RESEARCH ARTICLE

# Intelligent recognition method of *Mycobacterium tuberculosis* (MTB) dynamic microscopic images based on morphology and regional fusion

Furong Yu[1, *], Jiachen Liu[1], Daojun Chen[1], Dun Hu[1], Min Zhang[2]

[1]Department of Medical Technology, Anhui Medical College, Hefei, Anhui, China. [2]Hefei KingMed Center for Clinical Laboratory, Hefei, Anhui, China.

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**Tuberculosis is caused by a type of bacteria named *Mycobacterium tuberculosis*. Due to the quality difference of the original dynamic microscopic images of *Mycobacterium tuberculosis*, it is difficult to guarantee the recognition effect. In this work, the noise in the original dynamic microscopic image of *Mycobacterium tuberculosis* was removed by morphological processing, while the purpose of filling holes and disconnecting connected areas was achieved. Based on corrosion and expansion of the image, the original dynamic microscopic image of *Mycobacterium tuberculosis* was preprocessed by opening and closing operations. After dividing the target area and the background area with the help of the threshold, the adjacent *Mycobacterium tuberculosis* areas were merged into a continuous area by using the level set method in regional fusion, and finally the identification of *Mycobacterium tuberculosis* bacteria was realized according to the characteristics fed back from the image. This intelligent microscopic image processing technology, which preprocessed the original dynamic microscopic images of *Mycobacterium tuberculosis* from a morphological point of view, and then realized accurate identification of *Mycobacterium tuberculosis* images through regional fusion, could provide more accurate and reliable diagnostic information and technical support for clinical diagnosis and treatment.**

**Keywords:** morphology; regional integration; dynamic microscopic image; *Mycobacterium tuberculosis*; intelligent identification; open operation; closed operation; target area; background area; level set method.

***Corresponding author:** Furong Yu, Department of Medical Technology, Anhui Medical College, Hefei, Anhui 230601, China. Email: qinm98686@163.com.

## Introduction

Intelligent healthcare refers to the application of artificial intelligence technology to provide support and solutions for the healthcare field with computer vision and image processing technology and plays a crucial role [1]. Computer vision technology enables computers to simulate human visual abilities and extract and recognize useful information from images by analyzing and understanding images and videos [2]. In the medical field, computer vision can be applied to medical image diagnosis, disease classification, lesion segmentation, and other aspects, providing doctors with more accurate, fast, and reliable auxiliary diagnostic methods [3]. The intelligent recognition method for dynamic microscopic images of *Mycobacterium tuberculosis* is developed based on this background [4]. By combining morphological features and regional fusion technology, using computer vision and image processing technology to analyze and identify the dynamic microscopic images of *Mycobacterium* *tuberculosis*, doctors can effectively help with diagnosis and treatment of *Mycobacterium tuberculosis* [5].

