IJARCCE

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified
Vol. 5, Issue 10, October 2016

Precised Detection of CMBS using HCSD

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Abstract: Cerebral Microbleeds (CMBs) are small chronic brain hemorrhages which are caused by structural abnormalities of the small vessels of the brain. CMBs are increasingly found in various patient populations and disease settings, including first-ever and recurrent ischaemic or haemorrhagic stroke, Alzheimer's disease, vascular cognitive impairment and healthy elderly individuals. Previous clinical routine, CMBs are manually detected by radiologists and it may produce the errors and time-consuming. In this paper, we proposed a two-stage cascaded framework to detect CMBs from magnetic resonance (MR) images using 3D convolutional neural network (CNN). We first endeavour a 3D fully convolutional Network (FCN) technique to recover the candidates with high probabilities of being CMBs, and afterward apply a well-trained 3D CNN discrimination model to recognize CMBs from hard mimics. Within our framework, the Hierarchical Centroid Shape Descriptor (HCSD) is allows to select only those having a specific structure. We illustrate that proposed framework can be utilized to prepare efficient and accurate classifiers that could introduce further Computer-aided diagnosis.

Keywords: Cerebral microbleeds, convolutional neural networks, Hierarchical Centroid Shape Descriptor, MRI.

I. INTRODUCTION

Cerebral Micro bleeds (CMBs) are small foci of chronic blood products in normal (or near normal) brain tissue, have been an increasingly recognized entity since the widespread application in the early to mid 1990s of magnetic resonance imaging (MRI) techniques customized to detect magnetic susceptibility. Recently, CMBs have been recognized as an important biomarker of neurovascular pathology by providing evidence of micro vascular damage and leakiness [2].
The clinical manual detection process is time-consuming and very subjective with limited reproducibility. Due to increasing of medical data flow, the accurate detection of CMBs in the MRI becomes a fastidious task to perform. For that reason, the expansion of computerized detection methods would improve the pathological examination efficiency and reliability.

The computerized detection of CMBs faces several issues:

1. There is a huge variance about the size of CMBs with a dimension ranging from 2 mm to 10 mm.
2. The common distributed locations of CMBs make complete and accurate detection even harder.
3. There can be found significant amounts of hard CMB mimics, e. g., flow voids, calcification and cavernous malformations, (see the red rectangular box in Fig 1) which would resemble the appearance of CMBs in scans and greatly delay the detection process.

In order to accurately and efficiently detect CMBs from volumetric brain data, we propose a robust and efficient method is 3D CNNs. Particularly; our method consists of two-stage cascaded framework:

a. The screening stage.
b. The discrimination stage.

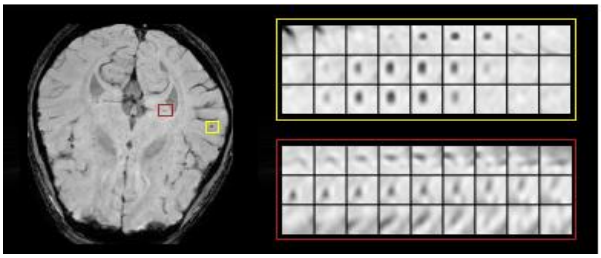

Fig 1. Better view of CMB and CMB mimics are denoted in yellow and red rectangular box.

In the screening stage, a small number of candidates are retrieved using a novel 3D fully convolutional network (3D FCN) model. Then the candidates obtained from the screening stage are carefully distinguished in the discrimination stage to detect CMBs from hard mimics. This stage removes a large number of false positive candidates. Within our framework, the Hierarchical Centroid Shape Descriptor (HCSD) is allows to select only those having a specific structure and yields the accurate final detection result. Before that, a pre-processing step is perform for removing the noise in an image and preserve useful information from the de-noised image.

The main aid of this work as follows:

1. A novel 3D FCN strategy is to successfully avoid redundant computations and dramatically increase the detection speed.
2. The 3D CNN adequately encodes the spatial contextual information and hierarchically extracted high-level features in a data driven way and demonstrates better performance.
3. The HSCD allows only selecting an accurate shape of the CMBs for better detection result.

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4. The proposed framework to efficiently and accurately detect CMBs and can be easily adapted to other biomarker detection tasks.

The remainder of this paper is structured as follows. Section II presents some previous work related to the CMBs. Section III describes our proposed framework in order to select CMBs accurately and efficiently from hard mimics. In section IV report the experimental result of CMBs detection by using the proposed approach. Finally, section V gives conclusion.

