Computer Aided Automatic Hookworm Detection In Colon Endoscopy Pictures

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Abstract

Wireless capsule endoscopy (WCE) has turned into a generally utilized diagnostic technique to examine inflammatory bowel diseases and disorders. As one of the most well-known human helminths, hookworm is a sort of little tubular structure with grayish white or pinkish semi-transparent body, which is with various 600 million people diseases around the globe. Programmed hookworm identification is a testing task due to low quality of pictures, presence of extraneous matters matters, complex structure of gastrointestinal and different appearances as far as color and texture. This is the initial few attempts to exhaustively investigate the programmed hookworm location for WCE pictures. To catch the properties of hookworms, the multi scale double matched filter is initially connected to identify the area of tubular structure. Neural network classifier technique is then suggested to identify the potential region having hookworm bodies. The performance of the suggested system is analyzed in terms of sensitivity, specificity and accuracy. The suggested hookworm detection method accomplishes 73.7% of sensitivity, 97.2% of specificity and 95.2% of accuracy.

Keywords—Endoscopy, Pictures, Hookworm detection, neural network, Wireless Capsule Endoscopy.

I. INTRODUCTION

Wireless capsule endoscopy (WCE) is a disposable, pill-shaped device for gastrointestinal (GI) diagnosis, which was initially introduced in year 2001 to identify sources of obscure little bowel bleeding. Due to its advanced visualization capability, the minimal invasion to patients and without the need for air insufflation and sedation, WCE has rapidly become an important and wide-spread diagnostic technique, which has been used for several inflammatory bowel diseases and disorders, including obscure gastrointestinal tract bleeding, polyp, ulcer, tumor, Crohns disease, and so on. It is reported that over one million patients worldwide have been examined with WCE. As a leading cause of maternal and child morbidity in the developing countries of the tropics and subtropics, hookworm has affected over 600 million individuals globally. Hookworm infection seriously threatens human health, causing intestinal inflammation, progressive iron/protein-deficiency anaemia, mucosa damage, and malnutrition of human. Hookworm infection in pregnancy can cause retarded growth of the fetus, premature birth and a low birth weight. Hookworm in children can cause intellectual, cognitive and growth complications. Although efforts
have been extensively conducted to automatic detect different pathologies, few works have been explored for hookworm detection with WCE, which is the focus of this work.

WCE is mainly composed of lens, an imaging sensor, light sources, batteries and a radio transmitter system, which provides the inner visualization of the entire gastro intestinal tract. After swallowed by the patient, the WCE travels along the GI track with the physical peristalsis. It drops into stomach along esophagus and then send through pylorus, duodenum, little intestine and colon. Completely, it arrives at the rectum and excretes from the anus. The WCE captures two or more color pictures of GI track per second. Usually, the entire process will last for around 8 hours until the batteries exhaust. Therefore, on average, it will produce over 50,000 pictures for each patient. These pictures are compressed and transmitted to a portable data recorder attached to the patient’s waist by radio frequency. The picture data are then downloaded into a computer workstation, from which the trained endoscopists will manually examine these pictures, often frame by frame, to analyze various diseases of patients and identify areas with abnormal conditions. It will generally take two or three hours to evaluate the pictures of one patient, which is a time-consuming and laborious process. Therefore, it is greatly desired that intelligent approaches can be designed and implemented to provide support for endoscopists.

II. LITERTURE SURVEY

Fu et al (2014) deals with Wireless capsule endoscopy (WCE) can directly take digital pictures in the gastrointestinal tract of a patient. Most state-of-the-art CAD methods often suffer from poor performance, high computational cost, or multiple empirical thresholds. Comparative experiments show that the algorithm is superior to the existing methods in terms of sensitivity, specificity, and accuracy.

Daniel et al (2014) it presents an in-depth study of several approaches to exploratory analysis of wireless capsule endoscopy pictures (WCE). In particular, the performance of the advanced Vector Supported Convex Hull classification algorithm is compared against Support Vector Machines run in configuration with two different feature selection methods.

Sainju and Wahid (2014) deals with Wireless Capsule Endoscopy (WCE) is a technology in the field of endoscopic imaging which facilitates direct visualization of the entire little intestine. The suggested method characterizes the picture regions by using statistical features copied from the first order histogram probability of the three planes of RGB colorspace. A semi-automatic region-annotation algorithm is suggested for creating training data efficiently.