For *Mycobacterium tuberculosis*, it is of great practical significance to accurately identify its medical microscopic images. First, it can help doctors diagnose *Mycobacterium tuberculosis* more accurately and reduce the possibility of misdiagnosis [6]. Secondly, through image recognition technology, the pathological changes under the microscope can be automatically analyzed to improve the diagnostic efficiency, and thus provide more time and energy for doctors to study the treatment plan [7]. In addition, this technology is helpful to telemedicine and medical education, enabling expert doctors to diagnose diseases remotely, and can also be used as an effective tool for training a new generation of doctors [2]. However, the medical microscopic image recognition of *Mycobacterium tuberculosis* still faces some major problems that need to be overcome. First, the difference in image quality is a key issue. Due to the influence of microscope adjustment parameters, sample preparation methods, and lighting conditions, the image quality may vary greatly [8], which may lead to the performance degradation of the recognition algorithm because the algorithm needs to learn and recognize according to the common features of images [9]. Second, the morphology and distribution of *Mycobacterium tuberculosis* increases the difficulty of identification. *Mycobacterium tuberculosis* presents a unique shape and color under the microscope, but their distribution in the image is often uneven, and may be covered by other cells or background noise [10], which requires the algorithm to have higher spatial and color discrimination ability to accurately detect and identify *Mycobacterium tuberculosis* [11]. Furthermore, the automatic identification system needs to have the ability to detect dynamic changes and abnormal situations. Under the microscope, the changes of cells and tissues are continuous, and abnormal conditions may suddenly appear. The automatic identification system needs to be able to track these changes in real time and give an alarm in time when there are abnormal situations [12]. Finally, the privacy and security issues also need paying more attention [13]. Medical images usually contain a lot of personal information, so strict privacy protection measures must be taken to ensure the personal information safety of patients. When transmitting and processing medical images, effective security measures are needed to prevent unauthorized access and malicious attacks [14]. In view of this, the medical microscopic image recognition method based on multi-view cross-validation has been widely concerned, and its recognition results are more accurate. However, there is room for further improvement in the fitting degree of expressing the target boundary. The medical microscopic image recognition method based on neural network is also one of the common technical means, which has greatly improved the recognition efficiency, but its application scope has some limitations.

In order to solve the problem of unstable recognition results caused by differences in the quality of original dynamic microscopic images of *Mycobacterium tuberculosis*, an intelligent recognition method for dynamic microscopic images of *Mycobacterium tuberculosis* based on morphology and regional fusion was proposed. Morphological processing was used to remove noise, fill holes, and disconnect connected areas. The original image was preprocessed using methods such as corrosion, dilation, open and closed operations. Then, the target area and background area were divided by threshold, and the level set method in region fusion was used to merge adjacent areas of *Mycobacterium tuberculosis* bacteria into a continuous area. The recognition of *Mycobacterium tuberculosis* bacteria was then achieved based on image features. The method based on morphology and regional fusion could effectively improve the recognition accuracy and stability of dynamic microscopic images of *Mycobacterium tuberculosis* bacteria. Morphological processing in the preprocessing steps could improve image quality and facilitate subsequent segmentation and recognition processes. The level set method in regional fusion could better handle the connection and boundary problems between *Mycobacterium tuberculosis* regions and improve the recognition effect. This research provided a more reliable intelligent auxiliary tool for *Mycobacterium tuberculosis* diagnosis and treatment, shortened the time for doctors to diagnose, reduced the workload of medical staff, and improved the treatment effect of *Mycobacterium tuberculosis* patients. Meanwhile, the method proposed in this study could also provide reference and inspiration for other fields of intelligent medical image recognition, promoting the application and development of computer vision and image processing technology in the medical field.

## Materials and methods

### Morphological processing of dynamic microscopic images of *Mycobacterium tuberculosis*

For medical microscopic image recognition, the noise from the original dynamic microscopic image of *Mycobacterium tuberculosis* was removed by morphological processing, and at the same time, the holes were filled, and the connected areas were disconnected [15]. In the morphological processing of dynamic microscopic images of tuberculosis, several different methods were used to optimize image quality and highlight target features. First, the open operation was used to remove smaller noise points and non-tuberculosis substances from the image. This process eliminated noise points and smaller substances by first performing corrosion operations followed by expansion operations to reconnect adjacent substances that might have been separated during the corrosion process [16]. Second, the closed operation was used to fill the pores and cracks inside the tuberculosis bacteria by first expanding the material around the pores and cracks, and then performing a corrosion operation to shrink the expanded material back into the pores and cracks [17]. Corrosion operation was a method of removing small particles from an image by translating structural elements in the image [18]. The expansion operation was then used to fill small cracks and holes in the image, expanding the surrounding material by translating structural elements in the image [19]. These morphological processing methods worked together to improve the clarity and analysis efficiency of tuberculosis images. When removing the smaller noise points and non-tuberculous substances from the original dynamic microscopic image, the open operation was introduced, which removed the noise points and smaller substances by etching first, and then performed the expansion operation to reconnect the adjacent substances separated in the etching operation [20, 21]. The specific processing mode could be expressed as follows.

