



Article A Fast Adaptive Binarization Method for QR Code Images Based on Dynamic Illumination Equalization

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Abstract: The advancement of Internet of Things (IoT) has enhanced the extensive usage of QR code images in various computer vision applications. Nonetheless, this has also brought forth several technical challenges. In particular, the logistics sorting system often encounters issues such as a low recognition rate and slow processing speed when dealing with QR code images under complex lighting conditions like uneven illumination. To address these difficulties, a method that focuses on achieving a fast adaptive binarization of QR code images through dynamic illumination equalization was proposed. First, an algorithm based on edge enhancement to obtain the position detection patterns within QR code images was applied, which enabled the acquisition of structural features in uneven illumination. Subsequently, QR code images with complex lighting conditions can achieve a fast adaptive binarization through dynamic illumination equalization. As for method validation, the experiments were performed on the two datasets that include QR code images influenced by strong light, weak light, and different shadow degrees. The results disclosed the benefits of the proposed method compared to the previous approaches; it produced superior recognition rates of 78.26–98.75% in various cases through commonly used decoders (Wechat and Zxing), with a faster processing speed of 0.0164 s/image, making it a proper method to satisfy real-time requirements in practical applications, such as a logistics sorting system.

Keywords: QR code; uneven illumination; binarization; feature extraction; image enhancement

1. Introduction

Recently, the development of wireless networks and computer vision has expanded the applications of Internet of Things (IoT) technology to various domains, including medicine, manufacturing, communications, and so on [1]. Within the IoT framework, the technology of QR codes has emerged as a critical component of the perception layer, playing a pivotal role in its overall advancement. Typically, a QR code possesses several advantages over other types of barcodes, such as ease of identification, simplicity in production, and robust error correction capabilities [2]. These characteristics make QR code images particularly well suited to fulfill the demanding requirements of information transmission. For instance, QR code images are useful in asset management as they enable quick and accurate data capture via scanning, improving inventory tracking and maintenance processes [3]. A QR code-based mobile payment reduces the reliance on physical payment methods. This manner empowers individuals and businesses with a cashless solution that can be adopted across various industries, enhancing financial inclusion and driving the digital economy forward [4]. QR code images are vital in logistics sorting as they help with package tracking and sorting. By attaching QR code images to packages, logistics companies can quickly



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Copyright: © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https:// creativecommons.org/licenses/by/ 4.0/). scan and identify each item, ensuring proper routing and delivery, minimizing errors, and improving overall operational efficiency [5]. The importance of QR code images in food tracking lies in their ability to enhance transparency and traceability in the food supply chain. By scanning QR code images on food packaging, consumers can access detailed information about the origin, ingredients, production processes, and safety certifications. Hence, it further promotes food safety and builds consumer trust [6]. Chemical sensors with QR code images also play a key role in safety applications, as users can identify hazardous substances and detect specific chemical properties, assisting in rapid responses to potential risks and making them valuable in environmental applications [7].

The recognition of QR code images encompasses various critical issues, including image localization, rotation and skew correction, distortion rectification, motion blur handling, damage restoration, and uneven illumination correction [8]. Particularly, the localization of a QR code is carried out after image binarization. It constitutes a distinct segment of the process [9]. Within the process, the successful repair of unevenly illuminated QR code images is essential, as even with accurate image localization, failure to address the illumination could result in unreadable images. Therefore, the repair and recognition of unevenly illuminated QR code images hold significant research value, much like the QR code localization problem. Based on that, this work concentrates on unevenly illuminated QR code images.

Usually, complex lighting conditions like uneven illumination during the logistics sorting process pose big challenges, as they render QR code images difficult or even impossible to identify accurately. Figure 1 illustrates a typical logistics sorting system in the field of IoT, where its efficiency closely relies on the recognition rate and processing speed. In this regard, several previous studies focused on using binarization methods. Di et al. [10] proposed an enhanced thresholding method based on the Wellner approach to identify unevenly illuminated QR code images on packaging in an automatic classification system. However, this method suffers from the drawback of a prolonged image processing time. Yao et al. [11] developed an improved algorithm that combines the Niblack algorithm and the Otsu algorithm, accomplishing a faster processing speed. However, it exhibits shortcomings in meeting the requirements of binarization recognition for QR code images under uneven illumination. Mustafa et al. [12] presented an enhanced Sauvola algorithm, but it only improves the threshold selection in the binarization process and fails to conduct adaptive binarization. Inspired by the idea of cognitive modeling, Chen et al. [13] used adaptive block window selection for QR code images, enabling better local binarization effects for unevenly illuminated images. However, it has a slow processing speed. Later, Chen et al. [14] designed a method that adaptively selects the binary window size based on QR code features and applies the integral image calculation block's sum of gray values to perform the adaptive binarization. Although this approach demonstrates a better image repair quality and good processing speed, it encounters difficulties in accurately detecting the appropriate binarization window size under uneven illumination.