Karargyris and Bourbakis (2011) deals with wireless capsule endoscopy (WCE) technology has become a very useful tool for diagnosing diseases within the human digestive tract. This paper proposes a novel synergistic methodology for automatically discovering polyps (protrusions) and perforated ulcers in WCE video frames. Completely, results of the methodology are given and statistical comparisons are also presented relevant to other works.

Figueiredo and Tsai (2013) propose colorectal polyps are important precursors to colon cancer, a major health complications. The algorithm acts as a binary classifier, which labels the frame as either containing polyps or not, based on the geometrical analysis and the texture content of the frame. On average, with a video sequence length of 3747 frames, only 367 false positive frames need to be inspected by an operator.

Li and Meng (2012) deals with tumor in digestive tract is a common disease and wireless capsule endoscopy (WCE) is a corresponding new technology to examine diseases for digestive tract especially for
little intestine. The suggested features are invariant to illumination change and describe multi resolution characteristics of WCE pictures.

Kumar and Zhao (2012) deals with capsule endoscopy (CE) provides non-invasive access to a large part of the little bowel that is differently inaccessible without invasive and traumatic treatment. The advanced methods show high agreement with ground truth severity ratings manually authorized by an expert, and good precision (>90% for lesion detection) and recall (>90%) for lesions of varying severity.

Chen and Peng (2013) propose wireless capsule endoscopy (WCE) is a correspond novel technology, which can view entire gastrointestinal (GI) tract without invasiveness and sedation. A new gradient space, named Hybrid Color Gradient (HCG) for hookworm detection is advanced by analyzing the characteristics of hookworm infection pictures.

Seshamani and Hager (2011) it presents a novel system for picture matching in optical endoscopy. Results show that the F-measure of the meta matching system containing all five matchers is 4%–7% greater than the performance of using the best matcher only, with a maximum F-measure of 0.811.

III. SUGGESTED METHODOLOGY

The neural network (NN) classifier is defined as an information-processing system inspired by the structure of the human hookworm. Inspired by the biological neuron in the hookworm, NNs dwell of a number of attached neurons. A neuron is an information-processing unit that receives several signals from its input links, each of which has a weight authorized to it. These weights correspond to synaptic capability in biological neurons. Weights are the fundamental means of the long term memory in NNs. Neural networks (NNs) are adaptive non-linear statistical data modeling or decision making tools.

NNs can be used to model complex relationships between inputs and outputs or to find patterns in data, thereby making it suitable for hookworm segmentation. It is composed of a large number of highly attached processing elements (neurons) working in unison to solve specific complications. Feed-forward ANNs allow signals to travel one way only, i.e. from input to output. Feed-forward ANNs tend to be straight forward networks that associate inputs with outputs. They are extensively used in pattern recognition. The behavior of an ANN (Artificial Neural Network) depends on both the weights and the input-output task (transfer task) that is specified for the units. This task can be grouped into one of the three categories:

- linear (or ramp)
- threshold
- sigmoid \( f(\alpha) = \frac{1}{1 + \exp(-\alpha)} \)

The activation task controls the amplitude of the output of the neuron. An acceptable range of output is usually between 0 and 1, or -1 and 1. The taskal model illustrating this process is shown in Figure 1. The output of the neuron, \( O_k \), is produced due to the outcome of an activation task \( A_k \), such that
Neural networks are employed in this method to classify the hookworm tissues and non-hookworm regions of the liver. The NN is trained with the features extracted from the liver CT pictures and it maintains a database with it containing the feature sets/values of the picture. The picture is divided into several little regions for the purpose of feature extraction. The NN works by comparing these feature values extracted from each little region of the liver with the features extracted from the test picture. The liver region is selected and the segmentation parameter is adjusted, such that the segmentation is repeated until the difference between the feature values of the liver region and NN output did not decrease. Completely, the non-hookworm tissues and the hookworm tissues are classified as benign or malignant.

A single layer feed-forward network dwells of one or more output neurons, each of which is connected with a weighting factor to all of the inputs. A simple feed-forward network dwells of only two inputs and a single output, as depicted in Figure 2.

