A Digital Image Processing-based Tool to Assist Medicine Blisters Fractioning

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Abstract— **This work presents a digital image processing-based tool for medicine blister fractioning, which uses a combination of image acquisition and segmentation to accurately detect individual medicine blisters and trace the cutting path that properly separates the pills in a blister pack. The proposed tool was evaluated using a set of photos of medicine blister packs, and the results showed that it was capable of accurately detecting and segmenting medicine blisters to a certain degree of accuracy.**

Keywords— **Blister, pills, detection, segmentation, automation.**

I. Introduction

According to the National Health Surveillance Agency (ANVISA), medication fractioning is defined as "the individualization of the packaging of a medication to enable the dispensing of the medication to the user in the quantity established by the medical prescription."

At HC UFPE, medication fractioning is carried out manually, using regular scissors, by a technician specialized in this function. This method of fractioning blister packs poses health risks not only to the hospital's patients, as they may ingest medications that have not been individualized properly but also to the technician, who may develop repetitive strain injuries in the hands [1]. Moreover, dedicating a specific professional solely to this task is a clear example of misallocation of human resources, as this technician could perform another more essential role in the hospital pharmacy processes.

Automating the fractioning process of blister packs can help reduce these risks and improve the efficiency of the process. By automating the process, hospitals can ensure that medications are dispensed accurately and safely, while freeing up valuable resources that can be used for other essential tasks. In this context, this work proposes a digital image processing-based system that traces the cutting paths on blister pills images, which can then be cut by an automated mechanism based on the paths obtained.

II. State of the art on image-based Pill detection/segmentation

Classical digital image processing techniques have been used to detect pills on blisters in a variety of contexts. Holtkötter et al. [2] designed a pill detection tool based on digital image processing, enabling the monitoring of pill consumption in mobile health applications without requiring extra devices. Utilizing the Circular Hough Transform as a feature extraction method, this tool is particularly effective for identifying pills with a circular shape. The tool comprises two main stages: the registration of an entire blister and the storage of reference values in a local database. It then proceeds to detect and classify consumed and remaining pills in similar blisters, ultimately determining the precise count of untaken pills.

The work by Yu et al. [3] provides a comprehensive review of the advancements in image segmentation methods. The authors systematically review three important stages of image segmentation, which are classic segmentation, collaborative segmentation, and semantic segmentation based on deep learning. They elaborate on the main algorithms and key techniques in each stage, compare and summarize the advantages and defects of different segmentation models, and discuss their applicability.

Classic segmentation is the oldest and most widely used method of image segmentation. It is based on the principle of thresholding, which involves setting a threshold value to separate the foreground from the background [4]. The advantages of using classic segmentation techniques include its simplicity, speed, and low computational cost. Classic segmentation is also robust to noise and can handle images with low contrast. Despite its limitations, such as its inability to handle complex images with overlapping objects and its sensitivity to the choice of threshold value, classical methods may still compete with deep learning approaches in certain scenarios, as show the works of [5] and [6].

III. Methodology

In order to develop a system as simple and effective as possible, a digital image processing approach is adopted to extract the necessary information from blister packs so that cutting paths can be traced. The system proposed here consists of two main phases: a preprocessing phase and a segmentation phase. The preprocessing phase is an adaptation of the image acquisition step proposed in the work by Holtkötter et al. [2]. The goal of this phase is to analyze the photo taken of the blister, locate the region where it is positioned, and extract it from the image, discarding all portions that are not of interest. Thus, a new image containing only the blister is obtained, smaller and lighter than the original photo. This step is necessary to optimize the processing in the second phase of the algorithm. The next phase of the procedure is the segmentation stage, aiming to effectively divide the image into regions, each containing a pill from the blister. The lines forming the boundaries between two individual regions constitute the cutting path to be traced to fractionate the blister. The procedure described for this phase is an adaptation of the segmentation proposed by Cleves et al. [7], which has the same goal of cutting path tracing. The algorithm of the second phase takes the image generated in the first phase as input, and the system as a whole is formed by the cascading execution of the two phases. The following sections present a description of the processes executed in each stage.

A. *Preprocessing*

First, the original photo is converted to grayscale so that it can undergo a blurring process through a median filter with a 5x5 kernel [8]. The median filter is an important step in processing because it reduces noise while preserving edges present in the image.

