frequency space. Moreover, traffic sign recognition algorithms tend to focus on traffic sign detection and recognition. They do little to deal with traffic signs in blurred images. In order to solve this problem, a new algorithm based on traffic sign border extraction is proposed as a method that can be used to restore motion-blurred images in the spatial domain. The border of the traffic sign is extracted using the image's color information, and then the width of the border can be measured in all directions. According to the width measured and the corresponding direction analyzed, the motion direction and scale of the image can be confirmed, and then it can be used to restore the motion-blurred image. This method has a lower computational cost and better performance. Meanwhile, the restored image ensures accurate and reliable detection of the traffic sign.

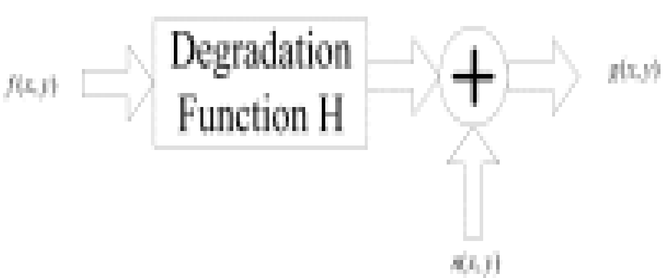
The remainder of this paper is organized as follows: Section II presents the generation of the motion-blurred image and the restoration principle of the motion-blurred image. In Section III, the parameters extraction model, which is based on border deformation detection, is given. Border parameter extraction algorithms are discussed in detail in Section IV. . Finally, a conclusion is presented in Section V.

II. METHODS

All of the experimental images in the paper are from the German Traffic Sign Recognition Benchmark (GTSRB) [10]. Physical traffic sign instances are unique within the dataset. There are more than 40 classes and more than 50000 images in total. In addition, the GTSRB dataset is free to use.

2.1 Restoration principle of motion-blurred images

A motion-blurred image is generated by the relative motion between the target and the camera during the image's exposure time. The study of motion blur produced by uniform motion is of general significance, because the variable speed and the linear motion blur can be approximately considered as uniform motion in the shooting moment. Following motion-blurred degradation and additive noise superposition, the output result is a blurred image [11]. This degradation process can be shown in



In this model, the output is calculated by means of the following formula [23]

$$g(x, y) = f(x, y) \otimes h(x, y) + n(x, y) \quad (1)$$

where $g(x,y)$ is the blurred image, $f(x,y)$ is the undegraded image, $n(x,y)$ is system noise, $h(x,y)$ is the point spread function (PSF), and $\otimes$ is the convolution in spatial domain. Since the space domain convolution is equal to frequency domain multiplication, the frequency domain representation of Eq (1) is $G(u,v) = F(u,v)H(u,v)+N(u,v)$.

Motion-blurred restoration involves reversing the image degradation process and adopting the inverse process to obtain clear images. Motion-blurred is one case that was featured in the model of Lin et al [11]. The model assumes that the target or camera moves at a certain speed and direction, and a distance, *s*, is moved during the exposure time, T. Regardless of the effect of noise, it can be presented by the formula

$$g(x,y)=1T\int 0Tf(x-x(t),y-y(t))dt.$$

In addition $x(t)$,$y(t)$ are the time-varying components of motion in the x-direction and y-direction.

The Fourier transform of $g(x,y)$ is

$$G(u,v)=\int -\infty\infty \int -\infty\infty g(x,y)e-j2\pi(ux+vy)dxdy=1T\int 0Te-j2\pi[ux(t)+vy(t)]dtF(u,v) \quad (2)$$

The spectrogram of the blurred image is the modulus square of Eq (2), which leads to an un-degraded image where the phase shift is absorbed, since its value multiplied by its complex conjugate is equal to unity. By defining $H(u,v)=1T\int 0Te-j2\pi[ux(t)+vy(t)]dt$. Eq (2) can be expressed in the form of $G(u,v) = F(u,v)\bullet H(u,v)$, so it is possible to restore the motion blurred image if $H(u,v)$ is known.

The inverse Fourier transform of H is $h(x,y) = 1/vT = 1/s$. This shows that, the unknown variable is *s*, which includes the direction and scale. So theoretically, if the two parameters are known, it is possible to obtain the spectrogram and restored image of the blurred image. Therefore, a new method based on the border in the spatial domain is proposed to extract the parameters quickly and efficiently.