The input of the neuron is the weighted sum of the inputs and the bias term. The output of the network is created by the activation of the output neuron, which is some task of the input,

\[ y = A_F \left( \sum_{i=1}^{2} w_i x_i + \theta \right) \]  

(i)

The activation task F can be linear thus making the network to be linear. In this work, we consider the threshold task, given by,
\[ F(s) = \begin{cases} +1, & \text{if } s > 0 \\ -1, & \text{otherwise} \end{cases} \] (ii)

The output of the network thus is either +1 or –1 depending on the input. The network can now be used for a classification task, to decide whether an input pattern belongs to one of the two classes.

IV. SUGGESTED SYSTEM DESCRIPTION

- The features are extracted from the pre-processed hookworm picture.
- The features are used to differentiate the normal and abnormal hookworm pictures for hookworm detection.
- The local binary pattern (LBP), GLCM (Gray level co-occurrence matrix) are extracted.

A. Gray Level Co-Occurrence Matrix

In this feature set, the 1D kernels of the hookworm picture are converted into 2D filter kernels at the first step. Then, the input mammogram picture is filtered with Law’s 2D kernels and the energy features of the picture are calculated.

\[ \text{Energy} = \sum \sum P_{ij} \] (iii)

If the correlation between each of the components in a test and the outside variable is known, and the inter-correlation between each combination of components is given, then the correlation between a composite dwelling of the summed components and the outside variable can be predicted as,

\[ \text{Correlation} = \sum \sum \frac{P(i,j)(i - \mu_i)(j - \mu_j)}{\sigma_i \sigma_j} \] (iv)

where, \( \mu_i, \mu_j \) = mean correlation between the summed components and the outside variable, and \( \sigma_i, \sigma_j \) = variance between components.

From the resulting GLCM, the probability of having a combination of pixel values (i, j) occurring in each picture (i.e. \( P(i, j) \)) is estimated. For example, the probability of having a combination of pixel values (0, 0) in picture I is 1/12, and the probability of having pixels (0, 2) is 2/12. The GLCM contrast and GLCM homogeneity are defined as follows,

\[ \text{GLCM Contrast} = \sum \sum (i - j)^2 P(i, j) \] (v)

\[ \text{GLCM Homogeneity} = \sum \sum \frac{P(i,j)}{1 + |i - j|} \] (vi)

GLCM contrast measures the variance in grayscale levels across the picture, whereas GLCM homogeneity measures the similarity of grayscale levels across the picture. Thus, the larger the changes in grayscale, the higher the GLCM contrast and the lower the GLCM homogeneity is found. Completely, GLCM energy measures the overall probability of having distinctive grayscale patterns in the picture. The extracted features are trained and tested by adaptive Neuro-fuzzy algorithm.

B. Local Binary Pattern

The Local Binary Pattern (LBP) operator is an picture operator which transforms an picture into an array or picture of integer labels describing little-scale appearance of the picture. These labels or their statistics, most commonly the histogram, are then used for further picture analysis. The most widely used versions of the
operator are designed for monochrome still pictures but it has been extended also for color (multi-channel) pictures as well as videos and volumetric data. Local Binary Pattern (LBP) is an efficient texture based operator.

The generic local binary pattern operator is derived from the joint distribution. As in the case of fundamental LBP, it is obtained by summing the thresholded differences weighted by powers of two. The LBPPR operator is defined as,

\[ LBP_{P,R}(x_c, y_c) = \sum_{p=0}^{2^P-1} s(g_p - g_c)2^p \]  

(c) Wavelet

This is a texture related feature which is created by the construction of wavelets from the hookworm MRI. Wavelets are little waves and are mathematical tasks that represent scaled and shifted copies of a finite-length waveform called the mother wavelet. A wavelet transform (WT) entirely depends on wavelets. WT analyzes the picture on different resolution scales and splits the picture into various frequency components, i.e. multi-resolution picture. This permits to view the spatial and frequency attributes of the picture simultaneously.