Next, the gradient magnitude of the grayscale image is computed using the Sobel operator [9], which is applied in both horizontal and vertical directions, calculating the spatial gradients of the image intensity. The Euclidean norm of these gradients yields the gradient magnitude, emphasizing areas of the image with significant intensity changes.

Fourth, Otsu's thresholding [10] is applied to the normalized gradient magnitude image obtained from the previous step.

In the next step, with the aim to obtain a white-filled region corresponding to the blister position in the original photo, morphological operations [11] are performed on the binary image obtained after Otsu's thresholding in previous step. Two consecutive dilation operations are applied using both horizontal and vertical structural elements, enhancing the connectivity and continuity of relevant structures in the image. Following this, a closing operation is performed using a square structural element, further consolidating the identified regions.

Using a square structural element in this process is important because it ensures uniform treatment in both horizontal and vertical directions. The square shape is well-suited for preserving the overall geometry of the structures present in the image while filling the need for a robust closing effect.

Subsequently, the largest connected component in the binary image obtained after morphological operations is identified. By finding contours in the binary image, the algorithm locates individual connected regions. The largest contour is then determined based on its area, signifying the primary object or region of interest in the image. The bounding box of this largest contour is extracted, providing precise spatial coordinates for the subsequent cropping step. This step is critical for isolating and focusing on the most significant part of the image: the region of the blister.

Lastly, the original image is cropped based on the bounding box obtained from the largest connected component identified in the previous step. The cropping operation isolates the region of interest, removing irrelevant portions of the image and retaining only the area of the blister. By isolating and extracting the relevant content, the image is prepared for further analysis in the segmentation phase of the whole digital image processing.

B. *Segmentation*

In the initial step of the pills detection phase, the result image from the preprocessing phase is converted from RGB format to grayscale.

In the second step, a median blur filter is applied to the grayscale image.

In the third step of the pill detection process, the blurred grayscale image is thresholded by means of Otsu's thresholding method.

This step is essential in preparing the image for subsequent morphological operations and segmentation, as it establishes a clear distinction between the pills and the background, facilitating the extraction of relevant features in the subsequent steps of the algorithm.

In the fourth step, a circular structuring element is defined, and morphological operations, specifically erosion and dilation, are applied to create a mask. The structuring element is designed in the shape of a circle and is used to modify the binary image obtained through thresholding. Erosion and dilation morphological operations help refine the shape and boundaries of the detected objects. Erosion removes small-scale structures and fine details, ensuring a more uniform representation of the objects, while dilation expands the remaining regions, helping to connect fragmented areas and enhance the overall shape of the objects. The resulting mask helps in isolating the distinct regions corresponding to individual pills from the background, setting the stage for more precise and accurate segmentation in subsequent stages of the algorithm.

In the fifth step of the pills detection, a rectangular structuring element is employed for additional erosion to create another mask, followed by the blackening of specified border areas. This step is essential for refining the binary mask and preparing it for the subsequent watershed segmentation. The rectangular structuring element used for erosion helps to eliminate any remaining background while preserving the information on each pill's position in the image. Blackening the border areas of the mask is necessary erase any remaining background information next to the image's borders, thus preventing the watershed segmentation algorithm from considering the image boundaries as potential segmentation lines, which could lead to undesired effects. By selectively blackening specific regions near the image borders, the algorithm focuses on the position of the pills, contributing to more accurate and meaningful segmentation results. This step plays a critical role in optimizing the image mask for the watershed algorithm.

In the sixth step, the algorithm performs watershed segmentation [12] on the eroded and modified mask. This step involves calculating the distance transform of the eroded mask, identifying local maxima in this distance transform, and applying the watershed algorithm. The distance transform measures the distance of each pixel to the nearest zero-value pixel in the mask, providing a representation of the spatial distribution of objects. The local maxima, determined based on a threshold, serve as markers for the watershed algorithm, guiding the segmentation process. Watershed segmentation is crucial for precisely delineating the boundaries between individual pills in the image. It helps separate touching or overlapping objects by considering the gradient of pixel intensities, and the markers ensure that the segmentation is initiated from distinct regions. This step is necessary to achieve accurate and meaningful segmentation results, enabling the identification and isolation of individual pills in the original image. The watershed algorithm was chosen to perform the segmentation because it is particularly valuable in image processing tasks where accurate segmentation of distinct objects or regions is required, such as in medical image analysis or object recognition.

