A Study on Automatic Hookworm Detection in Wireless Capsule Endoscopy Images

C. Jaikkumar, J. Jaison Velanganni and R. Vijay Prasath

Abstract---Wireless Capsule Endoscopy (WCE) has become a widely used diagnostic technique to examine inflammatory bowel diseases and disorders. As one of the most common human helminthes, hookworm is a kind of small tubular structure with grayish white or pinkish semi-transparent body. Automatic hookworm detection is a challenging task due to poor quality of images, presence of extraneous matters, complex structure of gastrointestinal and diverse appearances in terms of Color and texture. This project is demonstrated with the detection of hookworm in human to cure and remove that in the human body

I. INTRODUCTION

HCOOKWORM infection seriously threatens human health, causing intestinal inflammation, progressive iron/proteindeficiency anemia, mucosa damage, and malnutrition of human. Hookworm infection in pregnancy can cause retarded growth of the fetus, premature birth and low birth weight. Hookworm in children can cause intellectual, cognitive and growth problems



II. EXISTING SYSTEM

Hybrid color gradient and contourlet transform are utilized to detect hookworms. However, this work is evaluated in a relative small and balanced image which is not applicable for practical scenarios with unbalance dataset. The characteristics of hookworms are quite different from bleeding, ulcers and polyps. The boundary and body of hookworms are also different from the patterns of existing pathologies. It remains

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unclear whether existing approaches for other lesion detection are also effective for hookworm detection.

III. DISADVANTAGES

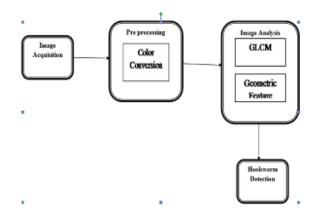
- The Contour let Transform is a redundant transform, and for coding applications this can be a disadvantage.
- > The method is fails to recognize that boundary is smooth.
- ▶ It can be suitable for simple statistical model

IV. PROPOSED SYSTEM

In this project by observing its unique properties, we propose serials of novel techniques to capture its characteristics, aiming to reduce the number of images a clinician needs to review. Experiments from different aspects demonstrate that the proposed method is a robust classification tool for hookworm detection, which achieves promising performance. The contributions of this work are as follow, Gray Level Co-occurrence Matrix (GLCM) is proposed to detect the tubular regions in WCE images. The piecewise parallel region detection and the uncurled tubular region are proposed to detect the parallel regions and represent the extracted regions, respectively

V. ADVANTAGES

- This method can detect the hookworm accurately.
- Due to its tubular structure it will extracted without unwanted region.



VI. BLOCK DIAGRAM

VII. MORPHOLOGICAL IMAGE PROCESSING

Binary images may contain numerous imperfections. In particular, the binary regions produced by simple are

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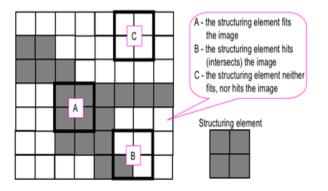
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distorted by noise and texture. Morphological image processing pursues the goals of removing these imperfections by accounting for the form and structure of the image. These techniques can be extended to grayscale images.

VIII. BASIC CONCEPTS

Morphological image processing is a collection of nonlinear operations related to the shape or morphology of features in an image. Morphological operations rely only on the relative ordering of pixel values, not on their numerical values, and therefore are especially suited to the processing of binary images. Morphological operations can also be applied to grey scale images such that their light transfer functions are unknown and therefore their absolute pixel values are of no or minor interest.

Morphological techniques probe an image with a small shape or template called a **structuring element**. The structuring element is positioned at all possible locations in the image and it is compared with the corresponding neighborhood of pixels. Some operations test whether the element "fits" within the neighborhood, while others test whether it "hits" or intersects the neighborhood:



A morphological operation on a binary image creates a new binary image in which the pixel has a non-zero value only if the test is successful at that location in the input image.

