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Research Article

Comparation Analysis of Otsu Method for Image Braille Segmentation: Python Approaches

Ardi Anugerah Wicaksana [1], Anik Nur Handayani [2,*]

[1] Universitas Negeri Malang, Malang, Indonesia, afwatul.maqbullah.2105366@students.um.ac.id
[2] Universitas Negeri Malang, Malang, Indonesia, aniknur.ft@um.ac.id

Correspondence should be addressed to Anik Nur Handayani; aniknur.ft@um.ac.id

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Abstract:

Braille serves a fundamental medium for literacy among individuals with visual impairments, enabling them to access education information independently. As the demand for digital accessibility increases, converting physical Braille documents into machine-readable text becomes essential. However, this task presents technical challenges, especially in the accurate segmentation of Braille dots from scanned images. The complex nature of Braille, which consists of raised dots with subtle contrast, varying lighting, and noise in scanned inputs, makes traditional segmentation approaches less effective. This study aims to evaluate and compare the effectiveness of several classical image segmentation techniques: Otsu, Otsu Inverse, Otsu Morphology, and Otsu Inverse Morphology in enhancing Braille image pre-processing. The methods were tested using set of Braille image datasets and evaluated based on six quantitative image quality metrics: Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), Mean Absolute Error (MAE), Structural Similarity Index (SSIM), Feature Similarity Index (FSIM), and Edge Similarity Index (ESSIM). The results demonstrate Otsu with Morphological Operations method consistently outperformed the others in terms of PSNR (27.6798) and SSIM (0.5548), indicating superior image fidelity and structural preservation. On the other hand, standard Otsu method achieved the lowest MSE value (113.3485), highlighting its effectiveness in minimizing pixel-wise error. Overall, the combination of morphological operations with thresholding significantly improved Braille dot segmentation accuracy across various metrics. These findings suggest when optimized classical techniques, can offer a practical and efficient alternative to deep learning-based solutions. This approach opens new opportunities for developing lightweight Braille recognition systems that are both accessible and reliable.

Keywords: Braille; Image Segmentation; Otsu Method; Python.
Dataset link: https://drive.google.com/drive/folders/1tx9ro7uNC2TiQKN3T4NVDzuUSmoq0Bwy?hl=ID

1. Introduction

Braille is a tactile writing system widely used by visually impaired individuals for reading and writing, utilizing a pattern of two horizontal and three vertical dots [1], [2]. As technology advances, automated Braille recognition and processing have become essential in promoting accessibility [3]. One of the fundamental steps in Braille image processing is image segmentation, which involves distinguishing Braille dots from the background. A widely used technique for this purpose is Otsu's thresholding method, a global thresholding technique that automatically determines an optimal threshold value to separate foreground and background in an image [4], [5]. However, the effectiveness of Otsu's method can vary depending on factors such as image quality, noise, and lighting conditions. Therefore, an in-depth analysis is required to assess its performance in Braille image segmentation, especially when implemented using Python-based image processing tools.

Traditional methods for Braille image segmentation often rely on manual or semi-automated techniques, which can be time-consuming and inconsistent. The Otsu method, despite its efficiency, may struggle with images containing uneven illumination [6], low contrast [7], or noise [8], leading to inaccurate segmentation. Additionally in the past, real-world image documents may present challenges such as degraded paper quality [9], and variations in printing techniques [10]. From the many shortcomings, this study tries to overcome one of the problems, namely noise, and many studies are explored to improve the segmentation accuracy. However, a comprehensive comparison of Otsu's method under different conditions, particularly in a braille image, remains an open research challenge.

This study aims to evaluate the effectiveness of Otsu's thresholding method in Braille image segmentation using Python-based approaches on colab platform. The effectiveness of the Otsu method also get benefits from integration with various techniques by enhancing its thresholding capabilities, allowing for improved segmentation across diverse image types [11]. So, the model will be implemented on four scenarios Otsu, Otsu Inverse, Otsu with Morphology, and Otsu Inverse with Morphology to compare the segmentation accuracy of Otsu's method under varying conditions, including different noise levels, and variations in segmentation. In addition, this study attempts to explore the extent to which Otsu threshold can segment braille image datasets with morphological operations that can reduce noise and inverse image techniques in improving segmentation results. By examining the differences in these comparative results, this study hopes to offer new insights into the advantages and limitations of each in applying the Otsu thresholding method, along with practical recommendations for developing future image segmentation research [12].