IV. Application example

In this section, an application example of the proposed tool is presented. The example includes step-by-step instructions on how the preprocessing and segmentation steps were implemented in Python [13], using mainly the packages OpenCV [14] and skimage [15]. By following these instructions, readers can gain a better understanding of how the tool works and how it can be implemented in real-world computer systems.

A. Preprocessing stage application

Figure 1 shows an example of applying the image preprocessing algorithm to a blister pack. In this case, a blister pack containing white pills is photographed and processed to be reduced, so that the resulting image can be passed to the second phase of processing: the segmentation step. Below, each step of the preprocessing is presented in the order in which it occurs and described in its more technical aspects.

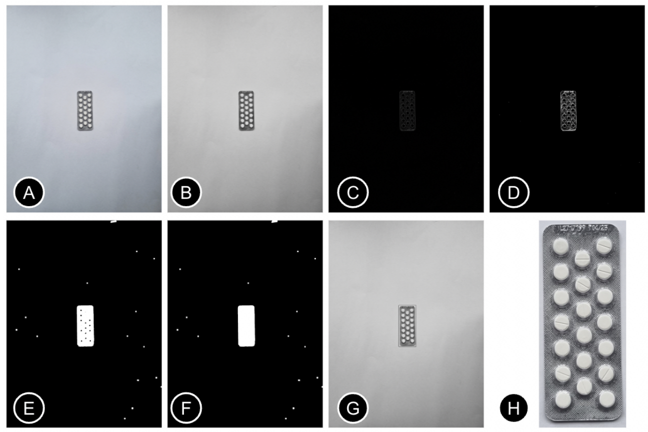

Fig. 1: Preprocessing stage steps: A)Original image; B)Median blur; C)Gradient magnitude; D)Thresholded image;E)Dilated image;F)Closed image;G)Region of interest; H)Cropped image

Figure 1.A: The goal of this preprocessing stage is to reduce the size and weight of this image, making the segmentation step lighter and faster.

Figure 1.B: The application of the filter causes blurring of the image, eliminating higher frequency components (texture of the blister pack) and preserving the edges present in the image (regions of the blister pack and the pill compartments).

Figure 1.C: The Sobel operator is then applied to the blurred grayscale image. The horizontal and vertical components are then combined to compute the overall gradient magnitude of the image using Euclidean normalization [0, 255].

Figure 1.D: The image then undergoes a binarization process based on Otsu's thresholding method.

Figure 1.E: The binary image resulting from the thresholding process then undergoes two morphological dilation operations, each using a rectangular structuring element.

Figure 1.F: The image then undergoes a closing operation.

Figure 1.G: A procedure to find the largest connected component in the resulting image is then applied.

Figure 1.H: Following the identification of the largest connected component, the original image is cropped based on the coordinates (x, y) and dimensions (width, height) of the bounding box previously found.

B. Segmentation stage application

Figure 2 shows an application example of the whole image processing's second step: the segmentation phase. In this step, the cropped image of the blister is further processed in order to obtain the cutting path to be used to unitarize the pills. A brief description of each step, related with the corresponding image in figure 2, is presented below.

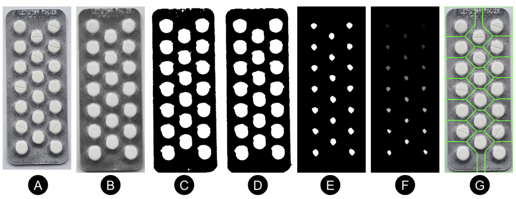

Fig. 2: Pill detection steps: A)Cropped image; B)Median blur; C)Thresholded image; D)Eroded and dilated;E)Further eroded; F)Local maxima;G)Segmented image.

Figure 2.A: The cropped image obtained in the final step of the preprocessing stage is used as input in this phase.

Figure 2.B: The input image is then converted from RGB format to grayscale and is passed through a median filter.

Figure 2.C: The grayscale blurred image is then binarized by means of Otsu's thresholding method.

Figure 2.D: The resulting binary image then undergoes a sequency of morphological operations.

Figure 2.E: A second erosion morphological operation is performed, to increase the black area so it covers also the region outside the blister.