The **structuring element** is a small binary image, i.e. a small matrix of pixels, each with a value of zero or one:

- The matrix dimensions specify the *size* of the structuring element.
- The pattern of ones and zeros specifies the *shape* of the structuring element.
- An *origin* of the structuring element is usually one of its pixels, although generally the origin can be outside the structuring element.

1	1	1	1	1		0	0	1	0	0	0	0	1	0	0	➡ ← Origin			
1	1	1	1	1		0	1	1	1	0	0	0	1	0	0		1	1	1
1	1	1	1	1		1	1	1	1	1	1	1	1	1	1		1	1	1
1	1	1	1	1		0	1	1	1	0	0	0	1	0	0		1	1	1
1	1	1	1	1		0	0	1	0	0	0	0	1	0	0				
Square 5x5 element Diam							ond-shaped 5x5 element			Cross-shaped 5x5 element				Square 3x3 element					

A common practice is to have odd dimensions of the structuring matrix and the origin defined as the centre of the matrix. Structuring elements play in morphological image processing the same role as convolution kernels in linear image filtering.

When a structuring element is placed in a binary image, each of its pixels is associated with the corresponding pixel of the neighborhood under the structuring element. The structuring element is said to **fit** the image if, for each of its pixels set to 1, the corresponding image pixel is also 1. Similarly, a structuring element is said to **hit**, or intersect, an image if, at least for one of its pixels set to 1 the corresponding image pixel is also 1.

0000000000000						
B 00011000000 00111100000				Α	В	С
01111110000	$S_1 = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$	fit	s ₁	yes	no	no
01111110000 001111110000	6 10		s ₂	yes	yes	no
$\begin{array}{c} 0 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ \end{array}$	$s_2 = 1111$	hit	s ₁	yes	yes	yes
A 000001111110 00000000000000	010		S ₂	yes	yes	no

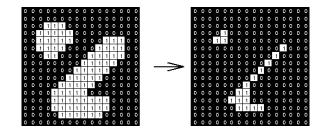
Zero-valued pixels of the structuring element are ignored, i.e. indicate points where the corresponding image value is irrelevant.

IX. FUNDAMENTAL OPERATIONS

More formal descriptions and examples of how basic morphological operations work are given in the Hypermedia Image Processing Reference developed by Dr. R. Fisher et al. at the Department of Artificial Intelligence in the University of Edinburgh, Scotland, UK.

EROSION AND DILATION

The **erosion** of a binary image *f* by structuring а element s (denoted $f \Theta s$) produces a new binary image $g = f \Theta s$ with ones in all locations (x, y) of a structuring element's origin at which that structuring element s fits the input image f, i.e. g(x,y) = 1 is s fits f and 0 otherwise, repeating for all pixel coordinates (x,y). Erosion with small (e.g. $2 \times 2 - 5 \times 5$) square structuring elements shrinks an image by stripping away a layer of pixels from both the inner and outer boundaries of regions. The holes and gaps between different regions become larger, and small details are eliminated:



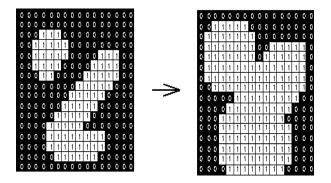
Larger structuring elements have a more pronounced effect, the result of erosion with a large structuring element being similar to the result obtained by iterated erosion using a smaller structuring element of the same shape. If s_1 and s_2 are a pair of structuring elements identical in shape, with s_2 twice the size of s_1 , then $f \ominus s_2 \approx (f \ominus s_1) \ominus s_1$.

Erosion removes small-scale details from a binary image but simultaneously reduces the size of regions of interest, too. By subtracting the eroded image from the original image, boundaries of each region can be found: $b = f - (f \Theta s)$) where f is an image of the regions, s is a 3×3 structuring element, and b is an image of the region boundaries.

