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Water level recognition based on strong edge and sparse constraints

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ABSTRACT

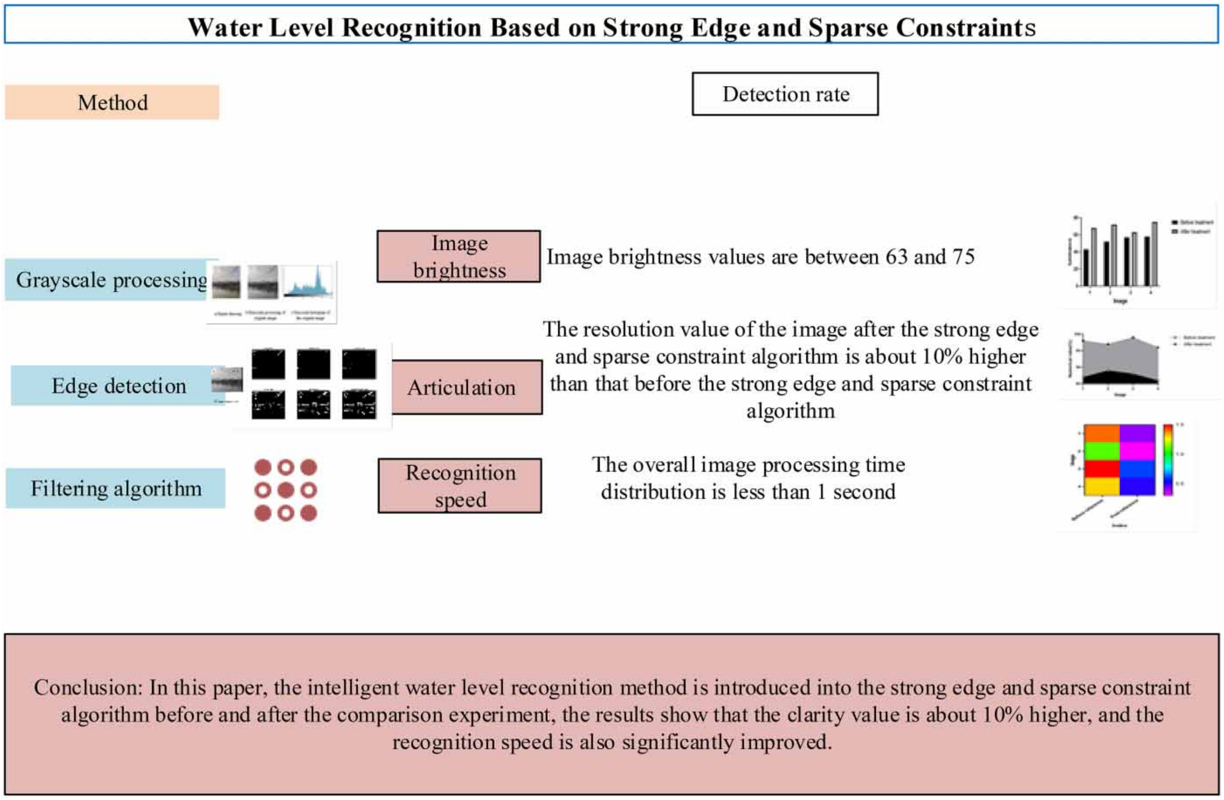
This paper takes the intelligent water level recognition instrument of Qingming Shanghe Park in Kaifeng as the experimental object, introduces the algorithm of strong edge and sparse constraint into the intelligent water level recognition instrument, and compares the recognition effect of the intelligent water level recognition instrument before and after the introduction of strong edge and sparse constraint algorithms. The results showed that the clarity value was approximately 10% higher, and the recognition speed was also significantly improved. The improvement of recognition speed can effectively promote the work efficiency of the whole method. Strong edges and sparse constraints can effectively improve the accuracy of water level identification, provide scientific and effective data and information for subsequent water resource management, and meet the needs of water resource managers to effectively grasp the law of water level. This can provide technical support for identification methods in other fields, and the ultimate goal is to promote the protection and management of water resources and reduce the harm of natural disasters on people.

Key words: sparse constraint, sparse constraint classification algorithm, strong edge, water level recognition

HIGHLIGHTS

- Traditional water level recognition method and image processing technology were analyzed in detail.
- Intelligent water level image recognition method was quoted, and strong edge and sparse constraint algorithms were introduced into this method.
- The results showed that the clarity value was approximately 10% higher, and the recognition speed was also significantly improved.

GRAPHICAL ABSTRACT



1. INTRODUCTION

Water is an indispensable material resource for human survival and development. Detection and protection of water resources have become common responsibilities of human beings. With the development of science and technology, new recognition technology has been widely used in various fields, and the water level recognition method is also developing toward intelligence and digitalization. The water level recognition method has changed from manual detection to the intelligent camera recognition method. Choosing an appropriate recognition method according to the characteristics of water level changes is the requirement of the current complex water quality environment. How to effectively identify water level changes by using new technology has become a focus issue in the field of water resource management.