In summary, the current main issues in binarizing unevenly illuminated QR code images are as follows:

- 1. The loss of vital decoding information during the binarization process;
- 2. An inadequate processing speed that fails to satisfy real-time requirements for practical applications, such as a logistics sorting system;
- 3. The limited adaptability of the binarization approach to complex lighting conditions.

To solve the above issues, a method that aims to achieve the fast adaptive binarization of QR code images through dynamic illumination equalization is proposed in this work, which initially uses an image detection approach derived from edge enhancement to identify the structural features of the position detection patterns impacted by uneven illumination. Subsequently, the structural features are applied to perform equalization through illumination feature extraction based on adaptive morphological closing, which can effectively minimize the contrast, brightness, and color discrepancies between different regions of unevenly illuminated QR code images. Moreover, by adopting the structural features, an adaptive binarization window is constructed, facilitating adaptive binarization processing on equalized images accordingly. As for method evaluation, the experiments are conducted through two commonly used decoders (Wechat and Zxing), along with a comparative study with the previous methods. Therefore, an impressive recognition rate and faster processing speed for binarizing unevenly illuminated QR codes can be validated.



Figure 1. A typical logistics sorting system with QR code images in the field of IoT.

The rest of this work is organized as follows: Section 2 reviews the related work in the field of QR code images. Section 3 describes the proposed fast adaptive binarization method. Section 4 shows the experimental results from various cases with a comparative study. Section 5 presents the discussions of the proposed method in different aspects. Finally, Section 6 summarizes this work.

2. Related Work

QR code images are generated by binary information, where dark modules represent 0 and light modules denote 1, thereby constructing the functional areas within the image [15]. Moreover, the functional areas encompass several essential components, including position detection patterns, timing patterns, alignment patterns, and so on [16]. These patterns mainly incorporate vital characteristics of the image, such as the version format, decoding direction, and the start and end points of decoding [17]. Typically, a QR code can be categorized into four levels in terms of error correction, level L (7%), level M (15%), level Q (20%), and level H (30%) [18], which have pivotal roles in the repair and recognition of a QR code that has been subjected to light damage.

On the other hand, the repair and recognition of unevenly illuminated QR code images mainly use binarization techniques, which are divided into global binarization and local binarization [19]. Global binarization involves partitioning the pixel attributes of the entire image through a specific procedure. Generally, it produces satisfactory results when applied to images with relatively simple uneven illumination. Nonetheless, due to the necessity of a global image threshold, complex unevenly illuminated images that are processed employing this method suffer from a loss of image details in the resulting binarized image. Mathematically, the global binarization of 8-bit images is

$$g(x,y) = \begin{cases} 255, f(x,y) > T\\ 0, f(x,y) \le T \end{cases}$$
(1)

where each input image pixel f(x, y) is converted to the output image pixel g(x, y) based on the threshold value T [20].

Regarding local binarization, the image is initially divided into several regions using a window with the size of $w \times w$. Then, the average gray value of each region is calculated and applied to (2) to obtain the standard deviation $\sigma(x, y)$ corresponding to each average gray value. After that, the pixel threshold of each area is acquired by (3). Finally, the pixel threshold of each region is used to convert the unevenly illuminated QR code into a local binary image, achieving a more detailed binary result than the global binarization.

$$\sigma(x,y) = \sqrt{\frac{1}{w^2} \sum_{i=x-\frac{w}{2}}^{x+\frac{w}{2}} \sum_{j=y-\frac{w}{2}}^{y+\frac{w}{2}} (f(i,j) - m(x,y))^2}$$
(2)

$$T(x,y) = m(x,y) \left[1 + k \left(\frac{\sigma(x,y)}{R} - 1 \right) \right]$$
(3)

where m(x, y) represents the gray mean value in the $w \times w$ neighborhood, k is a userdefined modified parameter and its range is (0,1), and R denotes the dynamic range of the standard variance, and if the input image is an 8-bit gray image, R = 128. Here, (2) is used to compute the standard deviation within a $w \times w$ neighborhood. Assuming that the current coordinate point is denoted as (x, y), the neighborhood centered around this point spans $w \times w$. Consequently, the ranges of the pixel coordinates i and j in (2) encompass from x - w/2 to x + w/2.

