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Segmentation Algorithms in Cervical Cancer Image Analysis

Dr. Kavita. R. Singh[1], Khushi Khanorkar[2], Riya Thombre[3], Shruti Waghmare[4], Vedant Lambade[5], Pushkar Dahikar[6], Ritesh Gajbhiye[7]

[1-7] Department of Computer Technology, Yeshwantrao Chavan College of Engineering, Nagpur, India.
Email : singhkavita19@gmail.com[1], khanorkarkhushi14@gmail.com[2], riyathombre1@gmail.com[3], shrutiwaghmare2004@gmail.com[4] , vedantlambade15@gmail.com[5], pushkardahikar@gmail.com[6] ,riteshgajbhiye0310@gmail.com[7]

Abstract

Cervical cancer continues to pose a global health challenge, particularly in low-resource settings where access to trained experts and advanced diagnostic tools is limited. Conventional approaches to image interpretation in colposcopy are time-intensive, require significant expertise, and remain prone to variability in results. This paper provides a comparative investigation of two segmentation methods—Adaptive Thresholding and HSV-Morphological Cervical Segmentation—for the automated processing of colposcopy images in cervical cancer screening. In the first method, Adaptive Thresholding was used as a local binarization technique, aided by preprocessing techniques such as grayscale conversion, Gaussian blurring, and Contrast Limited Adaptive Histogram Equalization. The second method, HSV-Morphological Cervical Segmentation, made use of color space conversion to HSV coupled with Gaussian blurring, morphological processing, edge detection, and contour filtering to segment the cervical area more accurately under uneven illumination conditions and when there are specular reflections. Experimental findings show that although both techniques yield viable segmentation pipelines, the HSV-Morphological technique resulted in structurally uniform masks and achieved precise segmentation in outlining cervical boundaries relative to Adaptive Thresholding. In order to facilitate practical application, the constructed segmentation pipelines include visualization and dataset-level processing aspects, providing computationally efficient.

1. Introduction

Medical image analysis plays a key role in modern healthcare diagnostics as it revolutionizes the way how diseases are diagnosed, monitored and treated. Among other medical imaging modalities, the cervical cancer screening by visual inspection is recognized as one important application area where correct interpretation can have great impact on patient outcomes. The development of pre cancerous lesions to invasive carcinoma takes a number of years. Widely recognized for its diagnostic accuracy, colposcopy is an effective, non-invasive method for cervical assessment, enabling detailed visualization of the cervix through it, as it is a specialized binocular stereomicroscope [1]. Colposcopy remains the gold standard for detection and management of pre-cancerous cervical lesions. It's this reason that there isn't specifically developed software for processing images in colposcopic diagnostics and still trained personnel play an important role in precise analysis interpretation [1]. Preprocessing helps to improve image quality by normalizing intensity, improving contrast, and removing noise and SR—crucial in colposcopy for revealing diagnostic details obscured by artifacts. Image segmentation divides a digital image into multiple segments or regions of interest. It's a fundamental task in computer vision and medical imaging. In fact, it may be stated that Segmentation groups pixels with similar visual characteristics and assigns them unique labels. The segmentation framework was divided into three major stages: Localization of the cervical region to be extracted (ROI), lesion segmentation using a CNN-based model and projection of the results onto the original image [2].