Changes in water level have a great impact on the ecology and living of residents. An accurate grasp of water level changes can reveal some natural environmental problems. Therefore, many experts have made a series of analyses on the impact of water level changes. Gronewold Andrew D identified Lake Ontario as the lowest water level in Lawrence's Great Lakes, rising to a record high since 2017, which triggered flooding and displaced many families. An investigation revealed that the change was due to negligence in water management. The main reason was that the water level identification method was not in place and the information on water level change was not effectively grasped (Gronewold & Rood 2019). Buckley Mark L believed that wave-driven water level's changes and coastline's rise were important causes of coastal floods caused by storms. In order to study the mechanism of wave-driven water level changes along the coastline of reefs, he conducted a series of laboratory trough experiments on uniform sounding profiles along the coast (Buckley *et al.* 2018). Peng Dongju held that the lunar node cycles at tidal stations in Tokyo Bay, English Channel, and Bristol Channel had the greatest impact on high water levels, ranging from 30 cm, and that the impact of node cycles on high water levels in these areas might be greater than that of global average sea level rise (Peng *et al.* 2019). Mohammadi Hamidi Somayeh assumed that droughts have been severe and water levels have fallen significantly in recent decades. The prominent features of these changes have caused problems to surrounding habitats, and severe and sustained droughts have threatened many parts of the world at different times, resulting in profound changes in the level of economic and social development. The shortage of water resources caused the price of potable water to rise, which, in turn, made it difficult for residents to use water (Hamidi *et al.* 2019). Putman Annie L reckoned that global water resource changes could be seen through water level changes; so water level changes needed to be identified in order to timely grasp the state of development of water resource changes (Putman *et al.* 2019). Greve Peter identified water shortage as a key environmental problem worldwide and analyzed water level changes to determine changes in the uncertainty range of water shortage conditions (Greve *et al.* 2018). Shen Chaopeng held that in-depth learning represented a significant advance in the ability of neural networks to capture features associated with automatic design problems and highly complex data distributions, and could help solve the challenges faced by water level recognition research. Water level recognition was susceptible to the water environment and bad weather (Shen 2018). Analysis of the impact of water level changes can effectively carry out an in-depth analysis of the problems, and then, provide useful information reference for subsequent water resources management.

With the development of science and technology, water level recognition has introduced different technologies to further promote the development of water level recognition technology. Many experts have analyzed the introduction of new technology for water levels. Mohammadimanesh Fariba drew a detailed quantitative map of the water level changes of submerged vegetation, and detected water flow patterns and discontinuities. This can show that advances in remote sensing technology have promoted the monitoring and management of wetlands in several fields, including classification, change detection, and water level monitoring (Mohammadimanesh *et al.* 2018). Huang Chang reckoned that surface water observation was a functional requirement for studying ecological and hydrological processes, in which optical remote sensing image technology could estimate river flow and provide valuable information for water level recognition in unmeasured areas, which could effectively and accurately predict the flow, water level, and water quality of the river in unmeasured areas (Huang *et al.* 2018). William R Moomaw combined recent research on the status and climate vulnerability of freshwater and brackish wetlands and their contribution to climate change, requiring a precise understanding of water level changes to accommodate flexible ecosystem approach services (Moomaw *et al.* 2018). J Sheffield considered that water management promoted sustainable development and that satellite remote sensing could play a role in identifying coastal water level changes and enhancing water management (Sheffield *et al.* 2018). Jakob Zscheischler deemed that floods, wildfires, heat waves, and droughts interacted across multiple spatial and time scales and that effective recognition of water level changes could effectively prevent floods and droughts (Zscheischler *et al.* 2018). Gustavo Naumann assumed that higher evaporation demand and frequent increases in air temperature were contributing to the continued deterioration of drought conditions in many parts of the world, indicating that the main effects of long-term drought were related to the reduction of groundwater and reservoir water levels. Lower water levels led to a gradual reduction of water on the land, which, in turn, led to drought (Naumann *et al.* 2018). Arjen Luijendijk considered that coastal areas were one of the most densely populated and developed land areas in the world. Through sophisticated image inquiry and analysis methods, the occurrence of sand beaches and the rate of change in coastal water levels among them have been assessed on a global scale (Luijendijk *et al.* 2018). An effective grasp of water level change by using science and technology can not only analyze the cause of water level change, but also promote the development of water level recognition technology.

In order to solve the problem that traditional water level recognition methods cannot quickly, timely, and accurately identify water level changes in complex water environments, a strong edge algorithm can be used to clearly display the edge of the water level line in the form of an image. This image can be clarified by the intelligent water level recognition method, and the blurred image can also be processed clearly. On this basis, sparse constraints can be applied to narrow the range of data of water level recognition and record the identified water level line with accurate values. To meet the requirement of timely recognition of small changes in the water level line, the strong edge algorithm and the sparse constraint method were applied in the practical research of water level recognition, in this paper. Compared with the traditional water level recognition method, this method could not only improve the timeliness and accuracy of water level recognition, but also provide accurate water level change data for water resource management personnel when carrying out water management. The method could provide data support for later water governance and planning work, and better carry out water management work. It also could ensure the safety of residents near water and provide certain reference opinions for other recognition methods.

2. TRADITIONAL WATER LEVEL IDENTIFICATION

2.1. Traditional water level identification

Water level recognition plays an important role in hydrological detection. An effective grasp of water level change information can enable timely preparedness for natural disaster prevention measures, such as flood control and drought resistance, and also be conducive to promoting the development of agriculture (Elijah *et al.* 2018). There are three traditional ways to obtain water level change information: The first is manual observation, measurement, and data recording. There are many disadvantages in this way, which lead to inaccurate observation data. The main ones are as follows: Limitations of human eye recognition cause huge errors in the observed data. The information on water level change cannot be grasped in time when there is an emergency in the water area. It is impossible to check and record water level changes manually in bad weather. What is more, with the development of flow sensor technology, it is widely used in water level recognition due to its high sensitivity. A flow sensor communicates information through the flow of water, because the sensor is sensitive and can sense changes in time. However, due to its internal structure, the cost of water level recognition is high and the recognition range is limited. Finally, with the maturity of computer technology and image recognition technology, as well as their application in various fields, image recognition water level monitoring methods have been incorporated into video monitoring methods to increase the coverage and density of water level monitoring and enrich water level monitoring information. This water level recognition technology is now a commonly used water level recognition method.

With the development of science and technology, the water level recognition method becomes more intelligent. However, due to the immaturity of technology, there are minor errors in water level recognition data and data confusion caused by an improper data processing method. Hence, it is necessary to analyze and study new technical means and apply new technology suitable for water level recognition, so as to promote the development of the water level recognition method. Then, the information on water level changes is recorded and stored timely and accurately, by means of images and data, aiming to facilitate water resource management personnel to have detailed and accurate data for reference, when carrying out water management.