II. RELATED WORK

Previous automatic CMB detection methods mainly employed hand-crafted features based on shape, size and intensity information. The design of these hand-crafted features depends on the domain knowledge of CMBs. The Radon Transform to describe the shape information of CMBs, while applied the Radial Symmetry Transform (RST) to identify spherical regions as CMBs. To improve the capability of discrimination, proposed to measure the geometric features after performing a 2D fast RST. In addition, these low-level features are usually insufficient to capture the complicated characteristics of CMBs [1].
In [4], the authors show that the automatic brain tumor segmentation with deep neural networks. It described best architecture and identified certain modelling choices that have found important to obtain good performances. The time needed to segment an entire brain is around 20 minutes.
In [5], difficulties are observed in the segmentation of lesions of particularly small size. The separation of lesions into different categories, for instance according to their size, and their treatment by separate classifiers could simplify the task for each learner and help alleviating the problem.

The authors in [6] suggested a solution to train a deep network with a spatial pyramid pooling layer. The resulting SPP-net shows outstanding accuracy in classification/detection tasks and greatly accelerates DNN-based detection. The studies also show that many time-proven techniques/insights in computer vision can still play important roles in deep-networks-based recognition.
In conclusion, on SWI, higher MB numbers were detected in more patients, irrespective of MB location. On both sequences, MB number contributed to clinical and radiologic associations. On SWI, the associations found on GRE were corroborated; however, the higher MB numbers found on SWI compared with GRE did not improve these associations [7].
The authors in [8] propose to classify brain image as normal or abnormal by using neural network. The work realized by [9] describes a computer-aided detection system. This framework is based on histogram equalization and morphological mathematical operations. The mentioned experiments were performed on 125 MR images.

III. METHODOLOGY

The developed framework as shown in Figure 2 is accurately and efficiently detecting the true CMBs. The proposed framework includes screening stage and discrimination stage.
In the screening stage, the 3D FCN model takes a whole volumetric data as input and gives output as a 3D score volume. Each value on the 3D score volume represents the probability of CMB. Consequently, in the discrimination stage, we further remove false positive candidates by applying a 3D CNN discrimination model to distinguish true CMBs from challenging mimics with high-level feature representations.

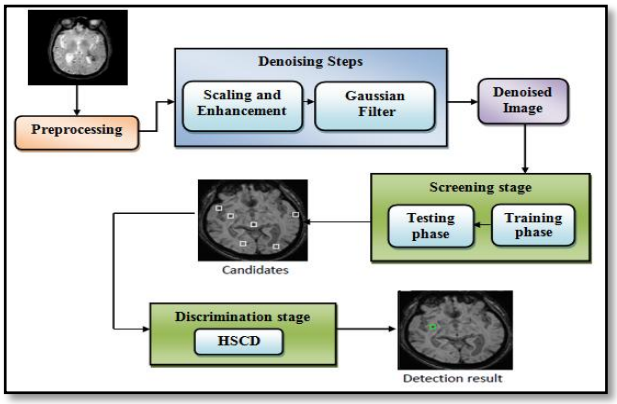

Fig 2. The proposed cascaded framework for CMBs detection.

A. 3D Convolutional Neural Network:
Convolutional Neural Networks are very similar to ordinary Neural Networks. They are made up of neurons that have learnable weights and biases. Each neuron receives some inputs, performs a dot product and optionally follows it with a non-linearity. The whole network still expresses a single differentiable score function: from the raw image pixels on one end to class scores at the other. And they still have a loss function (e.g. SVM/Softmax) on the last (fully-connected) layer and all the tips/tricks we developed for learning regular Neural Networks. It takes advantage of the fact that the input consists of images and they constrain the architecture in a more sensible way. In particular, unlike a regular Neural Network, the layers of neurons are arranged in 3D: width, height, depth**.** (Note that the word depth here refers to the third dimension of an activation volume, not to the depth of a full Neural Network, which can refer to the total number of layers in a network).

Commonly, a CNN alternatively loads convolutional (C) and sub-sampling, e. g., max-pooling (M), layers. In a C layer, small feature extractors (kernels) sweep over the topology and transform the input into feature maps. In a M layer, activations within a local community are abstracted to acquire invariance to local translations. After several C and M layers, feature maps are flattened into a feature vector, followed by fully-connected (FC) layers.