2. Literature Review

Automated cervical cancer screening using colposcopic images is one of the key interdisciplinary fields of analysis. The successful extraction of lesions and diagnosis relies on a critical step accurate and powerful segmentation of the cervical area in the obtained image. This review of literature summarizes important methodologies and developments that featured in this preprocessing pipeline. This review follows a standard segmentation workflow. It begins with the acquisition of cervical images, then addresses image enhancement to mitigate artefacts like uneven lighting, and concludes with the core task of extracting the Region of Interest (ROI), surveying methods from classical algorithms to deep learning. In the image acquisition stage, [5] proposed a method that was based on the analysis of images captured through this conventional method. This technique involves a magnified visual examination of the cervix using a colposcope, which functions as a low-power, binocular field microscope equipped with a bright light source. In [6], the images were acquired using a fixed-focus camera, they have also developed a prototype of the Cervitude Imaging System (CIS) with Prototype Portable Colposcope for image acquisition. In [8], image acquisition involved capturing images using different chemical solutions and filters to highlight various tissue properties, the technique is known as Multi-solution Colposcopic Imaging Sequence. Once the images are acquired, the Image Enhancement and Artefact Mitigation stage serves to prepare the data for accurate analysis by improving image clarity and minimizing artefactual distortions. In [7], the Specular Reflection (SR) Removal using Laplacian/Poisson Interpolation technique is used, this method identifies and removes bright white moisture spots (SR) by detecting white pixels across color channels, outlining them through dilation, and filling the regions. In [5], uses Intensity and Saturation channels in the HIS color space, this method identifies specular reflections by their high intensity and low saturation, using a two-stage color (segments images using color information) and spatial segmentation (region-growing algorithm). While it removes reflections via histogram transformation, the process remains susceptible to highlights. After the enhancement stage, the process proceeds to Region of Interest (ROI) Extraction, in [5, 6] K-means Clustering is used, but in [5] it is done in HSV Color Space, which is used to segment the cervical region. The method uses the centered cervix and the V component's intensity similarity to isolate the ROI from the background and in [6], it is done in LAB Color Space, which is applied to remove small dark spots and connect larger white areas, resulting in a binary mask of the cervical ROI. In [8], a Dual-encoder deep learning model with ResNet50 and MobileNetV2, attention mechanisms, lightweight ASPP, and a decoder with upsampling and skip connections technique is used for the extraction of ROI, as the model combines ResNet50 and MobileNetV2 backbones to extract multi-level features, enhanced with attention and ASPP. A decoder then uses transpose convolutions and skip connections to precisely segment the cervical ROI. The method offered in [9] is an Improved Faster R-CNN with ROI Align, which detects and extracts the cervical region of the colposcopic image. In [10], the PSPNet-ResNet50 model is applied directly to the entire colposcopic image to segment the LSIL+ lesion areas. The model employs ResNet50 for feature extraction and a pyramid pooling module for multi-scale context. In [11], the DeepLabV3+ model uses its Decoder module to combine low-level features (from Xception) and high-level features (from ASPP). After a 3×3 convolution, features are upsampled by a factor of 4 and bilinear interpolation produces the final segmentation masks.

3. Methodology

To investigate cervical cancer detection, we employed two segmentation techniques and compared their effectiveness in isolating the cervical region and detecting lesions. These methods collectively provide different perspectives on segmentation and are described in detail in the following sections. The methods for segmentation are Adaptive thresholding, HSV-Morphological Cervical Segmentation. Adaptive Thresholding is a local binarization technique that calculates pixel-wise thresholds from the intensity distribution in a specified neighborhood.

HSV-Morphological Cervical Segmentation integrates color space transformation with morphological processing. Through color space conversion to HSV, the algorithm exploits chromatic properties particularly hue and saturation to enhance the discrimination between cervical tissue and background.

A. Adaptive Thresholding

Adaptive thresholding is a local binarization technique used in image processing to separate regions of interest (ROI) from the background, also known as local or dynamic thresholding, it is an advanced image segmentation technique that computes multiple thresholds for different regions within an image. It is a traditional image processing technique that has been widely used for preliminary segmentation tasks. As opposed to global thresholding, which uses the same threshold for the entire image, adaptive thresholding calculates the threshold per pixel depending on its local neighborhood. Purpose in cervical images is to distinguish the cervix or cervical lesions (ROI) from the background tissue. Effective in colposcopy images where lighting is uneven, there are specular reflections, or color changes across the cervical area. Adaptive thresholding is helpful because it dynamically adapts to local image conditions, can segment cervical ROI even where there are bright spots, minimizes the necessity for global histogram equalization or intensive preprocessing, can be paired with morphological operations or deep learning segmentation to enhance ROI. In cervical cancer screening, adaptive thresholding plays several vital roles. The adaptive thresholding works by starting with conversion into suitable colour space. For a pixel at location (x,y)(x, y)(x,y), the threshold T(x,y)T(x, y) T(x,y) can be computed using the mean of the localwindow:

Mean Adaptive Thresholding:

$$T(x,y) = \text{mean}(W_{x,y}) - C$$

where $W_{x,y}$represents the local window (a small square or rectangular region centered on pixel (x,y)), $\text{mean}(W_{x,y})$is the average intensity of all pixels in that neighborhood, and $C$is a constant used to fine-tune the sensitivity.

Gaussian Adaptive Thresholding:

$$T(x,y) = \sum_{(i,j)\in W_{x,y}} G(i,j) \cdot I(i,j) - C$$

where the threshold is computed as the weighted sum of the neighborhood using a Gaussian weighting function $G(i,j)$, $I(i,j)$denotes pixel intensities, and $C$is the sensitivity constant.