2.2. Traditional water level image recognition method

Traditional water level image recognition methods mainly include online monitoring, data transmission, and terminal display. Among them, the function of online monitoring is to detect and capture water level changes through smart cameras, divide the captured images into areas, and extract images of the required areas. Data transmission can transfer the image processed by the online monitoring method in the form of data (Ravand 2020). The terminal display transforms the data transmitted by the data transmission method to the image, displays the transformed image through the display screen, and uses an intelligent processor to display information analysis in the image, as shown in Figure 1.

The intelligence of the traditional water level image recognition method is mainly the intelligent shooting of the camera. In this camera, machine learning technology is used to study and apply the continuously updated intelligent shooting technology. In addition, image processing technology is used to analyze and process a large number of images, so as to remove unnecessary data information and provide intelligent detection service for water level information that needs to be treated. Traditional water level image recognition methods mainly include two image shooting methods, i.e. regular shooting and

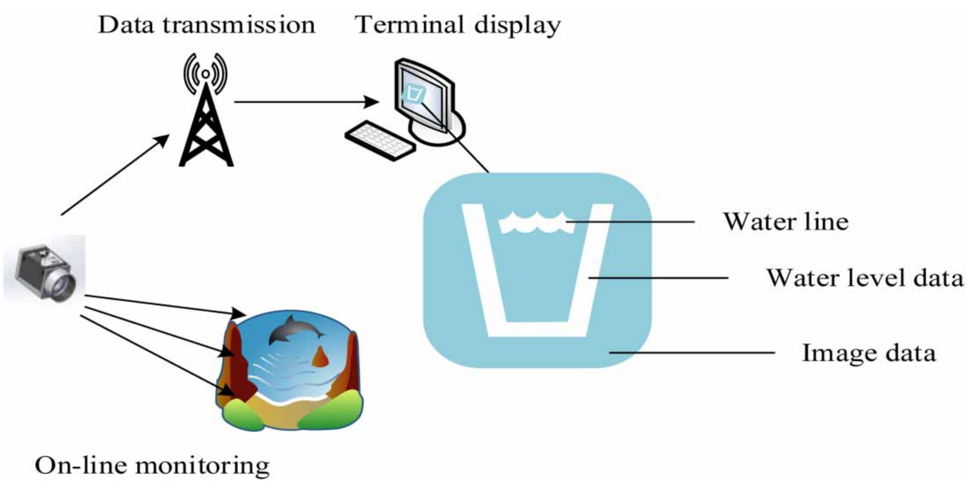


Figure 1 | Traditional intelligent water level recognition system.

independent shooting. It is necessary to choose the appropriate image shooting method according to water governance requirements.

2.3. Traditional water level recognition image processing method

With the development of modern science and technology, the image processing technology of water level recognition has been developed continuously, which provides an effective technical guarantee for water level recognition using the recognition method in the field of water resource management. Upgrading the image recognition technology promotes high clarity of images taken and clearer communication of information (Khan 2021). Each water level recognition image processing technology has its own advantages and disadvantages. Choosing a suitable water level recognition image processing method according to the characteristics of different recognition technologies has the great advantage of improving the water level recognition effect, as shown in Table 1.

There are three main image processing methods for water level recognition, which are grayscale transformation, edge detection, and image refinement. These three water level recognition methods are all based on image recognition technology, and different methods have many different discrepancies and roles in image recognition focus. The water level recognition method of grayscale transformation can improve the quality of water surface pictures taken by camera equipment. The method to improve the quality of pictures is to change the key points one by one according to a certain transformation relationship according to the requirements of target conditions, and then, to change the pixel grayscale value in the source image. The water level recognition method of edge detection can intelligently process irrelevant images and data information, when transmitting images and data in real time. While retaining the original structural attributes of images, it reduces the storage pressure of storage equipment because a lot of invalid information is removed and more useful information is stored in more storage space. The intelligent method of water level recognition information processing is to transfer images and data timely through the points with obvious changes in images. The water level recognition method of image refinement is mainly to create favorable recognition conditions for data compression and information recognition by the computer recognition method. It can clearly express the image structure of recognition requirement information in extracting a large number of recognition information and is a method to display the image in frame pixels.

2.4. Traditional water level line calculation method

Locking the water level mark by a single machine position, different positions of the water level mark are marked in the form of coordinates. The coordinates of the areas are aggregated to form a pixel interval, aiming to detect the coordinates of the water level and determine whether the coordinates are in the pixel interval. The specific expression is

$$j_o = J_k + \frac{J_{k+1} - J_k}{u_{k+1} - u_k}(u_o - u_k)\ (o = 1, 2, 3, \ldots, n,\ k = 1, 2, 3, \ldots, n) \tag{1}$$

where j_o is a single unit; J_k is the lower limit of the actual taken pixel range; J_{k+1} is the upper limit of the actual taken pixel range; u_k is the lower limit coordinate of the identified pixel interval; and u_{k+1} is the upper limit coordinate of the identified pixel interval.

Table 1 | Water level recognition image processing methods

Method	Usage	Advantage
Grayscale transformation	A method of changing the grayscale value of each pixel in the source image point by point according to a certain transformation relationship according to some target condition.	It can improve the quality of the captured picture and display the captured image in a clearer picture.
Edge detection	Identify points in a digital image where brightness changes significantly.	Intelligently weed out irrelevant data information, reducing the amount of data and preserving structural properties in the image.
Image refinement	A method for extracting skeletal pixels that can express the topology of an image.	Create conditions for data compression and recognition in computer systems.

The coordinate of the water level line is directly substituted into the curve equation to calculate the water level. The specific algorithm is as follows:

$$D_{\mu_o} = \beta(u_o) - j(u_o)\ (o = 1, 2, 3, \ \ldots, n) \tag{2}$$

$$D_{\mu_o^2} = \sum_{o=1}^{n} D_{\mu_o}^2 = \sum_{o=1}^{n} [\beta(u_o) - j(u_o)]^2 = \min \tag{3}$$

The calculated final water level is $j = j_o(o = 1)$.