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1) 3D Convolutional Layers:
In a C layer, a feature map is produced by convolving the input with convolution kernels, adding a bias term, and finally applying a non-linear activation function. By denotes the i-th feature map of the m-th layer as $\mathbf{a}_i^m$ and the k-th feature map of the previous layer as $\mathbf{a}_i^{m-1}$, a C layer is formulated as:

$$\mathbf{a}_i^m = \sigma(\sum \mathbf{a}_i^{m-1} * \mathbf{N}_{ki}^m + \mathbf{b}_i^m) \quad (1)$$

Where,
$\mathbf{N}_{ki}^m$ and $\mathbf{b}_i^m$ are the filter and bias term connecting the feature maps of adjacent layers, the * denoting the convolution operation and the $\sigma(.)$ is the element-wise non-linear activation function.

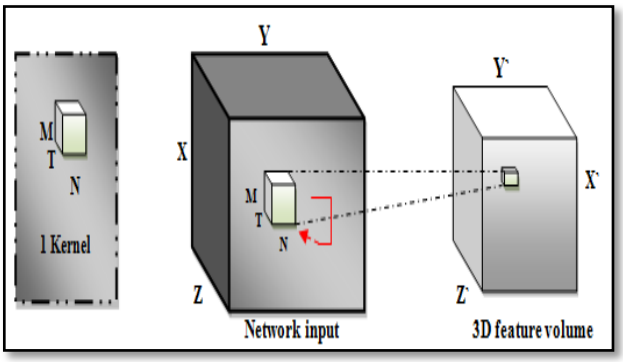

Fig 3. 3D convolution kernel

In 3D convolution kernel, as shown in Figure 3 given volumetric image with size X × Y × Z, when we use 3D convolution kernel to create a 3D feature volume, the input to the network is the whole volumetric data. Consequently, a 3D kernel is created within the 3D topology (see the red line in Fig 3).

By simply the kernel sharing across all 3D, the network can take full good thing about the volumetric contextual information. Generally, the subsequent equation formulates the taken advantage of 3D convolution procedure in an element-wise manner:

$$\mathbf{v}_{ki}^m(a,b,c)=\sum_{m,n,t}[\mathbf{a}_i^{m-1}(a-m, b-n, c-t) * \mathbf{N}_{ki}^m(m, n, t)] \quad (2)$$

Where,
$\mathbf{N}_{ki}^m$ is the 3D kernel in the m-th layer which convolves over the 3D feature volume $\mathbf{a}_i^{m-1}$,$\mathbf{N}_{ki}^m(m, n, t)$is the element-wise weight in the 3D convolutional kernel. Following Eq. (1) and Eq. (2), the 3D feature volume is obtained by,

$$\mathbf{a}_i^m = \sigma(\sum \mathbf{v}_{ki}^m + \mathbf{b}_i^m) \quad (3)$$

2) 3D CNN Hierarchical Architecture:
After that the 3D convolutional layers, we can hierarchically construct a deep 3D CNN model by stacking the C, M and FC layers, as shown in Fig 4.

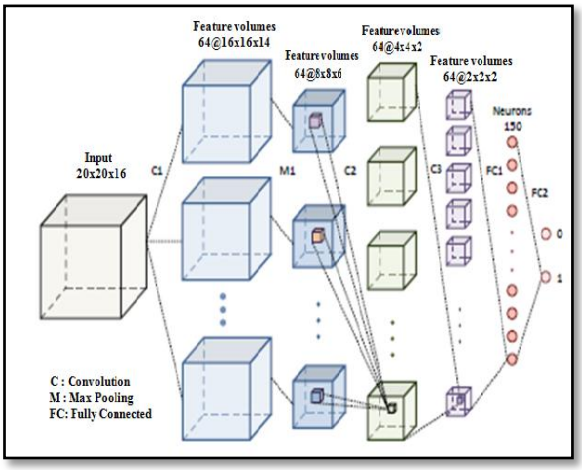

Fig 4. The hierarchical architecture of the 3D CNN model.

Specifically, in the C layer, multiple 3D feature volumes are produced. In the M layer, the max-pooling operation (i.e., that the feature volumes are sub-sampled based on a cubic neighbourhood) is performed in a 3D fashion. In the FC layer, 3D feature volumes are flattened into a feature vector as its input. The ultimate output layer employs the softmax activation to yield the prediction probabilities.

B. Image Pre-processing:
Image pre-processing can significantly increase the reliability of an optical inspection. Pre-processing improves the quality of image while conserving the original image information. It includes removal of blurring and noise, increases the contrast range to enhance the image information.

So pre-processing the image is an important and useful task for accurate detection of CMBs. Images are contaminated with noise. So, such noise often a necessary pre-processing step in image processing applications. Pre-processing steps includes, image scaling, image enhancement and Gaussian filter for removing a noise as shown in Fig 5.