Cervix segmentation was performed with an adaptive thresholding-based method. The input image was preprocessed initially by transforming it into grayscale, and then Gaussian blurring was employed to reduce noise but preserve critical anatomical features. Contrast Limited Adaptive Histogram Equalization (CLAHE) was further utilized to enhance the boundaries of the cervix, which enhanced local contrast throughout the image. Segmentation was subsequently conducted with a hybrid thresholding approach that blended Adaptive Thresholding and Otsu's Thresholding. Adaptive thresholding derived a local threshold per pixel using neighborhood intensity values, rendering the technique invariant to changing illumination that is prevalent in colposcopy images. Concurrently, Otsu's algorithm automatically calculated a global threshold with minimal intra-class variance. The overlap of the two masks guaranteed accurate detection of the cervix area even in adverse illumination conditions. In order to improve the coarse segmentation, morphological closing was used to cover up small holes. The approach provides robustness against inhomogeneous illumination, successfully suppresses noise, and achieves a computationally efficient segmentation pipeline for large-scale or real-time settings. The output images clearly illustrate the separated cervical area with dynamically identified boundaries.

Alogrithm For Adaptive Thresholding

1. Read and validate the input image I.
2. Convert I to grayscale.
3. Apply Gaussian blur for noise reduction.
4. Enhance local contrast using CLAHE.
5. Perform adaptive Gaussian thresholding → M_{adapt}.
6. Apply Otsu's global thresholding → M_{otsu}.
7. Combine masks: $M_{combined} = M_{adapt} \wedge M_{otsu}$.
8. Apply morphological closing and opening to clean the mask.
9. Detect contours and select the largest as the cervix region.
10. Generate cervix mask $M_{cervix}$and apply it to I.

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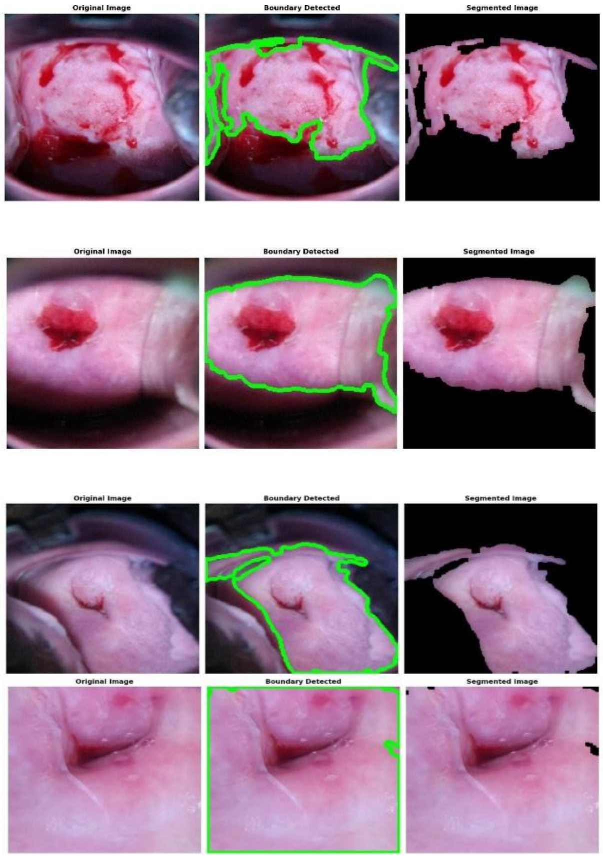

Fig. 3.1 Cervix Segmentation using Adaptive Thresholding.

B. HSV-MORPHOLOGICAL CERVICAL SEGMENTATION

This technique involves the use of conventional image processing to extract accurately the cervical region of the colposcopy images. The image input is re-sized to HSV color space which divides the color and brightness to deal with skewed hues and reflectance. HSV thresholding is used to isolate the cervical tissue colors (pink, red, etc.) to form an initial binary mask. The noise gets to be smoothed with Gaussian blurring and mask gets refined with morphology (opening, closing) where structures they are meant to achieve are filed in and small artifacts are cleared away. Boundaries are further improved and irrelevant areas are eliminated by canny edge detection and contour filtering. The last mask is added to the initial image in order to derive the segmented cervix and visualization is made to display the original image, mask image, and the overlay. This approach produces cervical segmentations suitable for further analysis or machine learning tasks.

Algorithm For Hsv-Morphological Cervical Segmentation

1. Change the input image into a fixed target size.
2. Convert the RGB image to the HSV color space.
3. Define the HSV ranges for cervical tissue (pink shades and red)
4. Threshold the HSV image to create an initial binary mask.
5. Smooth the mask using Gaussian blurring.

6. Perform morphology by using closing and opening morphological operations to improve the mask.
7. Use Canny edges to enhance the boundaries and merge them with the binary mask.
8. Remove small contours to get rid of contours below some minimum area.
9. Reconstruct and smooth the final cervix mask.
10. Apply bitwise AND with original input image to isolate the cervix.
11. Resize the final segmented output and mask to original input dimensions.