2.5. Traditional water level recognition image preprocessing

The traditional water level identification method has some deficiencies in detail. In this paper, the traditional method described above is used to preprocess the water level identification image of a certain place in Kaifeng, and the effect of image processing is shown in Figure 2.

As shown in Figure 2, Figure 2(a) is the original image taken. It can be found from the figure that the focus of the image is not prominent enough due to the clutter of color light and background, so the original image has been grayscale processed. Figure 2(b) is the image after grayscale processing, Figure 2(c) is the histogram after grayscale processing, and it can be clearly seen from Figure 2(b) that the image has changed from color to black and white. However, it is found that the image is still fuzzy, the edge is not clear enough, and the clarity of the image is not enough; so it is necessary to use the new method in this paper to effectively analyze the problem.

3. APPLICATION OF STRONG EDGE AND SPARSE CONSTRAINT IN WATER LEVEL IDENTIFICATION

3.1. Gradient domain cost function

In an image, there are generally edges between objects and background, as well as between objects, and edge enhancement is a processing method that can make the outline of an image more obvious, and it is a valuable regional processing technology. Edge enhancement is mainly to enhance the boundary in the image, while the part beyond the boundary will be weakened or directly removed. The images taken in water level recognition are usually far away and the water level line is fuzzy. Therefore, this paper uses the gradient domain cost function to process the input image, and then, enhances the edge of the image to achieve the purpose of water level recognition. Specifically, the image is transferred to the gradient range for gradient screening, and the threshold value of the gradient range is set to remove invalid edges. In this way, strong edges can be obtained, and the algorithm for extracting strong edges is as follows:

$$\begin{cases} \min\limits_{\Delta a, b} \alpha \|\Delta_h - \Delta' a \otimes b\|_2^2 + \dfrac{\|\Delta' a\|_1}{\|\Delta' a\|_2} + \beta \|b\|_1 \\ \qquad b \geq 0, \ \sum\limits_{o} b_o = 1 \end{cases} \tag{4}$$

Among them, $\Delta' a$ represents the extracted strong edge, α and β represent the weight.

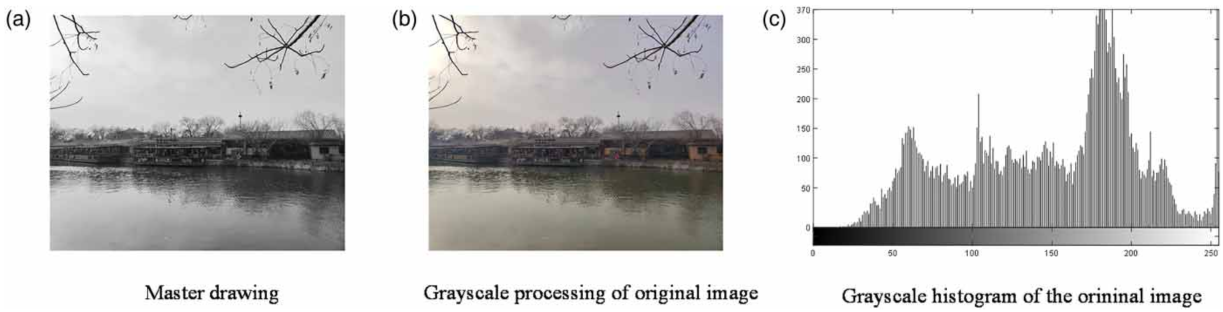


Figure 2 | Preprocessing effect of the water level recognition image by the traditional method.

However, the information on water level constantly changes and the variation law of water level in some special waters is uncertain. However, the sparse constraint method used in this paper can transform the inadequacy problem into an adequacy problem, ensure the stability and uniqueness of the results, and avoid failure in accurately extracting the required data information due to a large amount of data information. Thus, it is impossible to effectively control the waters. Therefore, after the image is extracted by the strong edge of formula (4), the fuzzy image content is clearly displayed by the sparse constraint method. The specific algorithm is as follows:

$$\min_{m,n} \alpha\|u - n*m\|_2^2 + \frac{\|m\|_1}{\|m\|_2} + \beta\|n\|_1 \tag{5}$$

Among them, $m = \Delta' a$, $n = b$, and $u = \Delta'_h$.

Through the application of the above strong edge and sparse constraint methods, the traditional water level identification instrument can strengthen the water level line and clear the image, even when the lake surface is not clear, so as to accurately and clearly identify the change of the water level line, as shown in Figure 3.

As shown in Figure 3, on the basis of traditional water level identification methods, strong edge and sparse constraint techniques used in this paper are added to the figure, which solves the problem that traditional water level identification images are not clear and cannot cope with the impact of bad weather, so as to better identify water level changes.

3.2. Reference to the intelligent water level image recognition method

The intelligent water level image recognition method is introduced to change the traditional way of collecting water level information by manual measurement. The captured image is recognized by the computer image processing method. By continuously updating the recognition function through machine learning technology, it can facilitate timely, fast, and effective recognition and processing of a large amount of video, image, data, and other information, thus achieving the requirements of intelligent recognition of water level changes. With the application of the intelligent water level image recognition method, the function is gradually improved in continuous practice, but the details of image processing are not perfect enough. Therefore, new technology is needed to improve the image processing function of the intelligent water level image recognition method, as shown in Figure 4.