The dilation of an image f by a structuring element s (denoted $f \bigoplus s$) produces binary а new image $g = f \bigoplus s$ with ones in all locations (x, y) of a structuring element's orogin at which that structuring element s hits the the input image f, i.e. g(x,y) = 1 if s hits f and 0 otherwise, repeating for all pixel coordinates (x,y). Dilation has the opposite effect to erosion -- it adds a layer of pixels to both the inner and outer boundaries of regions.



The holes enclosed by a single region and gaps between different regions become smaller, and small intrusions into boundaries of a region are filled in:



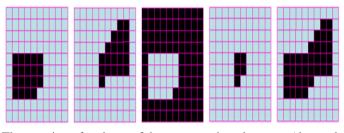
Results of dilation or erosion are influenced both by the size and shape of a structuring element. Dilation and erosion are *dual* operations in that they have opposite effects. Let f^c denote the complement of an image f, i.e., the image produced by replacing 1 with 0 and vice versa. Formally, the duality is written as $f \bigoplus s = f^c \bigoplus s_{rot}$ where s_{rot} is the structuring element s rotated by 1800. If a structuring element is symmetrical with respect to rotation, then s_{rot} does not differ from s. If a binary image is considered to be a collection of connected regions of pixels set to 1 on a background of pixels set to 0, then erosion is the fitting of a structuring element to these regions and dilation is the fitting of a structuring element (rotated if necessary) into the background, followed by inversion of the result.

X. COMPOUND OPERATIONS

Many morphological operations are represented as combinations of erosion, dilation, and simple set-theoretic operations such as the **complement** of a binary image:

$f^{c}(x,y) = 1$ if f(x,y) = 0, and $f^{c}(x,y) = 0$ if f(x,y) = 1,

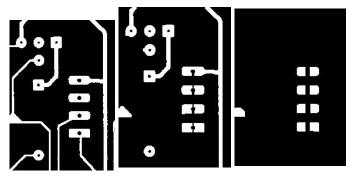
the **intersection** $h = f \cap g$ of two binary images f and g: h(x,y) = 1 if f(x,y) = 1 and g(x,y) = 1, and h(x,y) = 0 otherwise, and the **union** $h = f \cup g$ of two binary images f and g: h(x,y) = 1 if f(x,y) = 1 or g(x,y) = 1, and h(x,y) = 0 otherwise:



The opening of an image f by a structuring element s (denoted by $f \circ s$) is an erosion followed by a dilation: $f \circ s = (f \Theta s) \oplus s$



Opening is so called because it can open up a gap between objects connected by a thin bridge of pixels. Any regions that have survived the erosion are restored to their original size by the dilation:



Opening is an **idempotent** operation: once an image has been opened, subsequent openings with the same structuring element have no further effect on that image:

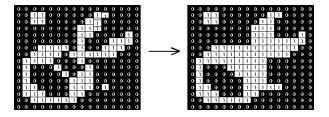
 $(f \circ s) \circ s) = f \circ s.$

The **closing** of an image f by a structuring element s (denoted by $f \cdot s$) is a dilation followed by an erosion:

$$f \bullet s = (f \bigoplus s_{rot}) \bigoplus s_{rot}$$



In this case, the dilation and erosion should be performed with a rotated by 180o structuring element. Typically, the latter is symmetrical, so that the rotated and initial versions of it do not differ.



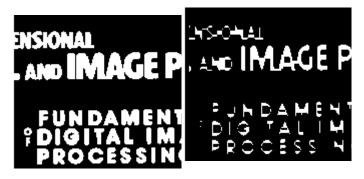
Closing is so called because it can fill holes in the regions while keeping the initial region sizes. Like opening, closing is idempotent: $(f \cdot s) \cdot s = f \cdot s$, and it is dual operation of opening (just as opening is the dual operation of closing):

$$f \bullet s = (f^c \circ s)^c; \quad f \circ s = (f^c \bullet s)^c.$$

In other words, closing (opening) of a binary image can be performed by taking the complement of that image, opening (closing) with the structuring element, and taking the complement of the result.