In addition to the aforementioned global and local binarization techniques, several studies have focused on addressing the challenges posed by unevenly illuminated QR code images. Zhang et al. [21] proposed a binarization algorithm based on background grayscale. Their approach involves dividing the image into multiple regions and adjusting the overall grayscale using the background grayscale of each region, which helps to reduce information loss during the image binarization process. However, its limited adaptability arises from dividing the image based on the image size rather than the size of the QR code itself. He et al. [22] presented double windows to characterize image contrast and offered adaptive window search capabilities. Their method adopts multiple rules to screen the threshold to distinguish the foreground and background and accommodate various lighting conditions. But it relies on the version size of the QR code and the size of a single module, which is prone to erroneous window size detection, resulting in suboptimal binarization effects, especially under uneven illumination. By improving the Sauvola algorithm, Zhou et al. [23] estimated the optimal R value based on the image size, which enhances the decoding accuracy of QR code images during image processing. Unfortunately, this algorithm requires precise version information and the module size of the images, making it impractical in complex lighting conditions. Jing et al. [24] designed a technique that combines molecular blocks and the Otsu algorithm to address the issue of missing details after processing QR code images under uneven illumination. However, its segmentation condition is relatively strict, limiting its universal applicability. Finally, Yang et al. [25] provided an algorithm that selects different thresholds that adopt various rules to achieve binarization after grayscale processing and Gaussian smoothing filtering. Although the results demonstrated that this solution yields more complete images with reduced noise, its binarization efficiency still requires improvement under uneven illumination.

3. Proposed Method

The previous techniques primarily address the challenges of low recognition rates and slow processing speeds associated with unevenly illuminated QR code images through binarization techniques. However, conventional binarization methods usually suffer from pixel classification errors when applied to such images, resulting in the loss of vital decoding information [26]. To overcome these limitations, a method for the fast adaptive binarization of QR code images through dynamic illumination equalization is proposed in this work. Its core is the identification of structural features within the position detection patterns that are impacted by uneven illumination. This task can be accomplished using an edge-

enhancement-based position detection pattern algorithm. Then, by accurately identifying the structural features, the difficulties associated with structural element construction in adaptive image enhancement, as well as the window construction issue in adaptive binarization, can be solved. As a result, a fast and effective adaptive binarization effect of QR code images with uneven illumination is realized.

3.1. Unevenly Illuminated Position Detection Pattern Algorithm

In this work, the position detection pattern algorithm for unevenly illuminated QR code images is obtained from a lossless position detection pattern algorithm, which contains two main steps. The first involves extracting the edge information from the lossless QR code images, and the second entails screening the results that adhere to the structural features of the position detection patterns from the extracted edge information. Nonetheless, unevenly illuminated QR code images are usually susceptible to the loss of vital edge information during the extraction process, incurring difficulties or even impossibility in recognition [27]. To this end, the position detection pattern algorithm based on edge fusion is considered, as illustrated in Figure 2.



Figure 2. The edge enhancement process of an unevenly illuminated QR code image. (a) QR code image with uneven illumination. (b) Edge 1 of (a). (c) QR code image with uneven illumination processed via global histogram equalization. (d) Edge 2 of (c). (e) Combinations of (b,d).

A QR code image with uneven illumination is presented in Figure 2a. The Canny algorithm [28] is adopted to extract edge 1, as denoted in Figure 2b. However, it is evident that edge 1 fails to capture the complete edge information of the unevenly illuminated QR code image. Thus, a global histogram equalization process is conducted, and the result is shown in Figure 2c. Next, the Canny algorithm is applied to this equalized image again, generating edge 2, as drawn in Figure 2d. Please note that edge 1 and edge 2 are not overlapping with each other so they can be fused, yielding a combined image with edge 3, accordingly, as depicted in Figure 2e. Such a fusion contains a more comprehensive representation of the edge information, which facilitates the reliability of the subsequent processing steps [29]. Mathematically, the global histogram equalization is expressed as

$$s_k = \sum_{j=0}^k \frac{n_j}{n}, k = 0, 1, 2, \dots, L-1$$
(4)

where *n* is the sum of pixels in the image, n_j is the number of pixels in the gray level, and *L* is the total number of gray levels in the image.

