Hookworm Recognition using Wireless Capsule Endoscopy Video

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Abstract—Wireless Capsule Endoscopy (WCE) is a relative work of fiction technology, which can analysis complete gastrointestinal (GI) tract without invasiveness and sedation. The main drawback related with WCE is that the vast number of recorded images must be examined by clinicians. It is a boring and time unbearable task. Developing an automatic computer-aided detection system to alleviate the burden of clinicians is required. In this paper, we planned a new hookworm image detection algorithm. This is the first few works to comprehensively explore the automatic hookworm detection for WCE images. Automatic hookworm detection is a demanding task due to reduced quality of images, presence of irrelevant matters, compound structure of gastrointestinal and varied appearances in terms of color and texture. The proposed approach achieves a promising performance and outperforms the state-of-the-art methods. Moreover, the high sensitivity in detecting hookworms indicates the potential of our approach for future clinical application.

Index Terms—Computer-aided detection, hookworm detection, wireless capsule endoscopy and classification.

I. INTRODUCTION

Individual hookworm illness is known as soil-transmitted helminthes infection by the nematode parasites includes necator americanus and ancylostoma. It is one of the majority GI diseases worldwide. World Health Organization estimates that about 740 million people are infected with hookworm. Hookworms exist in small intestine and effect in blood loss to cause anemia and starvation. The infections also hold up growth and mental development of children. The typical method for diagnosing the existence of hookworm is by identifying hookworm eggs in a stool test using a microscope. However, eggs are not easy to find in gentle infections. Most GI track diseases such as hookworm can be without difficulty detected by Wireless Capsule Endoscopy (WCE). WCE was initially invented by Given Imaging Ltd [2]. It is a noninvasive technology which can examine the entire GI track without anesthesia and air insufflation. As the consequence, it becomes a popular approach for GI track diseases assessment in lots of hospitals in modern years. A WCE is a capsule-shaped tool which consists of a camera, light source, battery, radio transmitter, and other electronic components. After swallowed by a patient, the WCE moves through esophagus, stomach, small intestine, large intestine, and excretes from the anus lastly. The entire process lasts for about eight hours. In GI track, the camera takes two photos per second and transmits photos to the record device. Clinicians obtain estimated 40-60 thousands color images of the entire GI track in each patient test. The clinicians must expend more than two hours to look through all the images for diagnostication of the diseases, such as bleeding, polyps, hookworm or tumor. It is time overwhelming and manual. Therefore, a computer-aided automatic disease detection system is really required. In recent times, the problem of WCE image recognition has paying attention from many researchers.

Fig. 1. Examples of WCE images having hookworms. Due to changeable quality of images, occurrence of irrelevant matters, compound structure of GI and varied appearances in terms of color and texture, automatic hookworm detection is a demanding task.

Fig. 1 shows some representative WCE images having hookworms. Automatic hookworm detection is a demanding task due to reduced quality of images, occurrence of irrelevant matters,
complex structure of gastrointestinal and varied appearances in terms of color and texture. First WCE images often suffer from noise and low visual quality because of compound circumstances in GI tract and reduced illumination conditions. The quality of images is extremely variable due to the unrestrained peristalsis-driven motion of the capsule as moving through the GI tract. Second, there are many other contents in GI tract, such as food, stool, bile and bubbles, which influence the detection of parasitosis. Third, the free motion of the camera and the contractions that the gut undertakes various orientations and perspectives of the scene. Different parts of the intestinal tract (stomach, duodenum, jejunum-ileum, and cecum) present a diversity of appearances with multiple colors and textures. Four, hookworms’ exhibit great variations in morphology and color. The hookworms attaching on mucosa demonstrate dissimilar shapes, widths and curve orientations. These challenges pose a great complicatedness for automatic hookworm detection in WCE images.

The remainder of this paper is organized as follows: section II introduces our proposed algorithm. Experiment and results are shown in section III. Finally, in section IV, we make a Conclusion and discuss the future work.

