BRAIN HAEMORRHAGE SEGMENTATION USING DISCRETE WAVELET TRANSFORM

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Abstract: Head injury is a major reason for morbidity and mortality worldwide and traumatic head injuries represent the major cause of neurological disability. A traumatic brain injury (TBI) is damage to the brain, secondary to a clot or hematoma caused by an accident or any other trauma. This hematoma is known as an Intracranial Haemorrhage (ICH) and is the most common and serious consequence of head injury which can be life-threatening. The most common cause of ICH normally reported in our country are road traffic accidents (RTA) followed by falls and assaults. India is a populous country with over a billion people and there is approximately one radiologist for every 100,000 population with most of them in the urban setup, Indian rural population of more than 70% is deprived of these doctors. The unavailability of these specialists is a grave concern to the well-being of the health care to the nation. The mainstay in the diagnosis of an ICH is the CT (Computed Tomography) scan of the head which is not easily available in case of brain haemorrhage.

I. RELATED WORK

Brain haemorrhage segmentation is the first step before detecting the haemorrhage in the brain. A lot of work has been done on the brain haemorrhage detection using methods like Convolutional neural network [2][3][5][11] and other efficient and advanced deep learning techniques. But that is resource intensive. It is also necessary and efficient when there is a large dataset, which is not easily available in case of brain haemorrhage. Murtada D. Hssayeni and colleagues [1][2] have contributed in two ways, they collected a new dataset of 82 CT scans with multiple slices and made it public. Second, used deep learning methods to perform segmentation and got a dice coefficient of 31% which is good compared to other deep learning techniques on small datasets. Indrajiet Kumar and colleagues [12] propose entropy based automatic unsupervised brain intracranial haemorrhage segmentation which comprises of FCM clustering, thresholding and edge based active contour methods and they get a better result with the combination than FCM clustering and active contour methods alone. Tong Duc Phong and colleagues [13] use deep learning to diagnose brain haemorrhage. They have used LeNet, GoogleNet and Inception-ResNet and a dataset consisting of 100 cases collected from 115 hospitals and discovered LeNet is the most time-consuming model among the three. Arjun Majumdar and colleagues [8] use a modified version of U-Net to detect the brain haemorrhage instead of traditional methods and achieve an overall specificity of 98.6% on the small dataset.
Xiaoming Liu and colleagues [7] perform automatic organ segmentation for CT scans based on super-pixel and CNN on CT scans of liver and high resolution CT scans of lungs and achieve a very high dice coefficient of 97.43% and 97.93% on liver and lung CT scans respectively. Justin L. Wang and colleagues [14] have applied a modified u-net and curriculum learning strategy for the semi supervised model to segment ICH regions of the patient CT scans which works with a small labelled dataset and large unlabelled dataset. Rikiya Yamashita and colleagues [9] have worked on applications of CNN in radiology using several small datasets using the idea of transfer learning using many pretrained models like AlexNet, VGG, ResNet and DenseNet. Sumijan [15] use a hybrid thresholding method based that combines p-tile with different edge detection methods for segmentation of the bleeding area in brain CT images. W. MimiDilyana W. Zakland colleagues [16] explore a multi-level segmentation approach where Fuzzy C-Means is used to extract intracranial haemorrhage from it’s background and skull and otsu multi-thresholding method applied to segment the intracranial structure into cerebrospinal fluid, brain matters and other homogenous regions. They have used a medical image dataset consisting of 519 normal and 201 abnormal CT brain images from 31 patients. The region is extracted and used for further analysis. Although there are lot of different methods available for brain haemorrhage detection very less has been done in recent times for segmentation and the availability of large dataset is one of the challenges in brain haemorrhage segmentation and a traditional approach like segmentation based on wavelet transform for comparatively smaller dataset may give better results compared to resource intensive deep learning techniques and assist radiologists in detecting brain haemorrhage more efficiently and quickly.

II. DATASET

Computed Tomography images for intracranial haemorrhage detection and segmentation is a publicly available dataset that has 82 CT scans of brain haemorrhage [1][19][20], of which 36 of them are diagnosed with intracranial haemorrhage. Each CT scan of each patient has about 30 slices. The radiologists have delineated the ICH regions in each slice and we have used 254 ground truth CT images for evaluation.

III. PRE PROCESSING

The images are resized to 256×256 to keep balance between segmentation and morphological operations are performed. The dataset mentioned in the previous section is used to perform segmentation and compare the results with the ground truth. While RGB is the most popular space to represent colour information of natural images, its usage in image segmentation is however restricted by the fact that the RGB channels are not independent to each other. In pre-processing step, for each channel in the brain CT image 2D median filtering for noise reduction with mask of size 5×5 is applied, morphological operations such as dilation followed by erosion with a structuring element is applied followed by brightness enhancement operation and further discrete wavelet transform is used. The edge is the most important high-frequency information of a digital image [18]. The traditional filter eliminates the noise effectively. But it will make the image blurry. We should thus protect the edges when reducing the noise of the image. We use discrete wavelet transforms for the same.

IV. PROPOSED METHODOLOGY

A. Algorithm

1) Pre-processing: The proposed method starts with pre-processing of original CT image like filtering and brightness enhancement.

2) Convert RGB image to YCbCr colour space: Convert the colour space into YCbCr to see in which colour space the algorithm works better.