Moreover, the image fusion is achieved by

$$I_3 = \beta I_1 + \partial I_2 + \varepsilon \tag{5}$$

where I_1 , I_2 , and I_3 are edge 1, edge 2, and edge 3, respectively, and ε is the offset.

Once edge 3 is obtained, an information screening process based on the structural features of the position detection patterns is applied, which can be characterized by an edge group with black and white modules arranged in a specific length ratio of 1:1:3:1:1. Here, the presence of the black and white modules group is typically limited to the area within the position detection patterns. Usually, during the coding stage, the QR code is designed to mask the regions outside of the position detection patterns, ensuring that the

black and white modules group is confined to the area. As a result, the location of the position detection patterns can be determined by examining the distance ratios between six adjacent edge points along the same row or column, and by screening these ratios, the precise coordinates of the position detection patterns are retrieved. This screening process enables the accurate localization of the position detection patterns based on their distinctive structural features, as listed below:

$$\begin{cases} \frac{P_{12}}{P_{2}} - \frac{9}{11} < T\\ \frac{P_{2}}{P_{3}} - \frac{11}{27} < T\\ \frac{P_{3}}{P_{4}} - \frac{27}{11} < T\\ \frac{P_{4}}{P_{5}} - \frac{11}{9} < T \end{cases}$$
(6)

The definitions of P1 to P5 are depicted in Figure 3. Assuming that the length of a single module is 9, the corresponding ratio of P1:P2:P3:P4:P5 is derived as 9:11:27:11:9. This ratio aligns with the proportional relationship of the black and white modules group, which is 1:1:3:1:1. Then, to identify a group of edge patterns that conform to this proportional relationship, *T* is applied. Based on empirical observations, it is set to 0.2. Hence, this threshold serves as a criterion for screening edge groups that exhibit the 9:11:27:11:9 ratio, facilitating the localization of the position detection patterns.



Figure 3. Example of an edge group for the position detection patterns.

Meanwhile, to optimize the screening results, the following restrictions should be included:

$$14 < win < \frac{15}{3} \tag{7}$$

$$IS = \frac{W+H}{2} \tag{8}$$

where *W* and *H* are the width and height of the image, respectively, and *win* denotes the average of the length and width of the smallest black rectangle in the position detection patterns.

Concerning the QR code images, the minimum size is 21×21 modules, and the size of position detection patterns is 7×7 modules, so in an image containing a complete QR code, the size of the position detection patterns will not exceed 21×21 modules, and the minimum is no less than $2 \times 7 \times 7$ modules. Following the above restrictions, the black and white modules group in edge 3 can be screened, and the *win* values can be acquired. Hence, a final *win* value is determined by lowering these *win* values through a multiple of 7 and then conducting mode collection. In summary, a flow chart that describes the position detection pattern algorithm is presented in Figure 4.



Figure 4. Flow chart of unevenly illuminated position detection pattern algorithm.

3.2. Fast Adaptive Binarization Method

The information on the position detection patterns reflects the structural features of the QR code images, such as the size of a single module, the version number, and so on, which provides the criterion for selecting the kernel size of the subsequent morphological closing [30]. Additionally, before the morphological closing, it is necessary to perform mean filtering on the unevenly illuminated image to remove noise [31], as expressed below:

$$f_m(x,y) = \frac{1}{M} \sum_{(x,y) \in s_{xy}} g(s,t)$$
(9)

$$M = win \times win \tag{10}$$

where s_{xy} denotes the center point of the filtering region at (x, y), M represents the filter window, g(s, t) refers to the original image, and $f_m(x, y)$ is the image obtained after mean filtering. Here, M is used to filter the pixel area within each module size range in the QR code.