As shown in Figure 4, traditional water level recognition methods are introduced to extract the strong edge algorithm and the sparse constraint algorithm. The strong edge algorithm can process image contour more obviously, while the sparse constraint algorithm can restrict the water level recognition area effectively. Then, water level changes are effectively recognized

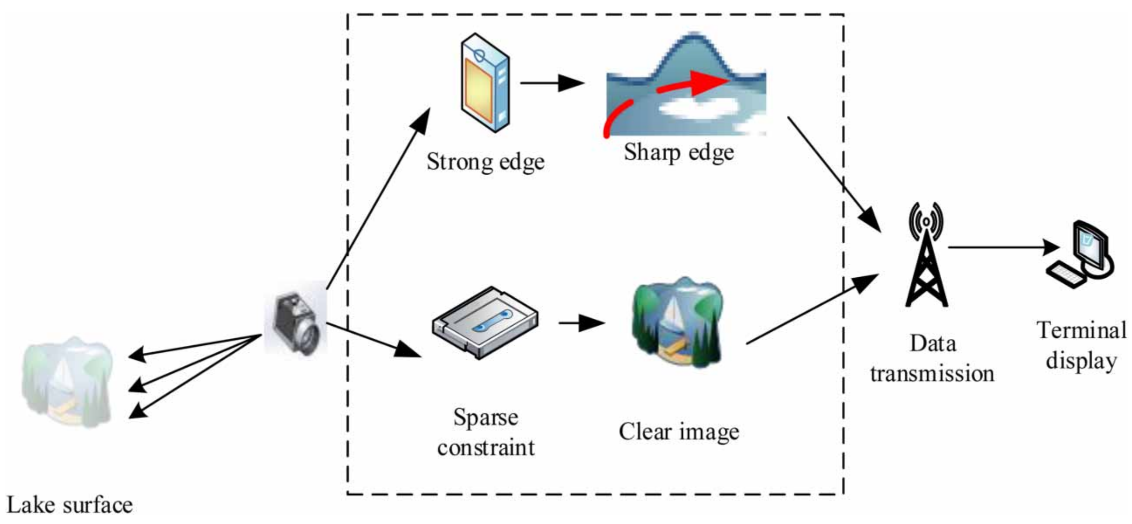


Figure 3 | Water level image processing diagram based on strong edge and sparse constraint technologies.

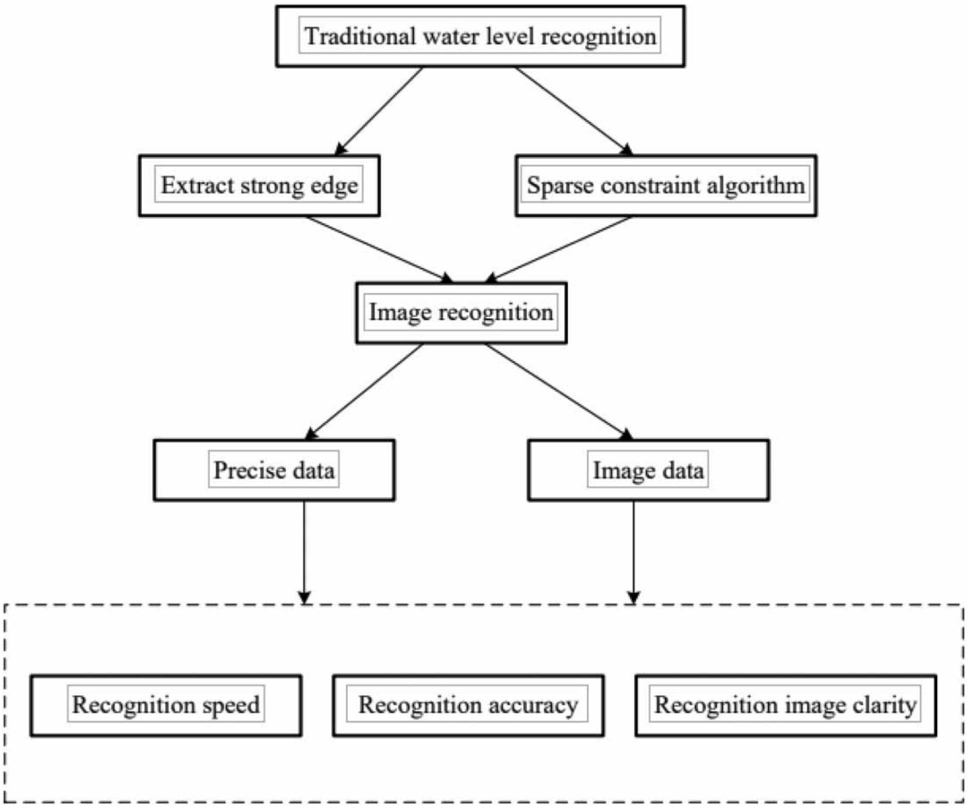


Figure 4 | Establishment of the intelligent water level image recognition system.

according to needs intelligently, and the identified image details are clear and complete. There is a significant improvement in the clarity of the recognition image, as shown in Figure 5.

Figure 5(a) is the original image and Figure 5(b) is the histogram of the original image. It can be clearly seen that the lines are more concentrated because the image is fuzzy. In addition, it can be seen from the histogram of Figure 5(d) that the lines are more dispersed and balanced, and the range of values is larger than that of Figure 5(b), indicating that after the original image is equalized, the clarity and brightness of the image are effectively improved.

4. IMAGE PROCESSING

4.1. Image edge processing

The water level recognition method has high requirements for image quality (Patra *et al.* 2018), while water level changes rapidly and frequently, and the information amount of images and data is large. Flexible processing of images and data can reduce the pressure of data storage equipment. The above intelligent water level recognition method can effectively improve the brightness of the image. It can be clearly seen that although the basic structure of the image is preserved in the original image, the edge structure of the image is blurred. Therefore, a series of image processing is required to accurately identify changes in the water level, as shown in Figure 6.

As shown in Figure 6, after edge processing of the original image, the process and effect of image edge detection and extraction can be clearly seen. From the figure, the water level line on the bank of the river can be clearly seen, and the edge processing of the image identified by the water level can be effectively carried out to facilitate the inspection of the detection personnel.