Previous studies have explored various additional image segmentation techniques for Otsu Thresholding to solve noise challenge. The first technique is Gaussian, Pre-processing methods that enhance image quality lead to better-defined edges and features, facilitating more accurate segmentation [13]. But Gaussian blur lack is averages pixel values, which can lead to blurring of edges and loss of detail, making it unsuitable for impulse noise like salt-and-pepper [14], The second technique is adaptive threshold. Studies show that adaptive thresholding can significantly improve segmentation quality by retaining more image information compared to K-means, which is sensitive to initial cluster parameters [15]. The challenge is found in SAR images which are inherently noisy, which can significantly affect the performance of adaptive thresholding methods, such that noise can lead to false positives or missed detections [16]. The third technique is Morphology operation, a basic operation that reduces or expands the boundaries of objects in a binary image [17]. Simple morphological operations can be combined to create more complex functions for advanced image analysis [18]. Morphological operations are particularly adept at reducing noise types such as Salt-and-Pepper and have been shown to improve segmentation accuracy in microscopic images [19]. Unlike traditional denoising methods that can blur edges, morphological techniques preserve sharp boundaries, ensuring that important details remain intact [20]. Furthermore, pixel intensity histograms to determine optimal thresholds often results in high accuracy in segmenting darker objects like invers image [21].

This study evaluates the user-friendly Otsu Thresholding technique for image segmentation using Python and Colab, making it accessible to practitioners with diverse technical backgrounds. By focusing on Braille image segmentation, it aims to provide an affordable and practical solution for resource-limited environments. The findings are expected to demonstrate Python with Colab as an effective alternative for comparative analysis of Otsu methods while paving the way for future research to enhance segmentation accuracy through additional image variables or integration with machine learning.

2. Method:

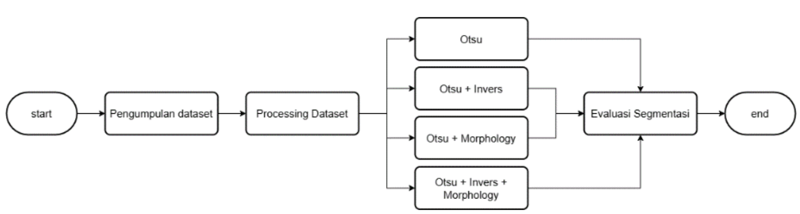

Figure 1. Research Flowchart

This study aims to compare the results of Otsu threshold-based segmentation using Python and Google Colab. The research process begins with data collection, pre-processing, Otsu Threshold Process on Braille images, followed by a combination of morphological operations and image inversion to produce comparative output of image segmentation results.

Research Design

The purpose of this study is to compare Otsu threshold-based segmentation outcomes using Google Colab and Python, for the research flow show in **Figure 1**. In order to generate comparative output of picture segmentation results, the study procedure starts with data collection, preprocessing, and the Otsu Threshold procedure on Braille images. This is followed by a combination of morphological operations and image inversion.

Dataset Collection

This study uses the Otsu threshold approach to test the braille image dataset with a combination of 2 consonant-vowel letters in sequence. In the pre-processing stage, the annotated braille letters undergo a cropping process according to the location of the bounding box coordinates so that 3153 braille letter images are created with details of 105-word groups. The dataset consists of Braille character images with varying dimensions ranging from 42×24 pixels to 39×36 pixels. While uniform resizing is commonly applied in image pre-processing, initial experiments with resizing to 256×256 pixels using black padding introduced significant bias in the thresholding process. The presence of large padding areas distorted the histogram distribution, resulting in ineffective segmentation using the Otsu method. Therefore, in this study, images were processed in their original dimensions to preserve the integrity of the thresholding process. In sample selection, a different approach is presented in single pixel imaging, which shows that high-quality imaging can be achieved with fewer samples [22]. So in this study only 10 word groups were selected, namely: ba, ca, da, fa, ga, ha, ja, ka, la, ma. For details of the samples dataset are shown in **Figure 2**.