The **hit and miss transform** allows to derive information on how objects in a binary image are related to their surroundings. The operation requires a matched pair of structuring elements, $\{s_1, s_2\}$, that probe the inside and outside, respectively, of objects in the image:

 $f \circledast \{s_1, s_2\} = (f \ominus s_1) \cap (f^c \ominus s_2).$



A pixel belonging to an object is preserved by the hit and miss transform if and only if s_1 translated to that pixel fits inside the object AND s_2 translated to that pixel fits outside the object. It is assumed that s_1 and s_2 do not intersect, otherwise it would be impossible for both fits to occur simultaneously. It is easier to describe it by considering s_1 and s_2 as a single structuring element with 1s for pixels of s_1 and 0s for pixels of s_2 ; in this case the hit-andmiss transform assigns 1 to an output pixel only if the object (with the value of 1) and background (with the value of 0) pixels in the structuring element exactly match object (1) and background (0) pixels in the input image. Otherwise that pixel is set to the background value (0).

The hit and miss transform can be used for detecting specific shapes (spatial arrangements of object and background pixel values) if the two structuring elements present the desired shape, as well as for thinning or thickening of object linear elements.

MORPHOLOGICAL FILTERING

Morphological Filtering of a binary image is conducted by considering compound operations like opening and closing as filters. They may act as filters of shape. For example, opening with a disc structuring element smooths corners from the inside, and closing with a disc smooths corners from the outside. But also these operations can filter out from an image any details that are smaller in size than the structuring element, e.g. opening is filtering the binary image at a scale defined by the size of the structuring element. Only those portions of the image that fit the structuring element are passed by the filter; smaller structures are blocked and excluded from the output image. The size of the structuring element is most important to eliminate noisy details but not to damage objects of interest.

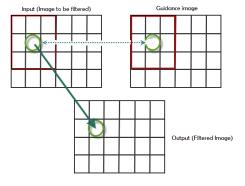
XI. GLCM

Texture is an important characteristic for the analysis of many types of images because it provides a rich source of information about the image. Also it provides a key to understand basic mechanisms that underlie human visual perception. In this paper four statistical feature of texture (Contrast, Correlation, Homogeneity and Energy) was calculated from Gray Level Co-Occurrence Matrix (GLCM) of equal blocks (30×30) from both tumor tissue and normal tissue of three samples of CT-scan image of patients with lung cancer. It was found that the contrast feature is the best to differentiate between textures, while the correlation is not suitable for comparison, the energy and homogeneity features for tumor tissue always greater than its values for normal tissue.

Several texture metrics that contain spatial information are based on the co-occurrence matrix, they also known as the spatial gray-level dependence matrix. Forming the cooccurrence matrices is an initial step that compiles spatial as well as statistical information for computing the texture metrics described later. The spatial information considered is the relative position of pairs of pixels, defined with distance *d* and orientation θ that describe the location of the second pixel with respect to the first .A co-occurrence matrix is formed for each such position. In this manner, each co-occurrence matrix prepares the data to emphasize primarily structure or streaks in a given direction and a grain size that is at least as large as the selected distance.

XII. GUIDED FILTER

The misguided filter function performs edge-preserving smoothing on an image, using the content of a second image, called a guidance image, to influence the filtering. The guidance image can be the image itself, a different version of the image, or a completely different image. Guided image filtering is a neighborhood operation, like other filtering operations, but takes into account the statistics of a region in the corresponding spatial neighborhood in the guidance image when calculating the value of the output pixel.



XIII. CONCLUSION

Computer aided detection of hookworm for WCE images is a challenging task. By observing its unique properties, in this paper, we propose a serials of novel techniques to capture its characteristics, aiming to reduces the number of images a clinician needs to review. Experiments from different aspects demonstrate that the proposed method is a robust classification tool for hookworm detection, which achieves promising performance.

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