4.2. Image noise reduction processing

Filtering algorithm is a common technique used in image processing and signal processing, and there are many different filtering algorithms (Okon *et al.* 2018). The following are three commonly used filtering algorithms and their formulas:

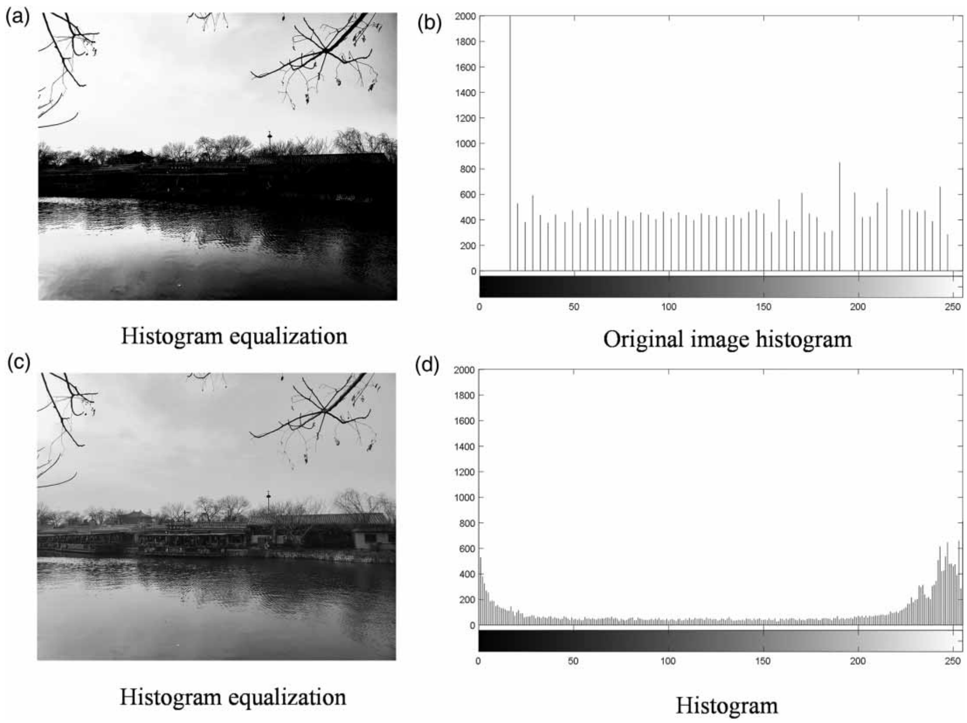


Figure 5 | Definition rendering of image recognition.

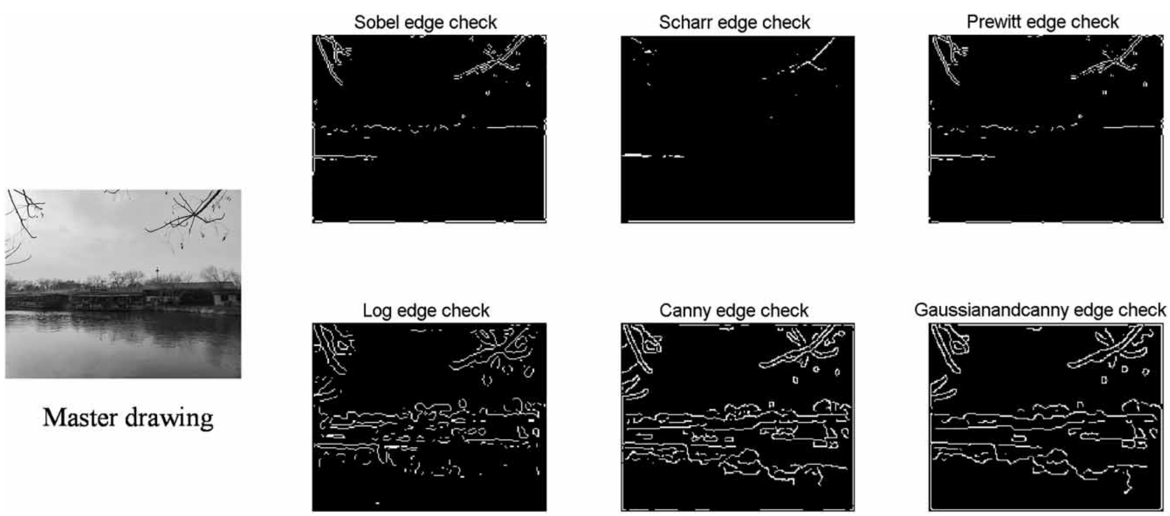


Figure 6 | Image edge processing effect.

4.2.1. Mean filtering

For a sliding window of size $n \times n$, the mean filtering formula is as follows:

$$\text{Output}(x,\ y) = \left(\frac{1}{n\hat{}2}\right) * \Sigma\,\Sigma\ \text{Input}(x+i,\ y+j) \tag{6}$$

4.2.2. Median filtering

For a sliding window of size $n \times n$, the median filtering formula is as follows:

$$\text{Output}(x,\ y)\ =\ \text{median}(\text{Input}(x+i,\ y+j)),\quad i=-\frac{n}{2}\ \text{to}\ \frac{n}{2},\quad j=-\frac{n}{2}\ \text{to}\ \frac{n}{2} \tag{7}$$

4.2.3. Gaussian filtering

For a sliding window of size $n \times n$, the Gaussian filtering formula is as follows:

$$\text{Output}(x,\ y)=\left(\frac{1}{2\pi\sigma\hat{}2}\right)*\Sigma\ \Sigma\ \text{Input}(x+i,\ y+j)*\exp\left(-(i\hat{}2+j\hat{}2)/(2\sigma\hat{}2)\right) \tag{8}$$

where Input(x, y) represents the pixel value of the input image at pixel position (x, y), Output(x, y) represents the pixel value of the output image at pixel position (x, y), i and j are the offset of each pixel in the sliding window, median represents the median obtained, exp represents the natural exponential function, and σ represents the standard deviation of the Gaussian kernel.

4.3. Effective extraction of the local area of the image

Noise may be generated by the interference of the water environment after image processing. Therefore, effective filtering and denoising are required for the image. Different filtering algorithms were compared and analyzed for the effect of image processing, as shown in Table 2.