Figure 2. Sample dataset image braille

Data Analysis Method

The data comparison process is carried out through four main stages: Otsu, Otsu inverse, Otsu morphology, and Otsu inverse morphology. The Otsu method determines the optimal threshold in image segmentation, while Otsu inverse inverts the segmented area. Otsu morphology combines Otsu with morphological operations such as dilation and erosion to clarify the structure of the object, while Otsu inverse morphology applies similar principles to the results of Otsu inverse. These four stages are used to improve the accuracy of image analysis.

a. Otsu

The Otsu method determines the optimal threshold for image segmentation by maximizing between-class variance, effectively distinguishing foreground from background [23]. The part formula for the Otsu threshold method is as follows.

$$\sigma_b^2(t) = \omega 0(t).\omega 1(t).(\mu 0(t) - \mu 1(t))^2 \quad (1)$$

$$t^* = \arg max \sigma_b^2(t) \quad (2)$$

This formula is a calculation of the variance $\sigma_b^2(t)$, where the variance $\sigma_b^2(t)$ is used to find the value of data distribution by multiplying the probability frequencies of 2 background classes $\omega 0(t)$ and foreground $\omega 1(t)$, then multiplied by the binomial square of the average probability of the background class $\mu 0(t)$ foreground $\mu 1(t)$. Finally, the search for the optimal threshold $t*$ where the value of t maximizes the variance between classes $\sigma_b^2(t)$ using the maximum argument.

b. Otsu Invers

The inverse Otsu technique flips the segmented areas, which can be beneficial in certain contexts where the focus is on background features rather than foreground objects [24]. The general formula for the invers image method is as follows

$$I\ invers(x,y) = 255 - I\ (x,y) \tag{3}$$

I invers(x,y) is the pixel value after inversion, which is obtained from the calculation 255 - *I(x,y)*, where 255 is the maximum intensity value in the 8-bit grayscale image and *I(x,y)* is the original pixel intensity value at the coordinates.

Original

50	50	50	50	50
50	200	200	200	50
50	200	255	200	50
50	200	200	200	50
50	50	50	50	50

Invers

205	205	205	205	205
205	55	55	55	205
205	55	0	55	205
205	55	55	55	205
205	205	205	205	205

Figure 3. Result of invers technique

Figure 3. show the different pixel from original image to invers image with invers formula that every original pixel always minus with value 255 to get invers result.

c. Otsu Morphology

Otsu morphology integrates morphological operations such as dilation and erosion, which help clarify object structures and improve segmentation results [25]. In applying morphological operations, this study uses a small matrix called a structural element or kernel. Kernels are used to perform operations around each pixel of the input image. This study uses a 3x3 square kernel to capture important patterns of the target object.

Original

50	50	50	50	50
50	200	200	200	50
50	200	255	200	50
50	200	200	200	50
50	50	50	50	50

Erosion

50	50	50	50	50
50	50	50	50	50
50	50	200	50	50
50	50	50	50	50
50	50	50	50	50

Dilation

200	200	200	200	200
200	255	255	255	200
200	255	255	255	200
200	255	255	255	200
200	200	200	200	200

Structured Element (Kernel)

1	1	1
1	1	1
1	1	1

Opening

50	50	50	50	50
50	200	200	200	50
50	200	200	200	50
50	200	200	200	50
50	50	50	50	50

Closing

200	200	200	200	200
200	200	200	200	200
200	200	255	200	200
200	200	200	200	200
200	200	200	200	200

Figure 4. Result of morphology operations

Figure 4 shows the pixels for morphological operations of erosion, dilation, opening, closing along with their kernels as examples. The general formula for the erosion morphologycal method is as follows

$$A \ominus B = \{z \in E | B_z \subseteq A\} \tag{4}$$

$$A \oplus B = \{z \in E | (B^{hat})_z \cap A \neq \emptyset\} \tag{5}$$

The morphological operations of erosion and dilation are fundamental in image processing. Erosion, defined by the formula third. systematically shrinks the foreground objects by removing boundary pixels where the structuring element B does not completely fit within A. This operation is useful for eliminating small noise, separating objects that are close together, and refining object shapes. Conversely, dilation, defined by fourth formula, expands the objects by adding pixels to their boundaries wherever the reflected structuring element $(B^{hat})_z$ overlaps with A. Dilation is effective for filling small holes, connecting fragmented components, and enhancing object connectivity. Together, these complementary operations are essential for preparing images for further analysis or feature extraction.