From the perspective of image restoration, the minimum mean square error filtering (Wiener Filtering) method is adopted, which can avoid the effect of white noise. The method is shown by the expression

$$F\hat{}(u,v)=[1H(u,v)|H(u,v)|2|H(u,v)|2+K]G(u,v) \quad (3)$$

where K is a modifying factor representing the power ratio of the noise and the signal. Because this value cannot be accurately obtained, a fixed value is replaced in practice. The inverse Fourier transform of F^(u,v) is the restored image.

2.2 Parameter extraction based on border in the spatial domain

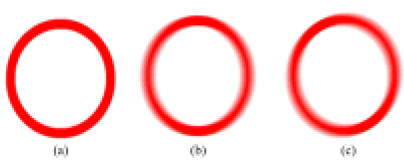
Through the above description about the restoration algorithms of motion-blurred images, it is obvious that extracting the movement direction and scale is a key step in the process, and that determining how to detect the two parameters quickly and accurately is the key problem. There were already some algorithms in existence that can extract these parameters, and most of these algorithms try to do it in the frequency domain by measuring the zero pattern of the blurred image. However, these methods lack of robustness and are easily affected by noise. Therefore, it is necessary to find a new method that can calculate the two parameters.

2.2.1 Border deformation description of motion-blurred traffic signs

Traffic signs usually have a color circle border and a black number, or some other patterns, within it, as shown in Fig 2(a) and 2(b). By analyzing the traffic signs in motion-blurred images, we found that no matter what the direction of motion is, the width of the border will deform regularly. Fig 2(c) and 2(d) feature the motion-blurred images of Fig 2(a) and 2(b). When comparing the blurred image with the sharp image, we can conclude that the border will become wider on the front and back sides in the direction of motion, and that the blurred image has lower color saturation. On the right and left sides, the boundary change is small compared with the sharp image.

Fig 2
Traffic signs images.

In order to explain the changing laws of the border clearly, the blurring process is simulated. Fig 3(a) shows the border of the traffic sign. We were then able to produce motion blur in the direction of 0° and 30°, and we were able to extend it by 15 pixels. Lastly, we obtained the border's motion-blurred images [see Fig 3(b) and 3(c)]



It can be clearly observed that motion causes the border's regularity to change. Fig 3(a) is the original border before it became motion blurred. Fig 3(b) moved in a direction of 0°. The border around the 0° direction had apparently become blurred and its boundary became wider. Moreover, its color saturation dropped much more markedly than in the border around the 90° direction. Fig 3(c) is an image that presents similar features, though the direction is 30°.

2.2.2 Parameter extraction model

In the case of horizontal motion [Fig 3(b)], each line of the image is a sequence that could be expressed as $f(x,y)$, and each sequence is considered as a one-dimensional sequence, which can be expressed as $f(x)$. Assuming that the value of the border pixels is 1, and others are 0..Both a and b are the boundaries of the traffic sign borders.

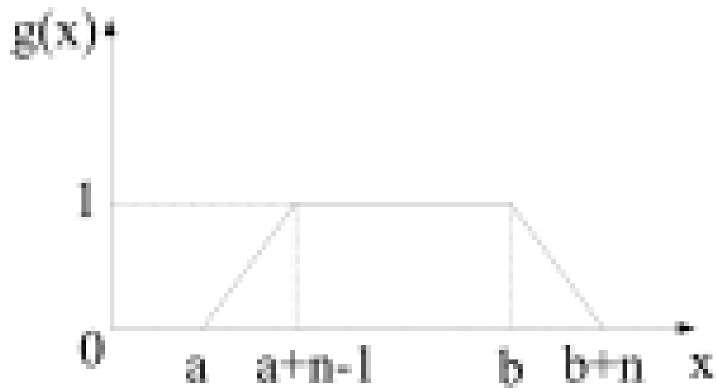
The sequence moved n pixels towards the right, and $n<b-a$. Through inverse Fourier transform, it can be known that $h(x) = 1/n$ $(0\le x\le n-1)$.Ignoring the effect of noise, we can express the sequence after motion as

$$g(x)=\sum_{k=-\infty}^{+\infty} f(k)h(k-x) \qquad (4)$$

By simplifying Eq (4), we can get

$$g(x)=\{1nx-a-1na\le x<a+n1a+n\le x\le b-1nx+b+1nb<x< b+n0others \qquad (5)$$

The corresponding illustration of the function x solution of Eq (5) is shown in Fig 4.