As shown in Table 2, the signal-to-noise ratio of median filtering was 27.553 dB, while the signal-to-noise ratio of mean filtering and Gaussian filtering were 26.684 and 25.498 dB, respectively. The signal-to-noise ratio of median filtering was significantly higher than that of the two. The running time of the three filtering algorithms was compared. Each algorithm processed the same image ten times. The processing results are shown in Table 2. The average time of mean filtering and Gaussian filtering for image processing was above 30 ms. The mean time of median filtering for image processing was 5.38 ms, which is much faster than the others. After analyzing the filtering effect and the speed of image processing, the median filtering method was selected to process the image. This is because the median filtering algorithm is fast and has a high signal-to-noise ratio.

In summary, the median filter algorithm can greatly help the speed of image processing. The water level recognition method generates a lot of images and data information in the work, while the water level change information required in water resource management is a certain time period or long-term change rule and does not need a lot of images and data information. Affected by the season, summer is prone to drought or flood. The information demand for water level changes is large, while winter water level changes little, so the information demand for water level changes is small. Therefore, a lot of image information needs to be quickly and effectively selected. The necessary information is retained, and unnecessary information needs to be effectively denoised. This not only reduces the workload of post-image processing, but also accurately preserves a small amount of useful image information, aiming to provide effective data information for water resource management, water area management, and natural disaster prevention.

Table 2 | The effect of different filtering algorithms on image processing

Filter algorithm	Signal-to-noise ratio (dB)	Average filter run time (ms)
Mean filtering	26.684	37.57
Median filtering	27.553	5.38
Gaussian filtering	25.498	32.35

5. IMAGE PROCESSING EFFECT EXPERIMENT

5.1. Effect of image noise reduction

A water area is randomly selected, four processed images are randomly extracted from the water level recognition method of the water area, and then, the image is denoised through the median filter algorithm. The preprocessing effect of the image is detected through the analysis of the signal-to-noise ratio of the image, experimental data are recorded, and experimental results are analyzed, as shown in Table 3.

As can be seen from Table 3, A is the signal-to-noise ratio data result of the image before image noise reduction is processed through the median filter algorithm, and B is the signal-to-noise ratio data result of the image after image noise reduction is processed through the median filter algorithm. According to B, it can be clearly seen that the signal-to-noise ratio of the image before image denoising is processed by the median filtering algorithm in A is between 23.447 and 24.527 dB, while that of the image before and after image denoising is processed by the median filtering algorithm in B is between 26.323 and 27.537 dB, and the overall signal-to-noise ratio is above 26 dB. The noise is small, and the noise reduction value in B is significantly higher than that in A, indicating that the image noise after image noise reduction is processed by the median filter algorithm is small, and the impact on the image is also small, so that the details of the image can be effectively preserved.

The median filter method can preserve the detailed structure of the image well. According to the requirement of paying attention to detail in water level image recognition, the median filter method is used to effectively eliminate the noise in the image. Median filtering is a nonlinear image processing technology, which can effectively eliminate the noise in the image, while effectively preserving the key details in the image. The median filtering image processing method resets the gray value of each image pixel according to the median gray value of all pixels in a certain area around the pixel. Then, the points with an excessive difference in the median gray value of pixels in the local area of the image are effectively eliminated.

5.2. Image brightness processing effect

Four processed images were randomly extracted from the water level recognition method in a water area. Then, the image was processed by the edge detection image processing method. By comparing brightness analysis of the image before and after image processing, the preprocessing effect of the image was detected, experimental data were recorded, and the experimental results were analyzed, as shown in Figure 7.

Table 3 | Comparison of effect before and after image noise reduction

	1	2	3	4
A	23.543	24.527	23.447	23.689
B	27.537	26.323	27.295	27.375
Difference value	3.994	1.796	3.848	3.686

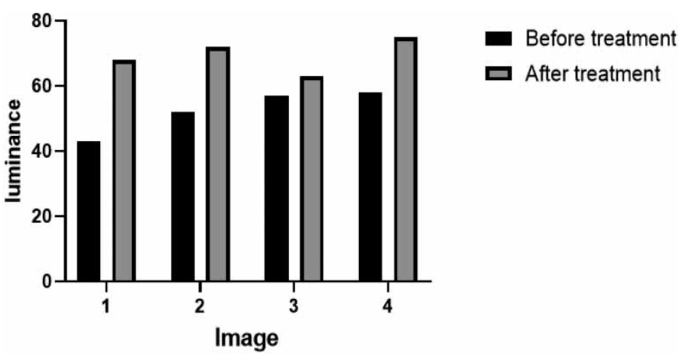


Figure 7 | Comparison of brightness values before and after image processing.

As shown in Figure 7, the data recorded before image processing by edge detection found that the brightness of the image is between 43 and 58, indicating that the overall brightness of the image is dark. After image processing by edge detection, the brightness value of the image is between 63 and 75, which means that the brightness has significantly improved. It shows that the edge detection image processing method has been an obvious help in improving the brightness of the detected image.

In summary, through the analysis and research of three image processing methods, this article selects the edge detection image processing method based on the characteristics and requirements of water level recognition, and conducts experimental analysis on the effectiveness of the edge detection image processing method. By comparing the brightness of the image before and after image processing, it can be seen that the brightness of the image, after edge detection is processed by the image processing method, has been significantly improved. Increasing the brightness of the image can enhance the detailed display of the picture and more clearly identify the numerical information of the water level line, facilitating the data recording of water level changes. Because the value on the marking rod of the water level line is small, the image is slightly blurred so that the water level value information cannot be seen.

6. EXPERIMENT OF IMAGE PROCESSING EFFECT

6.1. Experimental preparation

The water area of Qingming Shanghe Garden in Kaifeng was taken as the experimental object. Four captured water level images were randomly extracted from the traditional water level image recognition method in the water area. Then the image was processed through strong edge and sparse constraint algorithms for image details. By comparing the images before and after processing, the effect of detail processing of the intelligent water level image recognition method was reflected. The experimental data were recorded and the experimental results were analyzed.