$$A \circ B = (A \ominus B) \oplus B \tag{6}$$

$$A \cdot B = (A \oplus B) \ominus B \tag{7}$$

The morphological operations of opening and closing are combinations of basic erosion and dilation processes, used to refine the structure of objects in a binary image. Opening, defined as fifth formula, involves an erosion followed by a dilation using the same structuring element B, effectively removing small objects or noise while preserving the overall shape of larger structures. It is particularly useful for separating objects connected by thin bridges and smoothing object boundaries. In contrast, closing, defined as sixth formula, applies dilation first and then erosion, which helps to fill small holes, bridge narrow gaps, and connect adjacent objects without significantly altering their general form. Together, opening and closing play a critical role in image preprocessing, noise reduction, and structural enhancement.

d. Otsu Invers Morphology

Similar to Otsu morphology, Otsu inverse morphology applies morphological operations to the results of inverse Otsu, further refining the segmentation process and enhancing the clarity of the analyzed images [26]. The combination of image inversion, morphological refinement, and Otsu's method provided a robust approach for accurate and noise-resilient image segmentation

3. Results and Discussion

Results

This study evaluated the performance of several image segmentation approaches—Otsu, Otsu Invers, Otsu Morphology, and Otsu Invers Morphology—based on six quantitative image quality metrics: Peak Signal Noise Ratio (PSNR), Mean Square Error (MSE), and Mean Absolute Error (MAE) are intended to view absolute error [27], [28]. Meanwhile Structural Similarity Index (SSIM), Feature Similarity Index (FSIM), and Edge-based Structural Similarity Index (ESSIM) are intended to take into account the structure and visual perception [29], [30], [31]. Visualization of the results is presented in **Table 1** that summarizes the average values obtained from each method and **Figure 5** displays segmented output samples for visual inspection.

Table 1. Average metric experiment result

Average Metric	PSNR	MSE	MAE	SSIM	FSIM	ESSIM
Otsu	27.6784	113.3485	194.8579	0.5209	0.1964	0.7871
Otsu Invers	27.5735	117.0389	194.1048	-0.0518	0.1964	0.7871
Otsu Morphology	27.6798	113.3980	194.8908	0.5548	0.1794	0.7764
Otsu Invers Morphology	27.5795	116.8842	194.1147	-0.0520	0.1916	0.7856