After acquiring the mean filtering result of the QR code image with uneven illumination, the next step is to restore the contrast, brightness, and color discrepancies. To this end, an illumination feature extraction method based on morphological closing is performed on the previous mean filtering result. Mathematically, this method is denoted as

$$E_{closing}(f) = f \div (f^{\circ}b) \times C \tag{11}$$

where $^{\circ}$ means the morphological closing operation through the structural element *b*, *C* is the constant, and *f* is the input image. Moreover, the morphological closing operation is defined as

$$f^{\circ}b = (f \oplus b) \ominus b \tag{12}$$

where \oplus means the morphological dilation operation on *f* through the structural element *b*, and \ominus denotes the morphological erosion operation on *f* through the structural element *b*, as presented below:

$$[f \ominus b](x, y) = \min\{f(x + s, y + t), (s, t) \in b\}$$
(13)

$$[f \oplus b](x, y) = max\{f(x - s, y - t), (s, t) \in b\}$$
(14)

When the kernel size falls within a certain range, the morphological closing operation corresponds to the uneven illumination feature of the robust image, achieving an image enhancement effect accordingly. Additionally, from (13) and (14), it can be indicated that the

erosion at any location is determined by the minimum value in the region where *b* coincides with *f*, while the dilation at any location is decided by the maximum value in the region where *b* coincides with *f*. When b > win, the unevenly illuminated feature can be extracted in the morphological closing operation. Then, by dividing the uneven illumination feature from the original image, the restored QR code image eliminates the contrast, brightness, and color discrepancies in each region of the image:

$$T(x,y) = \frac{1}{r^2} \sum_{i=x-r/2}^{x+r/2} \sum_{j=y-r/2}^{y+r/2} f(i,j)$$
(15)

where T(x, y) is the mean value of pixels in the $r \times r$ neighborhood of the point (x, y), and f(i, j) is the gray value of point (x, y).

To conclude the above operations, a flow chart about the fast adaptive binarization method is illustrated in Figure 5, and the pseudo-code is summarized as Algorithm 1.

Algorithm 1: Pseudo-code of fast adaptive binarization method.

Input: QR code image with uneven illumination

Output: Binary QR code image

- 1. Filter1 \leftarrow Perform grayscale and median filter on the Input
- 3. Equ ← Perform global histogram equalization on the Close1
- Canny ← Perform marginalization based on the Canny operator on Close1 and Equ, and merge the results
- 5. If there is a group of pixels P1 to P5 in the Canny with a spacing ratio of 1:1:3:1:1 **then** Size = P4–P3
- 6. Filter2 ← Perform grayscale and Gaussian filter on the Input
- 7. Close2 ←Use Size as the structural element size to perform a closing operation on the Filter2
- 8. Equalization \leftarrow Input \div Close2 \times 200
- 9. Binarization ← Use Size as the window size and perform adaptive binarization operations on the Equalization



Figure 5. Flow chart of fast adaptive binarization method.

3.3. Effective Principle Analysis

An effective principle analysis is performed to validate the efficiency of utilizing the structural features of the position detection patterns, which can determine the window size in the morphological closing operation of the image equalization method. To this end, a

QR code image impacted by uneven illumination is selected and investigated, as shown in Figure 6a. Then, it is processed using the proposed method with varying window sizes, and the corresponding Peak Signal-to-Noise Ratio (PSNR) results are plotted as a curve in Figure 6b.



Figure 6. An unevenly illuminated QR code image and its Peak Signal-to-Noise Ratio (PSNR) results under various window sizes using the proposed method. (**a**) QR code image with uneven illumination; (**b**) PSNR results.

As seen in Figure 6b, when the window size is larger than 20, the PSNR of the binary image reaches the highest value, and the size of the smallest rectangular block in the position detection patterns with uneven illumination is 30×30 . Now, to verify the correlation between the smallest rectangular block of the unevenly illuminated position detection patterns and the image equalization, five different types of unevenly illuminated QR code images are analyzed, as presented in Figure 7, where the size of these images is 300×300 . Then, the PSNR results of different sizes (300×300 , 600×600 , and 900×900) for the five types of QR code images are illustrated in Figure 8.



Figure 7. Five different types of unevenly illuminated QR code images: (**a**) Type I; (**b**) Type II; (**c**) Type III; (**d**) Type IV; (**e**) Type V.

When the sizes of the unevenly illuminated QR code images in Figure 7 are adjusted to $300 \times 300, 600 \times 600$, and 900×900 , the sizes of the smallest rectangle of the corresponding unevenly illuminated position detection patterns are $30 \times 30, 60 \times 60$, and 90×90 , respectively. The PSNR results in Figure 8 reveal that the proposed method achieves the best value for the repaired image when the selected window size aligns with the minimum black rectangle size of the unevenly illuminated position detection patterns. Such a finding highlights the importance of an appropriate window size in achieving optimal image repair results. Hence, the proposed method is closely related to the size information of the smallest black rectangle in the position detection patterns. Additionally, the above consideration remains applicable irrespective of alterations made to the size or type of the unevenly illuminated image. It offers a foundation for selecting the window size in the morphological closing operation of adaptive image enhancement, ensuring a well-founded choice that contributes to faster image processing.