$$(f \Theta b)(x,y) = \min\left\{ f(x+s, y+t) \right\} \tag{1}$$

$$(f \oplus b)(x,y) = \max\left\{ f(x-s, y-t) \right\} \tag{2}$$

where $b(x,y)$ was the flat structural elements in the original dynamic microscopic image of *Mycobacterium tuberculosis.* $f(x,y)$ was dynamic microscopic image of the original *tubercle bacillus.* $s$ and $t$ were the action coefficients in different dimensions. Among them, formula (1) was the corrosion processing method of the original dynamic microscopic image of *Mycobacterium tuberculosis*, and formula (2) was the expansion processing method of the original dynamic microscopic image of *Mycobacterium tuberculosis*. The calculation method of opening and closing the original dynamic microscopic image of *Mycobacterium tuberculosis* was expressed as follows.

$$f \circ b = (f \Theta b) \oplus b \tag{3}$$

$$f \bullet b = (f \oplus b) \Theta b \tag{4}$$

Formula (3) was the open operation process of the original dynamic microscopic image of

*Mycobacterium tuberculosis*, while formula (4) was the closed operation process of the original dynamic microscopic image of *Mycobacterium tuberculosis* [22]. However, the appropriate size and shape of structural elements and the operation sequence needed to be selected according to the actual situation [23, 24]. The problems of excessive treatment of *Mycobacterium tuberculosis* caused by too large structural elements and poor treatment effect caused by too small structural elements should be avoided.

**Intelligent identification of dynamic microscopic images of *Mycobacterium tuberculosis* based on regional fusion**

Combined with the morphological processing results of the original dynamic microscopic image of *Mycobacterium tuberculosis*, this study introduced regional fusion in the specific identification stage. Briefly, the region of *Mycobacterium tuberculosis* was extracted by threshold segmentation technology. In the specific threshold segmentation, a gray threshold was set, and the pixels in the image were divided into two categories according to their gray values of target area and background area. The target area was usually given white (or high value), while the background area was given black (or low value). At this stage, a key step was to select an appropriate threshold. The selection of threshold has a great influence on the segmentation results. If the threshold was too low, it might lead to confusion between the target area and the background area. If the threshold was too high, it might cause the target area to lose details. The global threshold was a single threshold applied to the whole image, while the local threshold was determined according to the local area of each pixel. Therefore, the selection method of threshold in this study was expressed as below.

$$k = w_0(u_0 - u)^2 + w_1(u_1 - u)^2 \quad (5)$$

where $k$ was a threshold. $w_0$ and $w_1$ were the probability that random pixels in the dynamic microscopic image of *Mycobacterium tuberculosis* bacteria fell into the target area and the background area. $u_0$ and $u_1$ were the gray average parameters of the target area and the background area in the dynamic microscopic image of *Mycobacterium tuberculosis*. $u$ was the gray parameters of the whole dynamic microscopic image of *Mycobacterium tuberculosis*. Based on the segmentation, this study used the level set method in regional fusion to merge the adjacent *Mycobacterium tuberculosis* regions into a continuous region with the following specific calculation steps.

(1) Initialization:
An initial level set function was selected, which could be specifically expressed as:

$$E(k_m) = \sum e(k_m^n) \quad (6)$$

where $E(k_m)$ was a function represented an initial level set. $e(k_m^n)$ indicated the boundary parameters of *Mycobacterium tuberculosis* area. The level set function designed in this study was a function representing the boundary of the region. In the initial stage, each pixel could be assigned to an initial label as either *Mycobacterium tuberculosis* or background. On this basis, the level set function would be initialized as a set of these labels.

(2) Iterative update:
In each iteration, the level set function would be updated according to the image data and the current state of the level set function.