6.2. Experimental data

6.2.1. Clarity

The clearer the image before and after contrast processing, the better the clarity, and the better the detail processing effect of the intelligent water level image recognition method. The lower the clarity, the worse the detail processing effect of the intelligent water level image recognition method, as shown in Figure 8.

As shown in Figure 8, before the processing of strong edge and sparse constraint algorithms, the image clarity value ranges from 86 to 89%, and the average clarity value is about 87.5%; after the processing of strong edge and sparse constraint algorithms, the image clarity value ranges from 96 to 99%, and the average clarity value is about 97.5%. The sharpness value of the image after strong edge and sparse constraint algorithms is about 10% higher than that before strong edge and sparse constraint algorithms. Therefore, it can be concluded that the sharpness of the image after strong edge and sparse constraint algorithms are used to improve the overall performance of the intelligent water level image recognition method.

To sum up, after image processing with strong edge and sparse constraint algorithms, the picture content of the image is clearer. The water environment is complicated. Affected by bad weather and night brightness, the image content is relatively

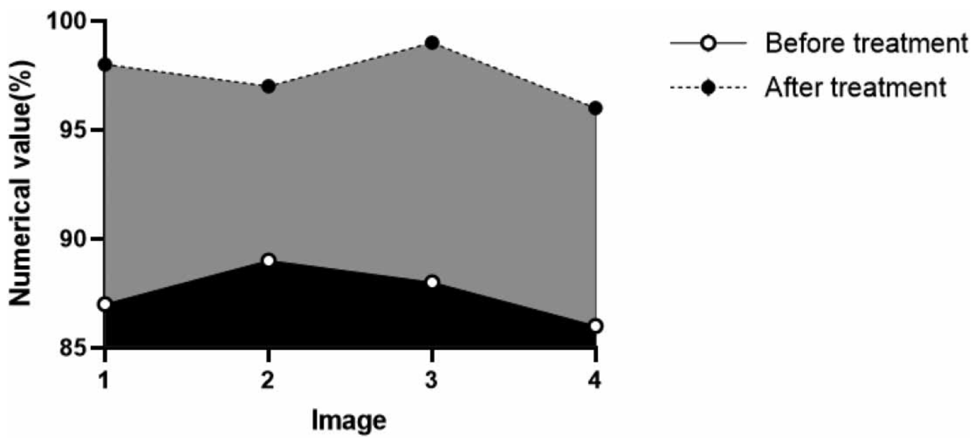


Figure 8 | Comparison of clarity results before and after image processing.

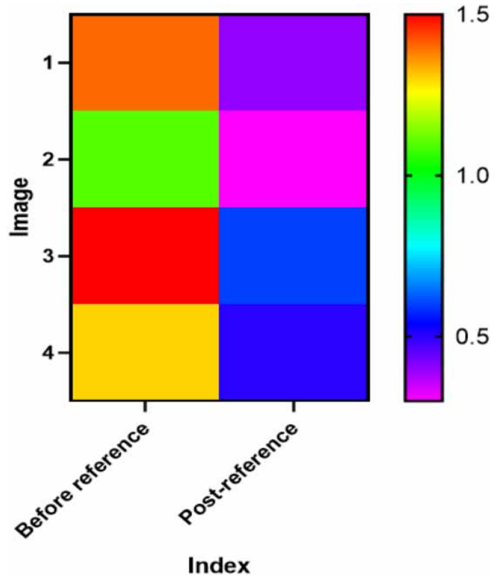


Figure 9 | Comparison of speed results before and after image processing.

blurry and the water level value cannot be clearly identified. Therefore, the water level recognition image needs to be processed. The blurred image taken in bad weather can also be clearly displayed, thus providing timely and accurate image and data information for the study of water level changes in bad weather.

6.2.2. Image processing speed

Time was compared before and after image processing. The longer the time, the worse the detail processing effect of the intelligent water level image recognition method. The shorter the time, the better the detail processing effect of the intelligent water level image recognition method, as shown in Figure 9.

As shown in Figure 9, it can be clearly seen from the figure that the distribution time of image processing before strong edge and sparse constraint algorithms is between 1 and 1.5 s, with a minimum value of 1.1 s and a maximum value of 1.5 s, and the overall distribution time of image processing is more than 1 s. The distribution of image processing time after strong edge and sparse constraint algorithms is between 0.3 and 0.6 s, the minimum value is 0.3 s, and the maximum value is 0.6 s. The overall distribution of image processing time is less than 1 s, and the overall speed is effectively improved, indicating that this method improves the image processing speed after strong edge and sparse constraint algorithms are used. This saves a lot of time for the subsequent water treatment work.

In conclusion, the time of image processing is greatly shortened by using strong edge and sparse constraint algorithms, which is of great help to improve the processing speed of the overall image method. Using strong edge and sparse constraint algorithms not only improves recognition speed, but also effectively ensures image clarity. This further indicates that strong edge and sparse restriction algorithms have a certain promoting effect on the overall development of water level recognition methods. The algorithm also provides a certain reference value for the development of recognition technology in other industries.

7. CONCLUSION

Water resources are indispensable for human survival and development. The detection and management of water resources can not only protect the beautiful homeland that human beings depend on for survival, but also effectively ensure the safety of residents. Therefore, it is necessary to use strong edge and sparse constraint algorithms to meet the needs of image detail processing for water level recognition. The aim is to provide some reference for modern intelligent water level image recognition methods. This paper describes the traditional water level recognition image processing method and analyzes the possible problems in image processing. To address this issue, this article utilized strong edge and sparse constraint algorithms for a series of image processing, and compared the preprocessed and postprocessed images with experiments. It was found that the brightness of the processed images was effectively improved. The edge enhancement of the water level identification image can effectively view the change of the water level line and provide scientific and effective image data information for the subsequent effective treatment of water resources.

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DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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