Figure 8. The PSNR results in five different types of unevenly illuminated QR code images under various sizes: (a) 300×300 ; (b) 600×600 ; (c) 900×900 .

4. Experimental Results

To fully validate the proposed method, the recognition rate and processing speed are employed as the evaluation metrics. The recognition rate measures the binarization quality of QR code images impacted by uneven illumination, and the processing speed reflects the efficiency of binarizing such images in real-time applications. Additionally, the PSNR and Structural Similarity Index Measure (SSIM) are used to assess the binarization of the unevenly illuminated QR code images. Generally, higher PSNR and SSIM values mean superior binarization results [32]. Furthermore, a comparative study of the previous works is conducted, and two popular decoders, Wechat and Zxing, are applied.

First, the dataset provided by Chen et al. [13] is used. It includes version 7 of the QR code image, a module size of 29×29 , an error correction level (Q), and is composed of 30 strong light images and 50 weak light images. Compared to the QR code images subjected to genuine uneven illumination, the simulated images often tend to be more idealized, indicating that simply changing the contrast or brightness or fusing images with masks to create unevenly illuminated QR code images are improper methods for constructing datasets. Thus, the materials sourced from real-world uneven illumination scenarios are considered. The experimental configuration is summarized in Tables 1 and 2.

Table 1. Experimental hardware configuration of this work.

Parameters
OS: Ubuntu 20.04.1 LTS
CPU: AMD Ryzen 7 3700x 8-core processor*16 3.6 GHz
Model: HP M226dw
Printed resolution: 600×600 dpi
Xiaomi 6 rear camera: 12 million pixels

Software	Version
Matlab	R2020a
Wechat—python libraries (Opencv)	4.6.0.66
Zxing—python libraries	1.0

The performance of each method on various types of unevenly illuminated QR code images is drawn in Figures 9–13. In detail, Figure 9 shows the effect of each method on the QR code image with strong local illumination in the coding area (Type I). Figure 10 displays the processing of each method on the QR code image with strong local illumination in the position pattern area (Type II). Figure 11 depicts the outcome of each method on the QR code image with a mixture of strong local illumination and weak local illumination (Type III). Figure 12 presents the result of each method on the QR code image with weak global illumination (Type IV). Lastly, Figure 13 exhibits the result of each method on the QR code image with strong global illumination (Type V).



Figure 9. The QR code image with strong local illumination in the coding area (Type I) and its processing by using various methods: (**a**) original image; (**b**) Yao et al. [11]; (**c**) Di et al. [10]; (**d**) Chen et al. [13]; (**e**) Chen et al. [14]; (**f**) proposed method.



Figure 10. The QR code image with strong local illumination in the position pattern area (Type II) and its processing by using various methods: (a) original image; (b) Yao et al. [11]; (c) Di et al. [10]; (d) Chen et al. [13]; (e) Chen et al. [14]; (f) proposed method.



Figure 11. The QR code image with a mixture of strong local illumination and weak local illumination (Type III) and its processing by using various methods: (**a**) original image; (**b**) Yao et al. [11]; (**c**) Di et al. [10]; (**d**) Chen et al. [13]; (**e**) Chen et al. [14]; (**f**) proposed method.

Table 2. Experimental software configuration of this work.



Figure 12. The QR code image with weak global illumination (Type IV) and its processing by using various methods: (**a**) original image; (**b**) Yao et al. [11]; (**c**) Di et al. [10]; (**d**) Chen et al. [13]; (**e**) Chen et al. [14]; (**f**) proposed method.



Figure 13. The QR code image with strong global illumination (Type V) and its processing by using various methods: (**a**) original image; (**b**) Yao et al. [11]; (**c**) Di et al. [10]; (**d**) Chen et al. [13]; (**e**) Chen et al. [14]; (**f**) proposed method.