II. METHODOLOGY

The proposed methodology has four steps of process to classify the WCE images. Figure 1 shows the overall architecture of the system.

A. GUIDED FILTER

We first identify a general linear translation-variant filtering process, which involves a guidance image I, a filtering input image p, and an output image q. Both I and p are given beforehand according to the application, and they can be identical. The filtering output at a pixel i is expressed as a weighted average:

\[ q_i = \sum_j W_{ij} (I) p_j \]  

(1)

where i and j are pixel indexes. The filter core \( W_{ij} \) is a function of the guidance image I and independent of p. This filter is linear with respect to p. Now we identify the guided filter. The key assumption of the guided filter is a local linear model between the guidance I and the filtering output q. Suppose that q is a linear transform of I in a window \( k \) centered at the pixel k:

\[ q_i = a_k I_i + b_k, \forall i \in w_k \]  

(2)

where \( (a_k, b_k) \) are some linear coefficients assumed to be constant in \( w_k \). We use a square window of a radius r. This local linear model ensures that q has an edge only if I has an edge, because \( \nabla q = a \nabla I \). This model is helpful in image super-resolution, image matting, and dehazing.

Fig 1: Overall System Architecture
B. SEGMENTATION

1) Multilevel Thresholding

Thresholding is an essential technique for image segmentation that tries to recognize and remove a target from its background on the base of the distribution of gray levels or texture in image objects. Generally, thresholding techniques are based on the statistics of the one-dimensional (1D) histogram of gray levels and on the two-dimensional (2D) Co-occurrence matrix of an image. Many 1D thresholding methods have been investigated. Locating the thresholds can be done in parametric or nonparametric approaches. In parametric approaches, the gray level distribution of an object class leads to discovering the thresholds. The pixels of an image are first classified as either edge or non-edge pixels.

According to their local neighborhoods, edge pixels are then classified as being comparatively dim or fairly light. Subsequently, one histogram is obtained for those edge pixels which are dim and an extra for those edge pixels which are light. The maximum peaks of these two histograms are selected as the thresholds. Instant preserving thresholding is a parametric method which segments the image based on the condition that the threshold image has the similar moments as the original image. In nonparametric approaches, the thresholds are obtained in a best manner according to several criteria. For instance, Otsu’s method chooses the optimal thresholds by maximizing the between-class variance with an exhaustive search. It divides the target image into two part, foreground and background. When an original image is necessary to divide into more levels, the original Otsu can be widespread to multi-level thresholds. As threshold numbers increases, computational time will increase drastically.

2) Vector Quantization

Vector quantization is mainly used to map the pixel intensity vectors into binary vectors indexing a partial integer of probable reproductions, is a trendy image compression algorithm.

The exact definition of vector quantization is the mapping process from the K-dimensional vector space $R^k$ to $W$ which is a fixed subset of $R^k$. Specifically, $Q: X \in R^k \rightarrow W$ is called the code book, and its members are called code words. VQ is nearly a method of locating a codeword from the codebook to symbolize the input vector.

C. FEATURE EXTRACTION USING REGION PROPS

1) Connected Component Labeling

Connected-component labeling is an algorithmic application where subsets of connected components are exclusively labeled based on a known heuristic. Connected-component labeling is used in computer vision to identify connected regions in binary digital images, though color images and data with superior dimensionality can also be processed. When incorporated into an image recognition scheme or human-computer communication edge, connected component labeling can work on a diversity of information. Blob extraction is usually performed on the resultant binary image from a thresholding step. Blobs might be counted, filtered, and tracked. Blob extraction is connected to but dissimilar from blob detection.

A graph, containing vertices and connecting edges, is constructed from related input data. The vertices include information required by the similarity heuristic, while the edges indicate linked 'neighbors'. An algorithm traverses the graph, labeling the vertices based on the connectivity and relative standards of their neighbors. Connectivity is determined by the medium; image graphs, for example, can be 4-connected or 8-connected.