From Eq 11 and Fig 4, we can see that when $a\le x\le a+n$, g(x) grows from 0 to 1. When $a+n\le x\le b$, the value of g(x) is 1, and when $b<x<b+n$, g(x) decreases from 1 to 0. In the image the saturation of the pixels in the middle of the border is the highest, and it decreases gradually from the middle to the edge of the border. The threshold is set as 1, $a+n\le x\le b$, and we consider it as the width of the sequence after blurring. This is to say that the width of the pixels whose saturation equals 1 in original sequence is d, and the scale of motion is n. Thus, the width following motion is $d' = d+n$.

When considering the entire border, the width of the border along the motion direction would apparently change, while the width of the border perpendicular to the motion direction changes little. Finally, the width between the two directions changes gradually, which is shown in Fig 5.

Fig 5: Binary image of motion-blurred border segmented by a certain threshold.

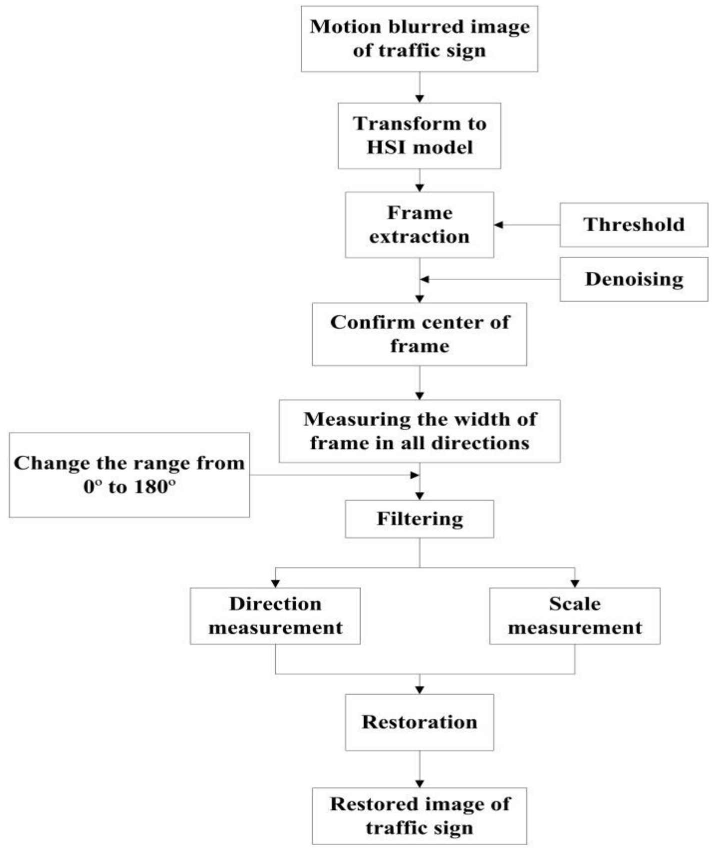
Given that the circle is isotropic, no matter which direction is the image blurred in, the width of the border would change in the same way, which makes it possible to confirm both the blurred direction and scale. Specifically, after measuring the width of all the directions, two maximum values ($d_{\max}$) and two minimum values ($d_{\min}$) could be extracted. By connecting two groups of points, respectively, these two lines are perpendicular, and the blurred direction is the direction of the minimum value line.

We can also obtain the scale from the width of the border. Assuming that the width of the border before the motion is d, it is easy to know that the maximum value is $d_{\max} = d$ and that the minimum value is $d_{\min} = d-n$, so the scale is $n = d_{\max}-d_{\min}$. However, the result is easily affected by threshold determination, so the results should be corrected. An appropriate coefficient (K) is introduced to the result, so we could obtain the corrected result, $n = K\,(d_{max}-d_{min})$.

Thus far, the parameters of direction and scale are extracted from the motion-blurred images.