As seen in Figures 9–13, the experimental results reveal differences in terms of the performances. Specifically, the proposed method shows superior image binarization results by effectively preserving the image details. In contrast, the approaches based on Yao et al. [11], Di et al. [10], and Chen et al. [13] exhibit binarization outcomes characterized by a loss of vital details. Furthermore, to conduct a quantitative comparison with Chen et al. [14], a thorough investigation is conducted based on the PSNR and SSIM across the aforementioned cases. Such metrics can provide a more in-depth evaluation of the performances, shedding light on their abilities to represent the original image while handling uneven illumination. The PSNR and SSIM results of the various methods are presented in Figure 14, and the details are summarized in Table 3, where the best result for each type is underlined.



Figure 14. The PSNR and SSIM results for different types of QR code images using five methods: (a) PSNR results; (b) SSIM results [10,11,13,14].

Figure 14 and Table 3 indicate that the proposed method and its binarization achieve superior PSNR and SSIM results in all types of unevenly illuminated QR code images. Meanwhile, to achieve a deeper comparative study of the method performance, further assessments of all the methods in terms of the recognition rates and processing speeds are conducted, as shown in Table 4, where the best result in each case is underlined. Please note

that "none" here means that the unevenly illuminated QR code images were recognized without using any processing methods, directly employing Wechat and Zxing.

Туре	Metrics	Yao et al. [11]	Di et al. [<mark>10</mark>]	Chen et al. [13]	Chen et al. [14]	Proposed Method
I	PSNR	3.6233	3.6467	3.8228	3.8622	5.4935
	SSIM	0.0747	0.0691	0.0814	0.0938	0.1853
Π	PSNR	3.6364	4.0827	4.2031	4.2256	<u>5.2199</u>
	SSIM	0.0929	0.1145	0.1230	0.1290	0.1774
III	PSNR	3.9251	3.8745	3.9076	3.9337	4.4706
	SSIM	0.1296	0.0950	0.0991	0.1030	0.1658
IV	PSNR	4.1405	4.1384	4.0535	4.1148	<u>5.3732</u>
	SSIM	0.1129	0.1270	0.1241	0.1247	0.2247
V	PSNR	3.8826	3.6375	3.6163	3.6217	5.5479
	SSIM	0.0825	0.0791	0.0781	0.0768	<u>0.2162</u>

Table 3. A comparative study based on PSNR and SSIM results using various methods.

Table 4. The average processing time (s/image) and recognition rate (%) of various methods.

	Average Processing	Recognition Rate (%)		
Method	Speed (s/Image)	Zxing	Wechat	
None	_	35.00	48.75	
Yao et al. [11]	0.0520	37.50	42.50	
Di et al. [10]	0.5953	53.75	71.25	
Chen et al. [13]	0.3165	88.75	92.50	
Chen et al. [14]	0.0199	92.50	97.50	
Proposed method	0.0164	<u>95.00</u>	<u>98.75</u>	

Table 4 indicates that the proposed method outperforms the compared approaches in terms of the recognition rates. Specifically, it realizes the highest recognition rate of 98.75% when using Wechat. In this regard, the best previous method achieves a recognition rate of 97.50%. In addition, the proposed method exhibits an impressive processing speed with 0.0164 s/image, faster than the previous speed of 0.0199 s/image. Such comparisons disclose that the proposed method is more suitable for real-time applications than the previous studies.

Finally, a public dataset provided by Szentandrasi et al. [33] is investigated. Please note that the simple process of cropping and the necessary perspective transformation of the images were performed in this dataset, as the images themselves had serious tilt distortion in addition to uneven lighting. The results are displayed in Table 5, where the best result in each case is underlined. From Table 5, it can be found that the recognition rate of the unevenly illuminated QR code image processed using the proposed method increases to 78.26% and 82.60% when decoding through Zxing and Wechat, respectively, which also reveals the robustness of the proposed method when applying it to various conditions.

Table 5. The recognition rate (%) of a public dataset provided by Szentandrasi et al. [33].

Method	Recognition Rate (%)		
Method	Zxing	Wechat	_
None	60.86	60.86	
Chen et al. [13]	65.21	69.56	
Chen et al. [14]	65.21	73.91	
Proposed method	<u>78.26</u>	<u>82.60</u>	

5. Discussion

First, based on the tight distribution structure of the black and white modules in QR code images, the illumination characteristics of the images can be obtained via dynamic morphometric operation, so the proposed method approximates the division of the closing operation result from the original image, which can effectively remove the unevenly illuminated background. This outcome offers a high-quality image equalization effect and subsequently enhances the performance of the image binarization process. Given the characteristics of the method, its robustness at the lowest error correction level, level L, can be ensured, as it remains unaffected by factors like the version of the QR code, data encoding, and the error correction level.