2) Region props

Region props are used for extracting the property of image region as the shape feature. Several region properties are there such as Area, Centroid, Convex length, Convex areas, Eccentricity etc. Now only Eccentricity is used. The eccentricity is the relation of the distance between the foci of the ellipse and its major axis length. The value is between 0 and 1. The end result is stored as a structure array. Texture features are extracted using gray level co-occurrence matrix (GLCM) [3]. Gray Level Co-occurrence Matrix is calculated. It’s a tabulation of different Combination of pixel brightness value occur in an image, it’s a square matrix. Now the energy is calculated. Energy essentially measures the textural information in terms of energy whether it is uniform or not. It essentially measures texture of gray-scale image signify homogeneity varying, reflecting the distribution of image gray-scale regularity of
weight and texture. It is well-known as uniformity or the angular second moment. Here another 1-D array is developed. At last the entire three 1-D array are merged in a single 1D array of extracted feature for single image. This process is repeated for every image. Then we apply Manhattan distance method algorithm for similarity measurement.

D. CLASSIFICATION

Hierarchical clustering is a process of cluster analysis which seeks to construct a hierarchy of clusters. Given a set of N items to be clustered, and an N*N distance (or similarity) matrix, the essential procedure of hierarchical clustering is this:

1. Create assigning each item to a cluster, so that if you have N items, you now have N clusters, each containing just one item. Allow the distances (similarities) between the clusters the similar as the distances (similarities) between the items they hold.
2. Find the neighboring (most similar) pair of clusters and combine them into a single cluster, so that now you have one cluster less.
3. Calculate distances (similarities) between the new cluster and each of the old clusters.
4. Repeat steps 2 and 3 until all items are clustered into a single cluster of size N. (*)

Step 3 can be done in special ways, which is what distinguishes single-linkage from complete-linkage and average-linkage clustering. In single-linkage clustering, we think the distance between one cluster and another cluster to be equal to the shortest distance from any member of one cluster to any member of the other cluster. If the information consists of similarities, we believe the resemblance involving one cluster and another cluster to be equal to the maximum similarity from any part of one cluster to any part of the other cluster. In complete-linkage clustering, we believe the space involving one cluster and another cluster to be the same to the maximum distance from any part of one cluster to any part of the other cluster. In average-linkage clustering, we think the space involving one cluster and another cluster to be equal to the average distance from any part of one cluster to any part of the other cluster.

After the clustering process the individual clustered regions are labels as a recognized type of worm.

III. RESULTS AND DISCUSSION

The experiments were conducted on a PC with a 1.80GHz Intel(R) Core(TM) i5-3337U CPU and 4GB RAM. All algorithms were implemented by Matlab 2016a. Each WCE image is a 24 bit RGB color image with the resolution of 256 x 256 pixels. To the best of our knowledge, this dataset is one of the largest datasets for automatic disease detection for WCE images. Unlike other works that select only a few hundreds to thousands of WCE images for evaluation, in this work, the whole dataset is used. Among the eleven patients, the eighth and ninth patients are heavily infected. Dataset has been annotated by the expert Gastroenterologist. Fig 3(a) shows an input frame and Fig 3(b)-(d) shows the guided filter result, segmentation result and classification results respectively. In fig (d) each cluster of worms are bounded by different colors. The performance of the proposed system is tested by the statistical measures. Table 1 shows the statistical performance results. Based on the derived results the proposed system’s ability to classify the worm is proved.

Fig 3: (a) Input WCE frame  
Fig 3: (b) Result of Guided Filter
IV. CONCLUSION

In this paper, we developed a computer-aided WCE image categorization scheme for hookworm detection. By observing its sole properties, we suggest a serial of novel techniques to capture its uniqueness, aiming to decrease the number of images a clinician wants to review. Experiments from dissimilar aspects show that the planned method is a robust categorization tool for hookworm detection, which achieves promising performance. Although good performance has been achieved, in our future work, we will continue working on new solution to further improve the performance in our future work. The vital goal is that automatic detection system can be used in a real condition to help endoscopists, and can still get more precise judgement than practiced endoscopists.

V. REFERENCES