(3) Region merging:
By iteratively updating the level set function, a continuous region would be finally obtained, which included adjacent *Mycobacterium tuberculosis* regions. The adjacent labels in the level set function were merged into one label to realize region merging.

The dynamic microscopic image of *Mycobacterium tuberculosis* could then be

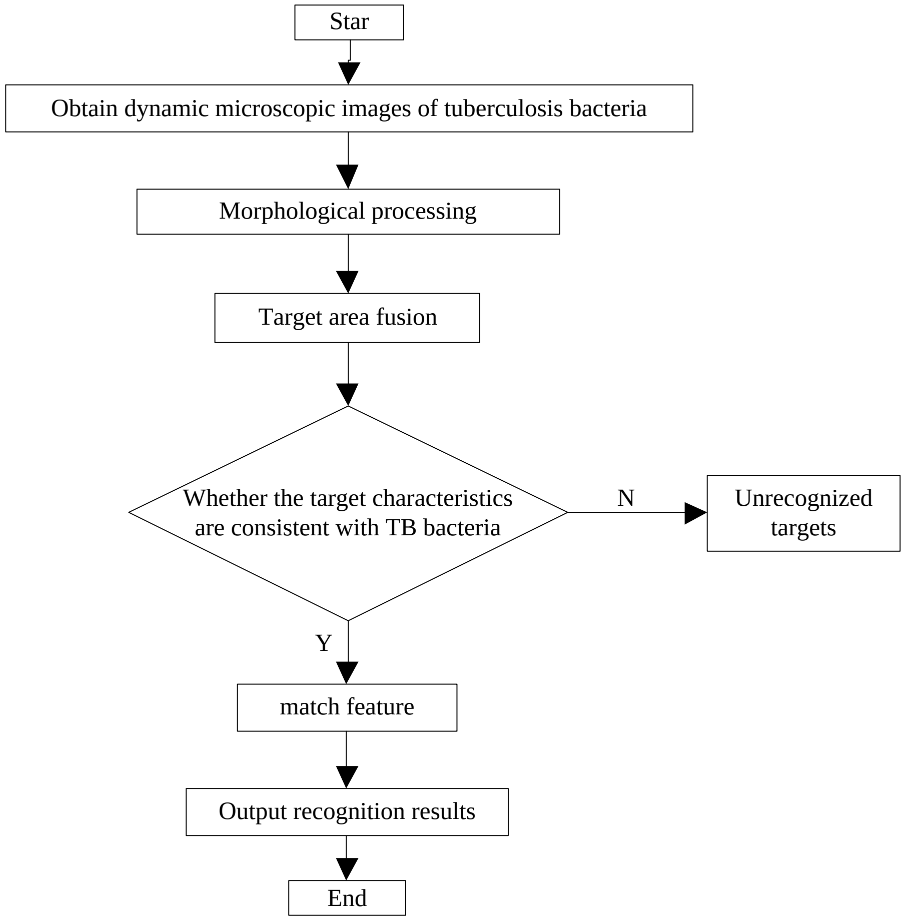


**Figure 1.** Dynamic microscopic image recognition mode of Mycobacterium tuberculosis.

recognized according to its characteristics (Figure 1). Combined with the identification process of dynamic microscopic images of *Mycobacterium tuberculosis*, the relationship between the target area characteristics of dynamic microscopic images of *Mycobacterium tuberculosis* and the characteristics of *Mycobacterium tuberculosis* itself were matched. When the characteristics of the target area of the dynamic microscopic image of *Mycobacterium tuberculosis* were consistent with the characteristics of *Mycobacterium tuberculosis* itself, it was automatically recognized as a *Mycobacterium tuberculosis* image, otherwise, it was automatically recognized as a non-*Mycobacterium tuberculosis* image. Through this method, the intelligent identification of dynamic microscopic images of *Mycobacterium tuberculosis* bacteria was realized. The reliability of identification results was guaranteed to the greatest extent. The influence of the quality of dynamic microscopic images of *Mycobacterium tuberculosis* bacteria on identification results was avoided.