Second, in order to avoid unnecessary interference, the dataset selection is tailored to eliminate factors beyond uneven illumination. From experiments and previous works, it is evident that the commonly used methods, such as the Otsu algorithm and the Sauvola algorithm, have not yielded remarkable results in unevenly illuminated QR code images [34–36]. Similarly, the binarization methods proposed by Di et al. [10] and Yao et al. [11] have not achieved impressive outcomes. This highlights the ongoing innovation in the field, exemplified by recent contributions like the fast adaptive thresholding method proposed by Chen et al. [14], to address unevenly illuminated QR code images. Therefore, it is clear that the research landscape is continuously evolving in pursuit of more appropriate solutions for the repair and recognition of unevenly illuminated QR code images.

Third, the motivation of this work is different from previous studies [13,14], which adopted the structural features of QR code images to optimize the region division determination in the local binarization method, achieving a better binarization effect of unevenly illuminated QR code images. In contrast, this work primarily explores how the structural features of QR code images effectively improve the image enhancement process before binarization. In practice, QR code images consist of tightly packed black and white modules. By comprehending the dimensions of individual QR code modules, the proposed method enhances the extraction and elimination feature extraction, which subsequently provides a robust foundation for image binarization. In short, although these studies concentrate on unevenly illuminated QR code images, the relevant concerns are entirely different.

Additionally, in general, the process of QR code image recognition can be divided into image preprocessing and image decoding, where effective image preprocessing can significantly enhance the quality of the decoding process for QR code information [37], while embedding additional elements on QR code images can reduce the decoding error tolerance, thereby elevating the risk of decoding failure. In such cases, image preprocessing becomes vital, as it outputs complete and accurate data from the QR code image, even under challenging conditions. This aspect underscores the importance of the unevenly illuminated QR code image recognition method presented in this work.

Finally, this work aims to repair and recognize the unevenly illuminated QR code image, and its main advantage is that the image enhancement method based on the morphological closing operation can convert the unevenly illuminated QR code image into a light-balanced image, which is more convenient for fast and high-quality binarization operation. In previous studies, such as the study by Yao et al. [11], which belongs to the class of the global binarization method, numerous details of binarization images were easily lost due to their globally uniform threshold. On the other side, several local binarization methods, such as those used by Chen et al. [13] and Chen et al. [14], can achieve better results, but they have not fully considered the importance of light equalization in the binary process of unevenly illuminated QR code images, so the performances are not the best. Now, the experimental results demonstrate that adopting the dimension-adaptive method based on the morphological closing operation to pre-equalize an unevenly illuminated QR code image can effectively enhance the binarization effect after equalization, which has not been investigated in previous studies. However, the limitation is that the proposed method relies on the dimensional features of a single module of a QR code image. Consequently, it

is necessary to use an excellent object detection method to detect a single module of a QR code image. Although the object detection method is not the main focus of this work, an image detection method based on edge enhancement will be further designed to solve this limitation in the future.

6. Conclusions

To address the challenge of recognizing unevenly illuminated QR code images, a fast adaptive binarization method through dynamic illumination equalization is proposed, which is initiated by extracting structural features from the position detection patterns under uneven illumination and using an edge-enhancement-based position detection pattern algorithm. Such structural features are then employed to enhance the image through adaptive structural element selection and local binarization based on adaptive window selection. The method evaluations were conducted through experimental datasets. The performances disclose that better image binarization results can be obtained by employing a photoequalized image based on the dynamic morphological closing operation, and indicate its superiority regarding the processing speed and efficiency in recognizing QR code images with uneven illumination compared to the previous works. Hence, it exhibits advantages for the binarization of QR code images under complex lighting conditions and satisfies practical applications, such as a logistics sorting system.

In the future, to achieve the integration of the proposed method into embedded devices, the algorithm will be implemented into the QR code decoder. Additionally, to further enhance the edge detection to improve the image recognition rate, several advanced methods in related fields, such as the end-to-end cross band 2D attention network [38], multiscale superpixelwise prophet model [39], self-attention enhanced deep residual network [40], and multistage stepwise discrimination with compressed MobileNet [41], will be investigated.

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