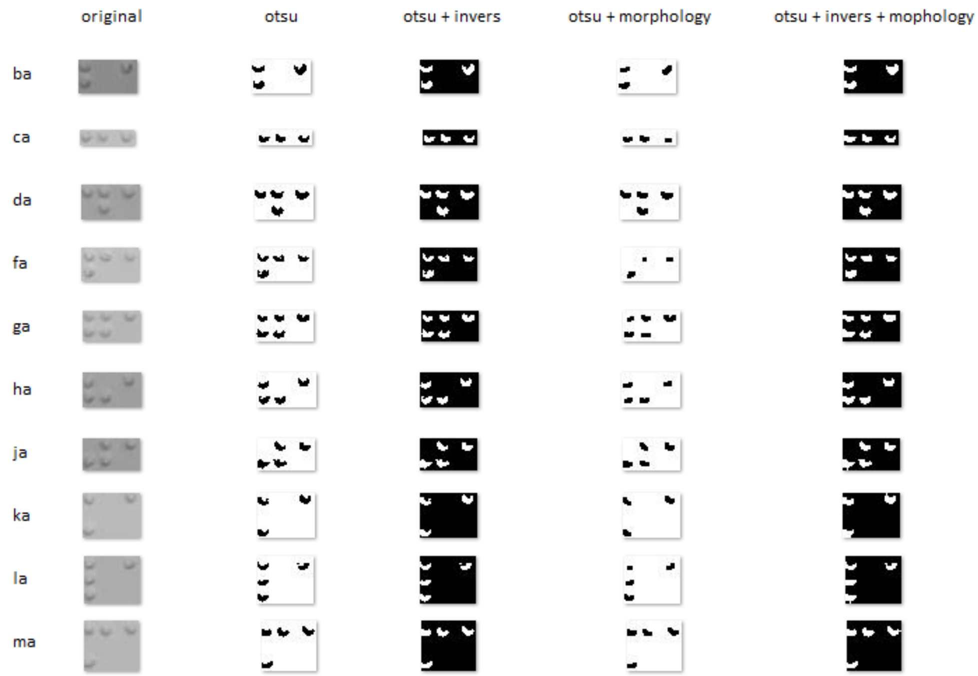

Figure 5. Result braille image segmentation

The results show that the Otsu Morphology method produces the highest PSNR value of 27.6798, indicating the best ability to preserve signal fidelity to the original image. Meanwhile, the Otsu method achieves the lowest MSE value of 113.3485, which reflects the smallest pixel-level error among all the tested methods. In terms of structural similarity, Otsu Morphology also outperforms others by achieving the highest SSIM value of 0.5548, suggesting superior structural resemblance to the reference image. On the other hand, Otsu Inverse and Otsu Inverse Morphology show negative SSIM values (−0.0518 and −0.0520), indicating a significant deviation in structural luminance from the reference image. The MAE values across all methods are relatively similar, averaging around 194, signifying comparable absolute pixel errors. FSIM and ESSIM scores are also consistent, with the highest ESSIM value (0.7871) achieved by both Otsu and Otsu Inverse.

These evaluations indicate that the Otsu Morphology method excels in preserving structural similarity and signal fidelity, even though its advantage over Otsu is minimal. This improved performance is likely due to the morphological operations that enhance edges and object shapes in the segmented images. These findings are consistent with previous studies that emphasize the importance of morphological operations in improving segmentation quality. The lowest MSE obtained by Otsu confirms its effectiveness in minimizing pixel-level errors, although its SSIM is slightly lower than that of Otsu Morphology. Meanwhile, the poor performance of the Otsu Inverse method suggests that inverse thresholding may be unsuitable for images requiring high visual detail preservation, it is important to note that this drop in SSIM is not necessarily due to image degradation, but rather to the polarity change caused by inversion, which mathematically alters the luminance distribution without necessarily affecting the visual usability of the Braille patterns.

In practical terms, the Otsu Morphology method is highly recommended for applications requiring fine visual details, such as character recognition or medical image segmentation. However, this study has several limitations. The image quality during data acquisition was suboptimal, potentially affecting segmentation accuracy. Moreover, the Braille image dataset used in this research was limited to a narrow subset of prefixes (ba, ca, da, fa, ga, ha, ja, ka, la, ma), which restricts the generalizability of the results across the full Braille character set.

Future research is encouraged to explore the use of higher-resolution imaging devices to improve segmentation quality and clarity. Expanding the dataset to include a wider variety of Braille character prefixes will also enhance the robustness and applicability of the proposed methods. Furthermore, integrating these segmentation techniques with advanced machine learning algorithms could lead to the development of a more accurate and intelligent Braille character recognition system.

Discussion

In comparison to previous research employing the CNN method, which achieved an average accuracy of 87.85% and a classification accuracy of 99.37% using a smaller dataset consisting of 544 images divided into three yoga classes [32], this study demonstrates the superior capability of YOLOv5 in classifying yoga postures. Using a larger dataset, YOLOv5 attained a higher accuracy rate of 90% and demonstrated flawless labeling with 100% classification accuracy. These results underscore the robustness of YOLOv5 in accurately and efficiently identifying yoga postures, emphasizing its significant potential for integration into real-time systems.

Overall, these results confirm the capability of YOLOv5 to classify yoga postures with high efficiency and accuracy, making it a promising tool for real-time applications. The results demonstrate YOLOv5's robust performance in accurately and efficiently classifying yoga postures, showcasing its potential for integration into real-time systems. Addressing lower accuracy in specific poses may involve diversifying the dataset, adding more varied poses, or optimizing the data augmentation pipeline. Future applications might include AI-driven systems that deliver real-time feedback, empowering yoga practitioners to train independently while minimizing injury risks and improving overall practice quality.

4. Conclusion

This study compared four image segmentation methods—Otsu, Otsu Inverse, Otsu Morphology, and Otsu Inverse Morphology—using six performance metrics. The Otsu Morphology method showed the best performance, with the highest PSNR and SSIM values, while the basic Otsu method achieved the lowest MSE. These results indicate that combining thresholding with morphological operations enhances image quality, particularly in preserving structure.

In the context of Braille image segmentation, Otsu Morphology proved effective in highlighting embossed dot patterns, which is essential for accurate Braille character recognition. This supports the hypothesis that structural enhancement improves segmentation outcomes. The study contributes a practical, lightweight method for Braille preprocessing, offering potential for use in assistive technologies. Future research should explore more diverse datasets and consider combining classical methods with machine learning for better performance in real-world applications.

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