Figure 2.F: The binary image resulting from the previous step is then used to label regions so they may serve as markers for the subsequent segmentation operation using the watershed algorithm.

Figure 2.G: The watershed algorithm is then be used to segment the image.

First, a all-white image, with the same size as input cropped image, is created. This image will be used as mask to the watershed algorithm. Then the watershed function of skimage package is executed, with the negation of the distance transform, the previously identified local maxima and the just initialized mask as parameters. The result of the watershed segmentation provides a segmentation map, where each region is assigned a unique label, which can then be used to draw these regions' contours on the input image. This final image is shown in the displayed figure.

V. Results

The algorithm was tested on a set of 60 photos of medicine blister packs to assess the cases in which its application is successful and identify situations where the algorithm needs improvement. The set of photos was initially subjected to the preprocessing stage, so that each photo was cropped, reducing it only to the region where the blister pack is located. For this stage of the process, none of the tests failed; in all examples, the algorithm was able to correctly recognize the blister pack region. This demonstrates the robustness of the preprocessing procedure and its importance in the context of the algorithm as a whole.

A. Segmentation success

The application of the second phase of processing was successful in a considerable variety of cases, as shown in figure 3. The blister pack images in this figure demonstrate that the algorithm was able to perform pill detection and cutting path tracing satisfactorily for different types of blister packs and pills.

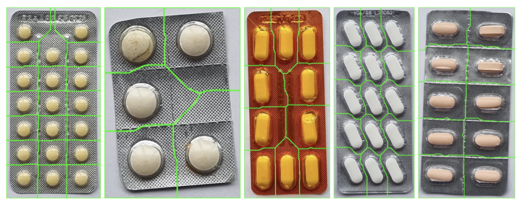

Fig. 3: Success examples.

Observing the cases shown in Figure 3, it can be noted that the algorithm works for different shapes and positions of pills in the blister pack. Whether for circular or rectangular pills, the algorithm successfully traced the cutting path to separate individual pills correctly. The procedure was successful even in the case of an asymmetrical arrangement of pills in the blister pack (figure 3 (second blister)). The algorithm was able to segment separate the pills in individual regions even in cases where rectangular pills were positioned in different directions relative to the blister pack base. Whether vertical (fig. 3 (third blister)), horizontal (fig. 3) (fifth blister) or inclined (fig. 3 (fourth blister)), the algorithm was able to perform the segmentation correctly, indicating that the shape and position of the pills should not be critical factors for the application of the processing.

B. *Segmentation failures*

In many cases, the segmentation process did not work properly, as can be seen in figure 4. In Figure 4 (left), the blister pack contains two-colored pills, with one half being lighter (white) and the other darker. This may have caused, during the image binarization step, the loss of significant information, with regions belonging to the pills being classified as background simply because they are of a darker color. This could have led to the failure in tracing the cutting paths. For blister packs with this specific type of pill, it may be necessary to develop a specific algorithm for extracting information from the image, with two separate thresholding steps, one for each half of the pills. The binary images thus generated would then be overlaid, as proposed by [16]. In Figure 4 (center), the result of the segmentation of a completely white blister pack, with opaque compartments of the same color as the rest of the blister, is shown. Along with the white background on which the blister pack was positioned, the captured image has low contrast, which may have hindered feature extraction, especially in the binarization step. This result suggests that images of this type may be more challenging to segment, requiring additional processing steps or even special image capture conditions (such as the use of a dark background, for example). In Figure 4 (right), the result of segmenting a blister entirely made of aluminum, with opaque compartments of the same material, is shown. For this type of image, the segmentation algorithm proved to be extremely inefficient, failing in all tests. This suggests that a specific algorithm needs to be developed to trace cutting paths in a blister of this type, as done in [7].

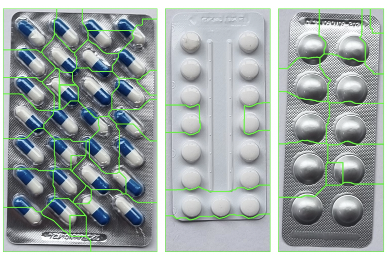

Fig. 4: Fail examples: Left) Bicolor pills; Center: Low contrast image; Right) All aluminium blister

C. *Equalization as possible improvement*

Figure 5 presents a case where the image segmentation algorithm does not work correctly, resulting in unsatisfactory cutting paths. However, for this specific case, the application of an equalization operation was sufficient to significantly improve the result, which, although still imperfect, shows better-defined and more effective cutting paths. This result suggests that there are cases of images for which equalization of the grayscale image can result in a better-segmented image; however, for images that had already resulted in good segmentations, the insertion of equalization caused the algorithm to fail. For this reason, equalization was not included as one of the default procedures of the segmentation algorithm.