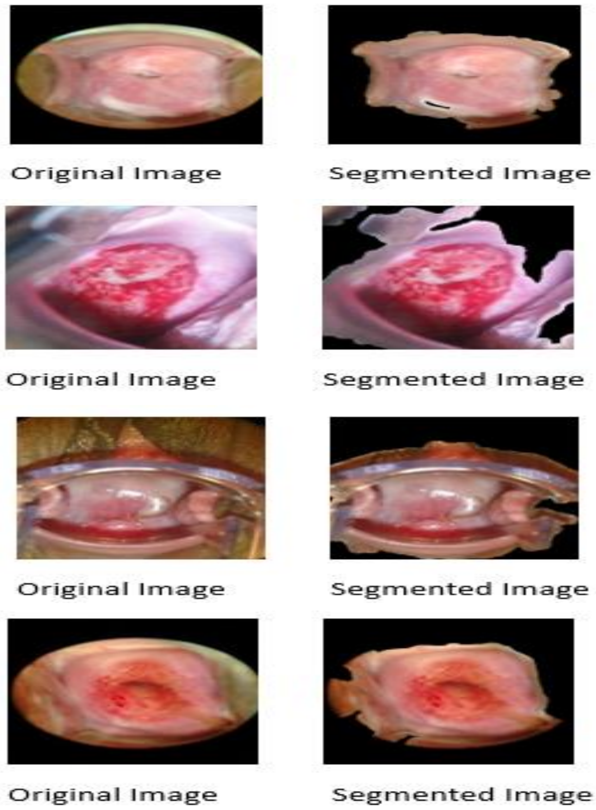

Fig. 3.2 Cervix Segmentation using HSV-Morphological.

4. Result & Discussion

Experimental results reveal that the HSV–Morphological Cervical Segmentation method is more accurate and robust in cervical boundary extraction than Adaptive Thresholding (AT). The HSV-Morphological technique is based on the usage of an HSV colour space where hue and saturation are separated from brightness and it can handle illumination variation and shadow effectively. Segmented mask is further refined with morphological operations, dilation erosion and closing to make ensure that cervical boundaries are smooth and continuous.

On the other hand, the Adaptive Thresholding algorithm is a gray level (intensity)based technique. It segments the cervix area by pixel intensity change and handles well with increased contrast, which is achieved by pre-processing operations such as Gaussian smoothing and CLAHE. But its reliance on intensity only causes to be suitable for situations sensitive to the illuminations and colour similarity of tissue and background. Therefore, it usually generates irregular and broken boundaries in weak light or low-contrast environments.

In contrast, the HSV–Morphological method yields a more robust and accurate segmentation visually. It can effectively reduce noise, fill thin lines and maintain anatomical accuracy of the cervix region when compared to other methods. Although slower since two more colour and morphological steps are included, the reliability gain in the segmentation compensates the time penalty.
The proposed HSV–Morphological segmentation is simpler but efficient compared to the state-of-the-art advanced segmentation techniques, i.e., Deep Learning approaches (e.g., U-Net, Mask R-CNN). Deep learning networks generate fine-grained, segment level outputs although necessitate large annotated datasets and computational intensity. On the other hand, clustering based algorithms such as K-Means and Fuzzy C-Means are instant segmentation methods but usually lead to noisy or irregular edges as they do not consider spatial context. Clustering-based techniques are more efficient for segmentation but tend to produce noisy or jagged edges because of spatial context loss.

In conclusion, the HSV–Morphological approach offers the best trade-off between efficiency and precision. It yields cleaner, smoother, and easier-to-understand cervical masks and is well-suited especially for resource-limited settings or small-scale clinical trials, but deep learning is still the best option for large-scale, precision-sensitive cervical image analysis.

5. Conclusion

This paper contributes to the field of automated cervical cancer screening in the sense that it compares the advantages of two traditional image segmentation algorithms such as Adaptive Thresholds and HSVMorphological Cervical Segmentation of colposcopy images. The significance of the accurate Region of Interest (ROI) extraction and artifact-free segmentation as the precondition of the further analysis and classification of the lesions is the focus of the paper. Experimental findings reveal that although Adaptive Thresholding is straightforward and effective, it is dependent on the grayscale leading to poor performance in irregular illumination. Conversely, the HSV-Morphological method, which is a hybrid of color-space segmentation and morphological refinement, is a critical method of minimizing reflections, shadows, and noise, producing precise and clinically useful masks. The approach provides a more resource-efficient cervical image preprocessing method to be used in the case of low resources and as a trusted input to deep learning frameworks.

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