Scaling is nothing but alter the size of the image. It is the most obvious and common way to change the size of an image (i.e., resize). The content of the image is then enlarged or more commonly shrunk to fit the desired size. But while the actual image pixels and colours are modified, without any loss of the image quality. The resize operator has been very carefully designed to try to produce a very good result for real world images.

Image Enhancement is increase or improvement in quality, value and it is the simplest and most appealing areas of digital image processing. It is the process of adjusting digital images so that the results are more suitable for display or further image analysis. Enhancement technique is bringing out detail that is highlight certain features of interest in an image. Example, increase the contrast of an image “it looks better”. By contrast the image is used to identify the noise.

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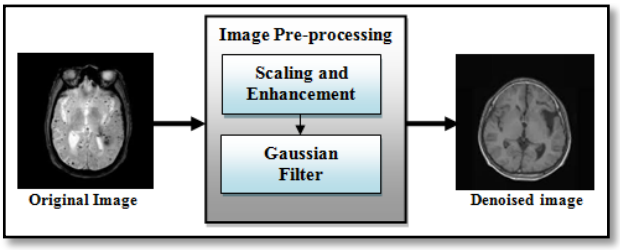

Fig 5. Image Pre-processing.

In our framework Gaussian filter is used to remove the low-frequency background noises. Thus noise removal filter takes a corrupted image as input and produce an estimation of the original image without any noise.

C. Two-stage cascaded framework:
After pre-processing the image, in order to detect CMBs from MR images, we employ 3D CNN based models to tap potentials of spatial information in all three dimensions and represent them as high-level features. We construct a 3D FCN model and 3D CNN model personalized for two different stages and integrate them into an efficient and robust detection framework. In this cascaded framework for CMB detection, each stage serves its own mission. The discrimination stage with the 3D CNN focuses only on the screened set of candidates to further single out the true CMBs from challenging mimics.

1) Screening stage:
In the screening stage, a small number of candidates are retrieved using a novel 3D fully convolutional network (3D FCN) model.

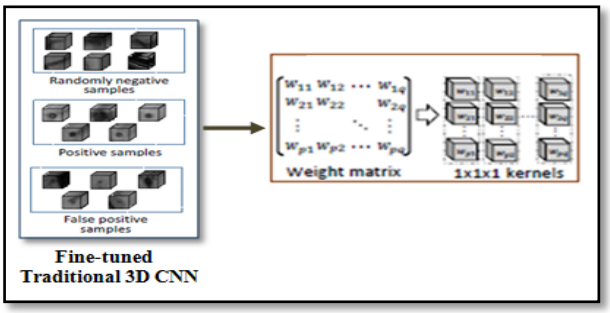

Fig 6. The traditional FC layers are converted into the convolutional fashion

1.1 3D Fully Convolutional Network:
We propose to use 3D CNN to robustly screen candidates by leveraging high-level spatial representations of CMBs learned from a large number of 3D training samples. We propose to extend the strategy into a 3D format for efficient retrieval of CMB candidates from MR volumetric data.

The screening stage with the 3D FCN aims to accurately reject the background regions (i.e., non-CMBs area) and rapidly retrieve a small number of potential candidates. The screening stage is including both training and testing phases.

During the training phase, the positive samples are extracted from CMB regions. We start from training an initial 3D CNN with randomly selected non-CMB regions throughout the brain as negative samples. Next, we add false positive samples acquired by applying the initial model on the training set. Finally, the initial model is fine-tuned with the enlarged training database.
Once training is done, the fine-tuned traditional 3D CNN is converted into the 3D FCN model by transforming the FC layers (i.e., the convolutional layer is the core building block of a CNN. The layer's parameters consist of a set of learnable filters (or kernels), which have a small receptive field, but extend through the full depth of the input volume) into the convolutional fashion (as shown in the brown box in Fig 6).

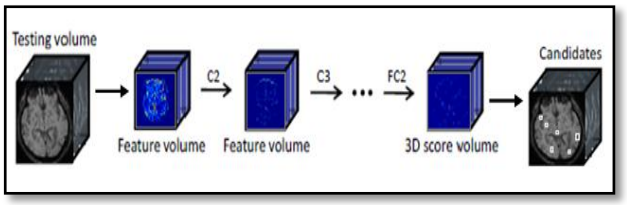

Fig 7. Testing phase (3D FCN)

During the testing phase as shown in Fig 7, the 3D FCN model takes the whole volume as input (with size 512*512*150 for our dataset) and generates the corresponding coarse 3D score volume as output. The value at each location of score volume indicates the probability of CMB. The proposed 3D FCN can take an arbitrary sized volume as input and produce 3D score volume within a single forward propagation, and hence greatly speed up the candidate retrieval procedure without damaging the sensitivity.
Due to the size of the generated 3D score volume is reduced compared with the original input as shown in Figure. Meanwhile, the locations on this 3D score volume can be traced back to the coordinates on the original input space as shown in Fig 8.