Fig. 5: Improving the result by equalization: Left) Result with no equalization; Right) Result after equalization.

D. *The effect of lighting*

Lighting appears to have a major impact in the segmentation process. Figure 6 shows two examples where the angle of incidence of light in relation to the blister's position causes the tracing of cutting paths to be distorted. In Figure 6 (right), the light, which falls on the blister from a point closer to the upper end, causes the upper regions of the pills to shine more than the lower ones, presenting a much lighter color. In Figure 6 (left), the effect of light incidence becomes even more evident. In the shown image, the light falls from a point closer to the upper end of the blister, causing its upper portion to shine much more than the lower part.

This result suggests that the light should be incident in a way that does not cause the blister's surface to shine excessively, creating extremely bright points in the image that, as in the previous example, significantly distort the segmentation result.

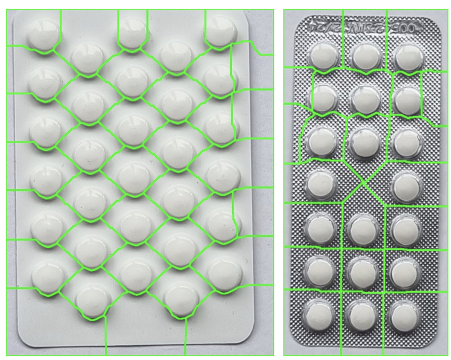

Fig. 6: Influence of lighting: Left) Lighting from above on low contrast image; Right) Effect of unequal distribution of light.

VI. Results analysis

The results suggest the proposed image processing algorithm works better for some cases, especially for aluminum blisters with transparent compartments and light-colored pills. The information about colors present in the images was more relevant than their structural characteristics, as the shapes and inclinations of the blisters or pills did not influence the result, while low image contrast had a negative impact on segmentation. Thus, it is clear that a one-size-fits-all algorithm is not feasible for any type of blister, and specific procedures should be developed for each case.

Furthermore, the conditions under which the high-definition photo of the blister is taken are also extremely important for the final result. The use of a background with a different color tone compared to the blister's structure, for example, can create higher contrast in the initial image, contributing to a greater chance of success in the segmentation step. Moreover, the incidence of light must be carefully regulated because it has a significant impact on the final result. It can be concluded that the conditions for capturing the photo must be tightly controlled so that the image characteristics can be more predictable and favor the segmentation process. It is advisable to even create a controlled enclosed environment for this purpose, as done in [7].

VII. Conclusion

The proposed tool has been evaluated using a dataset of real-world medicine blister pack images, and the results show that it is capable of accurately detecting and segmenting medicine blisters of different shapes and sizes, but with specific color and light conditions. Out of 60 images of blister packs, the method was able to trace proper cutting path for 17 images, all of them of aluminum blister packs with transparent compartments, light-colored pills and uniform lighting. The tool has several advantages over existing methods, including its simplicity and effectiveness to properly trace cutting paths on blisters under those conditions.

However, there are still some limitations and challenges associated with implementing this tool in real-world pharmacy settings. The tool may require further optimization to improve its ability to handle images of different types of blister packs or with varying lighting conditions. Moreover, it may be further optimized to increase speed and accuracy, and it may also require additional testing to ensure that it is robust enough to handle a wide range of medicine blister images.

Regarding the use of machine learning or deep learning for this task, it is worth noting that these approaches require large amounts of labeled data to train the models, which can be time-consuming and expensive to obtain. In contrast, the proposed tool uses classical vision techniques, which are less data-hungry and can be more easily adapted to different types of blister packs and pills. While deep learning-based approaches may achieve higher accuracy in some cases, the proposed tool provides a cost-effective solution for medicine blister fractioning that can be easily implemented in real-world pharmacy settings. Therefore, the proposed tool can be a valuable alternative to machine learning or deep learning-based approaches, especially for small-scale pharmacies or those with limited resources.

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