**Test preparation**

A comparative test was carried out to analyze the practical application effect of the intelligent recognition method of *Mycobacterium tuberculosis* dynamic microscopic image based on morphology and regional fusion. Medical microscopic image recognition methods based on multi-view cross validation and neural network were used as the control groups. A specific test dataset containing dynamic microscopic images of *Mycobacterium tuberculosis* bacteria from public datasets of

**Table 1.** Signal to noise ratio results.

| Test image type | Signal to noise ratio (dB) | | |
|---|---|---|---|
| | **Multi-view cross validation image recognition method** | **Neural network image recognition method** | **Proposed image recognition method** |
| 1 *Mycobacterium tuberculosis* bacterium | 28.6 | 24.3 | 23.1 |
| 2 *Mycobacterium tuberculosis* bacteria | 30.1 | 25.8 | 24.5 |
| 3 *Mycobacterium tuberculosis* bacteria | 27.9 | 23.6 | 22.4 |
| Suspected *Mycobacterium tuberculosis* bacteria | 31.5 | 26.2 | 25.1 |

medical laboratories, AI Research and Automated Laboratory Diagnostics, were used for the test with all the data related to tuberculosis and obtained from sputum samples. A total of 928 images of sputum and 3,734 boundary boxes of bacteria were included in this study, which ensured the diversity of datasets and different image types, resolutions, and lighting conditions. Before carrying out specific tests, each image in the test dataset was marked, and the tuberculous region was marked as the region of interest (ROI), while the background area was marked as non-ROI. The test dataset was divided into three subsets with 200 images in each subset. To avoid over-fitting or under-fitting in the testing process, the specific configuration of dynamic microscopic images of *Mycobacterium tuberculosis* bacteria in each subset was determined as 1 *Mycobacterium tuberculosis* bacterium in each image for 20 dynamic microscopic images, 2 *Mycobacterium tuberculosis* bacteria in each image for 30 dynamic microscopic images, 3 *Mycobacterium tuberculosis* bacteria in each image for 50 dynamic microscopic images, and without *Mycobacterium tuberculosis* bacteria in each image for 100 dynamic microscopic images of impurity bacteria.

## Results

To verify the morphological processing effect of the proposed recognition, the performance of the three methods was validated using image signal-to-noise ratio as an indicator that was one of the important indicators for evaluating image quality and usually used to measure the ratio of useful information to noise in an image. The higher the signal-to-noise ratio was, the more useful information contained in the image, indicating better quality. The signal-to-noise ratio results of the three methods were compared and shown in Table 1. Compared to the other two methods, the proposed method showed a higher signal-to-noise ratio in different environments and exhibited better performance in all situations. Especially in cases involving suspicious *Mycobacterium tuberculosis* bacteria, the signal-to-noise ratio of the proposed method was more significant, reaching 31.5 dB, which was 5.3 dB and 6.4 dB higher than that of other methods, respectively. The results indicated that the method proposed in this study had better accuracy and stability in identifying images with different numbers of *Mycobacterium tuberculosis*. Therefore, the method proposed in this study had significant advantages in *Mycobacterium tuberculosis* image recognition. To further validate the image processing performance of the proposed method, the Structural Similarity Index (SSIM) was used as an indicator to test the performance of different methods. The comparison results of image structure similarity indices for the three methods were shown in Figure 2. The results showed that, compared to the multi-view cross validation image recognition method and the neural