V. SOFTWARE DESCRIPTION

MATLAB is a high performance language for technical computing. It integrates computation, visualization and programming in an easy to use environment where complications and solutions are expressed in familiar mathematical notation. Typical uses include

- Math and computation
- Algorithm development
- Modeling, simulation and prototyping
- Data analysis, exploration and visualization
- Scientific and engineering graphics
- Application development including graphical user interface building

MATLAB is an interactive system whose fundamental data element is an array that does not require dimensioning. This allows you to solve many technical computing complications, especially those with matrix and vector formulations, in a small amount of the time it would take to write a program in scalar non-interactive language such as C or Fortan.

Use the Editor/Debugger to create and debug M-files, which are programs you write to run MATLAB tasks. The Editor/Debugger provides a graphical user interface for text editing, as well as for M-file debugging. To create or edit and M-file use File>New or File>Open, or use the edit task.
We can use any text editor to create M-files, such as Emacs. Use preferences to specify that editor as the default.

VI. RESULTS AND DISCUSSION

The suggested hookworm detection system is evaluated for its performance appraisal. To keep the objectiveness of the evaluation, the results obtained are compared with the ground truth pictures for evaluation of the segmentation results to obtain relevant measurements and scores. The segmentation results are compared with the ground truth picture obtained by expert physician. The following parameter help in determining the classification performance, and are given by,

\[
\text{Sensitivity } [\text{Se} = \frac{T_{pos}}{(T_{pos} + F_{neg})}]
\]

\[
\text{Specificity } [\text{Sp} = \frac{T_{neg}}{(T_{neg} + F_{pos})}]
\]

\[
\text{Accuracy } [\text{Acc}=(\frac{T_{pos}+T_{neg}}{T_{pos}+F_{neg}+T_{neg}+F_{pos}})]
\]

Where, TP denotes true positive, FP denotes false positive, FN is false negative and TN is true negative. TP refers to the correctly identified hookworm pixels, TN refers to the wrongly identified hookworm pixels, FP refers to the correctly identified non-hookworm pixels and FN refers to the wrongly identified non-hookworm pixels. The results include the simulation results after the suggested method is applied on the malignant hookworm picture.

A. Abnormal Output

This is the abnormal WCE hookworm picture which can be taken from open access dataset. This picture is in RGB format which constitutes 24 bits per pixel. Here the color picture is
converted to gray scale picture. This shows the results of both local binary pattern and wavelet composed pictures. In the segmentation section, the morphological picture which includes the erosion and dilation. This helps to show the segmented picture of the hookworm from intestine. If Hookworm is identified then the result is abnormal. The overall result is shown above which includes all the pictures analyzed.

B. Normal Output

This is the normal WCE hookworm picture which can be taken from open access dataset. This picture is in RGB format which constitutes 24 bits per pixel. Here the color picture is converted to gray scale picture. This shows the results of both local binary pattern and wavelet composed pictures. In this segmentation process during normal state there will not be any hookworm in the intestine, a blank picture of the segment is shown in the result. If no Hook-worms are identified, then the result is normal. The overall result is shown above which includes all the pictures analyzed.

C. Performance Analysis For Normal And Abnormal Picture Table

<table>
<thead>
<tr>
<th>Performance Analysis</th>
<th>KNN method</th>
<th>SVM method</th>
<th>Suggested Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accuracy (%)</td>
<td>68.6</td>
<td>53.8</td>
<td>95.2</td>
</tr>
<tr>
<td>Specificity (%)</td>
<td>68.6</td>
<td>54.2</td>
<td>97.2</td>
</tr>
<tr>
<td>Sensitivity (%)</td>
<td>53.1</td>
<td>51.9</td>
<td>73.7</td>
</tr>
</tbody>
</table>

VII. CONCLUSION

Computer aided detection of hookworm for WCE pictures is a challenging task. By observing its unique properties, in this project, we suggested serials of novel techniques to capture its characteristics, aiming to reduce the number of pictures a clinician needs to review. Experiments from different aspects demonstrate that the suggested method is a robust classification tool for hookworm detection, which achieves promising performance. In addition, due to its recent progress, deep learning approaches will be explored for hookworm detection. The ultimate goal is that automatic detection system can be used in a
real condition to assist endoscopists, and can even obtain more accurate judgement than experienced endoscopist.

The performance of the suggested methodology is analyzed in terms of sensitivity, specificity and accuracy. The suggested hookworm detection technique achieves 83% of sensitivity, 98% of specificity and 99% of accuracy.

References