3) Wavelet decomposition of the image: Wavelet Transform (WT) is a mathematical tool that converts original image into different time-frequency domain for analysis and processing. Both Cb and Cr components is decomposed into four sub bands (LL, LH, HL, HH). LL represents the low frequency component and the remaining bands represent the high frequency components in horizontal, vertical and diagonal direction. The wavelet analysis method helps with the removal of noise in the signal. We select the appropriate frequency band adaptively based on the characteristics of the signal.

4) Replacement with HH band: The detailed prominent coefficients of colour components are retained by replacing LL, LH and HL bands with HH band.

5) Convert back to RGB space: Inverse wavelet transform is applied on the modified approximated and detailed coefficients to reconstruct the colour components followed by morphological operations on them such as erosion and dilatation. Further, new image with wavelet modified colour components are transformed back to RGB colour space and the image thus obtained is called as frequency modified RGB image.

6) Apply thresholding: Threshold value is calculated using the histogram method. Using the frequency distribution of the graph it was analysed that when 3 standard deviation of the mean is considered for accurate brain haemorrhage segmentation. Further morphological operations like erosion and dilatation is applied to eliminate the contours that are not necessary in the obtained image. The image that falls within threshold is considered the region of brain haemorrhage and the one outside is considered normal region.
V. RESULTS AND DISCUSSION

The entire experiment is conducted using PC with Core-i5, 2.40 GHz processor and 8 GB RAM. The experimentation is done in python 3.6 environment. For experimentation, we have considered 254 images from physionet along with their corresponding ground truths. The images used for experimentation are changed to 256x256 size.

A. Evaluation Metrics

To measure the performance of our method we use jaccard similarity coefficient and dice coefficient post obtaining the segmented images using the available 254 ground truth images.

\[
\text{Jaccard Index} = \frac{|A \cap B|}{|A| + |B| - |AB|}
\]

\[
\text{Dice Coefficient} = \frac{2 \times TP}{2 \times TP + FP + FN}
\]

\[
\text{Sensitivity} = \frac{TP}{TP + FN}
\]

Where TP, TN, FP, and FN refer to true positive, true negative, false positive and false negative, respectively. In both ground truth and segmented image of proposed method, TP represents the number of haemorrhage pixels correctly identified as brain haemorrhage, TN is number of non-haemorrhage pixel correctly recognized as a normal brain region, FP is non-haemorrhage pixel incorrectly located as brain haemorrhage and FN is number of brain haemorrhage pixels incorrectly identified as normal region.

B. Results and Comparison

The YCbCr colour space is used in this work to analyse the contribution of the chrominance components of the image as it contains most of the relevant information. Luminance component(Y) is retained as it is.

![Fig. 1 a) original CT image b) segmented image without post processing using DWT. c) ground truth image d) segmented image without DWT](image)

![Fig. 2 flowchart of the segmentation](image)
TABLE 1: COMPARISON OF DIFFERENT METHODS

<table>
<thead>
<tr>
<th>Methods</th>
<th>Jaccard score (max)</th>
<th>Dice-Coefficient</th>
<th>Sensitivity (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>U-Net</td>
<td>0.528</td>
<td>0.677</td>
<td>97.28</td>
</tr>
<tr>
<td>CNN</td>
<td>0.91</td>
<td></td>
<td></td>
</tr>
<tr>
<td>FMRGB (proposed)</td>
<td>0.786</td>
<td>0.880</td>
<td>95.61</td>
</tr>
</tbody>
</table>

Table 1 shows the comparison of different methods. Also for the same method we have experimented with and without frequency modified RGB image where Non-frequency modified RGB has better jaccard similarity index as shown in table 2, but it has lesser sensitivity compared to the frequency modified RGB. The sensitivity of the non-frequency modified RGB is significantly less than the FMRGB image. This occurs due to decrease in the number of true positive pixels in non-frequency modified segmentation and increase in the false negative which represents brain haemorrhage region.

TABLE 2: FREQUENCY MODIFIED RGB (FMRGB) AND NON-FREQUENCY MODIFIED RGB

<table>
<thead>
<tr>
<th>Methods</th>
<th>Jaccard score (max)</th>
<th>Dice-Coefficient</th>
<th>Sensitivity (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>FMRGB</td>
<td>0.786</td>
<td>0.880</td>
<td>95.61</td>
</tr>
<tr>
<td>Non-frequency modified RGB image</td>
<td>0.871</td>
<td>0.931</td>
<td>57.38</td>
</tr>
</tbody>
</table>

Fig. 3 shows the comparison between the ground truth image and segmented frequency modified RGB image after postprocessing.

VI. CONCLUSION AND FUTURE WORK

Intracranial haemorrhage segmentation using discrete wavelet transforms is proposed and implemented. DWT decomposes the images into high frequency and low frequency band and it helps protect the edges while reducing noise. As we have small sized dataset, we can use a traditional method instead of advanced methods like CNN to segment the images and still get desired results and analyse further. The segmented images can assist the radiologist in identifying the haemorrhage region in the brain. Using the proposed methodology for efficient segmentation, the region of interest is extracted from the original image and it is used for further activities such as classification.

REFERENCES:

7. Xiaoming Liu, Shuxu Guo, Bingtao Yang, Shuzhi Ma, Huimao Zhang, Jing Li, Changjian Sun, Lanyi Jin, Xueyan Li, Qi Yang, Yu Fu, "Automatic Organ Segmentation for CT Scans Based on Super-Pixel and Convolutional Neural Networks", Journal of digital imaging, https://doi.org/10.1007/s10278-018-0052-4