2.3 Border deformation detection for image restoration

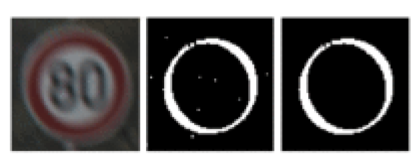
According to the border deformation characteristics of the motion-blurred images of traffic signs, the process of realizing the algorithm is drawn in Fig 6. The first step in the process is to remodel the image from RGB (Red, Green, Blue) to HIS (Hue, Saturation, Intensity); then, the traffic sign border should be extracted by defining the appropriate threshold of HSI. After setting the center of the border, we can measure the width of the border in all directions. Then, the two parameters of direction and scale can be calculated. At last, the motion-blurred image of the traffic sign can be restored using the results obtained with this method



2.3.1 Border extraction

There are some methods that can be used in border extraction [12,13]. Since the border is blurred, the traditional method cannot meet the requirements needed to extract the borders with accuracy and integrity.

The traffic sign's borders are red, so it is possible to confirm whether the pixel belongs to the border or not by checking its color. The RGB image cannot confirm the color directly, so the method is based on the HSI model. The HSI color space is well suited to describe color in a way that is practical for human interpretation In the HSI model, the variation of light does not greatly affects the value of hue . so it is easy to confirm what the color of the pixel is. The border of the traffic sign is red, and according to the statistical results, the H values of most border pixels fall in the range of 0° ~36° and 324 ° ~360°. In addition, in this method the intensity component was not used in the calculation, which reduces much computational capacity. There may be some noise in the resulting extraction; as such, we use a filter to remove it. The results of this method are shown in Fig 7.



Result of border extraction using the HSI model.

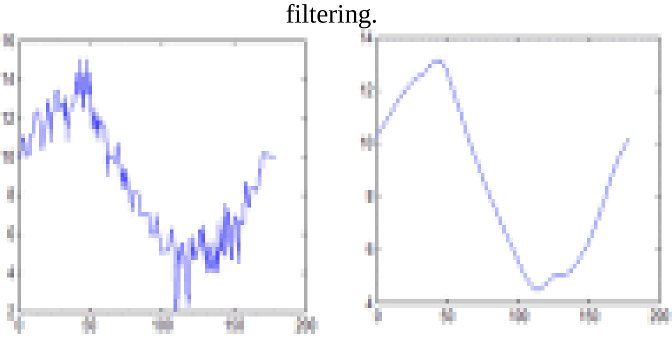
2.3.2 Measurement of border width in all directions

In order to measure the width of the border in all directions, we should count the pixels from the center of the circle to the edge of the image in all directions, confirming the center of the border is the first step. Theoretically, the blurred border is centro symmetric, so the center of the border is the center of gravity. Assuming the size of the image is M×N, the center of the border $O(O_x,O_y)$ is represented by

$$O_x=\sum_{n=1}^{N} n f(n)/\sum_{n=1}^{N} f(n) \text{ and } O_y=\sum_{m=1}^{M} m f(m)/\sum_{m=1}^{M} f(m).$$

In addition, $f(n)$ and $f(m)$ are the summation of the white pixels in the m column or in the n row.

To measure the width of the border, we compute the border by a step of 1°. Through theoretical analysis and experimental verification, we found that the parameters are the same when the motion blurred directions are θ° and (θ+180) °. So, the direction of the motion-blurred image can be normalized from 0° to 180°. The result of the measurement is shown in Fig 8(a). In order to eliminate noise, the result is processed by the mean filter. Fig 8(b) is the result after filtering.



(a) (b)

Measurement result of motion-blurred traffic sign.

Following this, we can then determine the two extreme points (the maximum point and the minimum point), and the direction of the minimum point is the motion direction. To ensure that the results are more precise, we use the direction of the maximum point to correct any errors.

III. CONCLUSIONS

This paper proposed a new method to measure two important parameters—direction and scale—of motion-blurred traffic signs in the spatial domain. . This method is robust, and it can reduce the impact of changing illumination on parameter extraction. Using the measured parameters to restore the motion-blurred traffic sign images, we obtained good results that could meet the system's requirements in image recognition. The results illustrated that the method can deal with recognition-based problems associated with motion-blurred traffic sign images. Compared with the methods based on the frequency domain, the impact of noise on parameters extraction is much smaller. In conclusion, application of the algorithm offers an advantage in traffic signs recognition. This method can improve the performance of the DAS and help to improve automatic driving and road safety.

As for future work, we will continue to investigate this subject by providing a more detailed background of this problem, and we will work to improve the robustness of border extraction with more suitable features in reducing the effects of the environment.

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