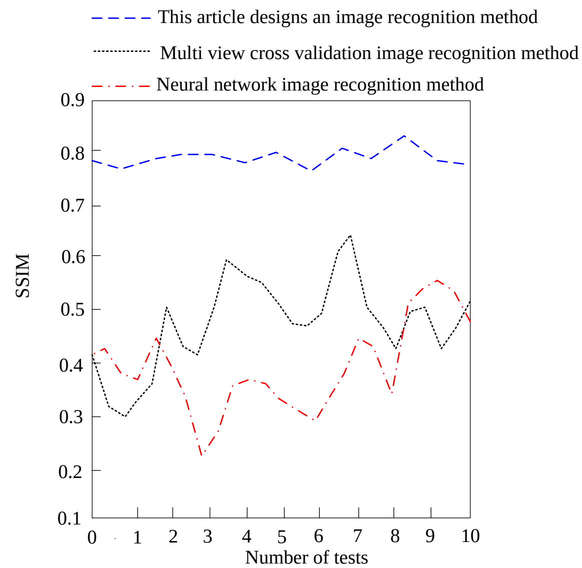


**Figure 2.** Structural Similarity Index (SSIM) results.

network image recognition method, the proposed method was higher, reaching a maximum of 0.85, while the other two methods both did not exceed 0.7. The results indicated that the proposed method could effectively process images of *Mycobacterium tuberculosis*, which helped to improve the effectiveness of dynamic microscopic image recognition of *Mycobacterium tuberculosis*.

To comprehensively evaluate the performance of the recognition method, F1 score was used as a specific scoring indicator. The F1 score is the harmonic average of accuracy and recall, which can reflect the overall performance of the recognition method. The higher the F1 score was, the better the performance of the corresponding recognition method was. The results showed that, for an image containing one *Mycobacterium tuberculosis*, the F1 scores of the multi-view cross validation image recognition method, the neural network image recognition method, and proposed method were 0.9726, 0.9834, and 0.9856, respectively. For images containing 2 *Mycobacterium tuberculosis* bacteria, the F1 scores of the multi-view cross validation image recognition method, the neural network image recognition method, and proposed method were 0.9645, 0.9633, and 0.9846, respectively. For images containing three *Mycobacterium tuberculosis*, the F1 scores of the multi-view cross validation image recognition method, the neural network image recognition method, and proposed method were 0.9632, 0.9617, and 0.9822, respectively. For images containing suspected *Mycobacterium tuberculosis*, the F1 scores of the multi-view cross validation image recognition method, the neural network image recognition method, and proposed method were 0.8426, 0.8534, and 0.9556, respectively. These results indicated that the image recognition method designed in this study exhibited high F1 scores in various test image types, demonstrating its superior overall performance.

## Discussion

Medical microscopic image recognition of *Mycobacterium tuberculosis* has important practical significance, but it also needs to overcome many technical challenges. In this study, the intelligent identification method of dynamic microscopic image of *Mycobacterium tuberculosis* based on morphology and regional fusion was studied. After preprocessing the original dynamic microscopic image of *Mycobacterium tuberculosis* from the morphological point of view, the accurate identification of the image of *Mycobacterium tuberculosis* was realized by means of regional fusion. Intelligent identification of dynamic microscopic images of *Mycobacterium tuberculosis* was an interdisciplinary research direction involving many fields including computer vision, machine learning, medical image analysis, and so on. Further research in this field may consider the following two aspects including feature extraction and representation learning and multi-modal data fusion. Currently, image recognition methods based on deep learning have achieved good results in feature extraction. However, how to better represent the morphological and dynamic characteristics of *Mycobacterium tuberculosis* is still a challenge. Future research should explore new feature extraction methods and representation learning methods to better describe the appearance and structural characteristics of *Mycobacterium tuberculosis*. Intelligent identification of dynamic microscopic images of *Mycobacterium tuberculosis* can be combined with data of other modalities such as pathology and molecular biology to provide more comprehensive and accurate diagnostic information. Future research may explore how to effectively fuse the data of different modes to improve the accuracy and reliability of diagnosis. The research on intelligent identification of dynamic microscopic images of *Mycobacterium tuberculosis* is a scientific field with important application prospects, and future research can be deeply explored and studied from many aspects to provide more accurate and reliable diagnostic information and technical support for clinical diagnosis and treatment.

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