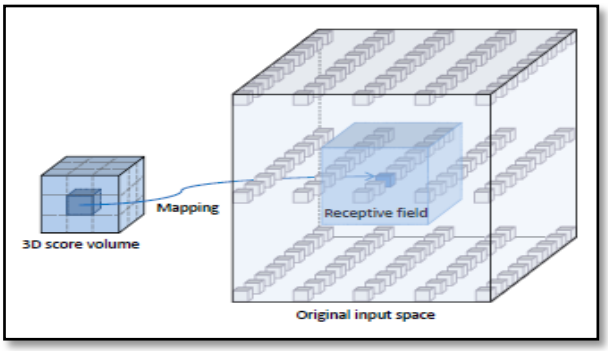

Fig 8. 3D score volume mapping onto original image

2) Discrimination Stage:
In this stage, 3D small blocks are cropped centred on the screened candidate positions. The size of these blocks was carefully validated. We first found that a number of false positives were produced in the first stage with a training

IJARCCE

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified
Vol. 5, Issue 10, October 2016

block size of 20x20x16. We set the input size as 20x20x16 in our experiments as shown in Table I, in order to discriminate the challenging candidates with a suitable receptive field. The extracted 3D candidate regions are classified by a newly constructed 3D CNN model. We notice that the randomly selected non-CMB samples are not strongly representative, especially when we aim to distinguish true CMBs from their mimics.

TABLE I Detection Result

3D block size	Sensitivity	Precision	FP_{avg}
16x16x10	91.45%	33.75%	4.20
20x20x16	**92.29%**	**40.53%**	**2.60**

To generate representative samples and improve the discrimination capability of the 3D CNN model while applying Hierarchical Centroid Shape Descriptor (HCSD), the obtained false positives (which take very similar appearance as CMBs) on the training set in the screening stage are taken as negative samples when training the 3D CNN in the second stage.

2.1 Hierarchical Centroid Shape Descriptor (HCSD)
The HCSD is selecting the true CMBs based on the shape structure. The HCSD is a binary shape descriptor built with the centroid coordinates extracted from a binary image. It extracted recursively by decomposing the image in sub-images. Because an image can be described by the spatial distribution of pixels, this method is based an image decomposition in the pixel domain by using kd-tree algorithm. The neighbourhood information like the centroid coordinates of local regions is extracted.

Nearest Neighbor Searching in kd-trees

```
def N(Point Q, kdTree t, int cd, Rect B):
if t == NULL or distance(Q, B) > best_dist:
return
dist = distance(Q, t.data)
if dist < best_dist:
best = t.data
best_dist = dist
if Q[cd] < t.data[cd]:
N(Q, t.left, next_cd, B.trimLeft(cd, z.data))
N(Q, t.right, next_cd, B.trimRight(cd, z.data))
else:
N(Q, t.right, next_cd, B.trimRight(cd, z.data))
N(Q, t.left, next_cd, B.trimLeft(cd, z.data))
```

IV. EXPERIMENTAL RESULT

A. Evaluation Metrics
We utilized three generally used metric to quantitatively assess the execution of the proposed CMBs detection technique including sensitivity (S), precision (P) and the average number of false positives per subject (FPavg). They are defined as follows:

$$S = \frac{TP}{TP + FN}, \quad P = \frac{TP}{TP + FP}, \quad FP_{avg} = \frac{FP}{N} \tag{4}$$

Where TP, FP and FN denote the total number of true-positive, false-positive and false-negative detection results, respectively. The N represents the number of subjects in the testing dataset.

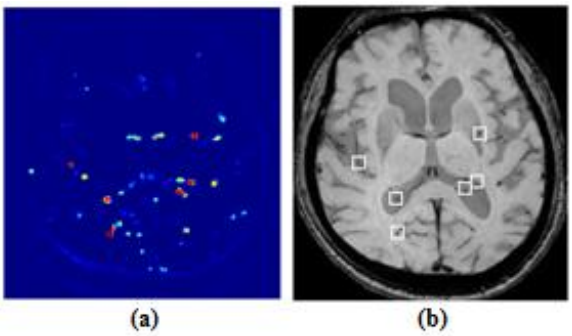

Fig 9. (a) Examples of score volume generation
(b) Candidate generation

The models converged in around 50 minutes. The 3D FCN deduction would take around 1 minute to prepare an entire MR image with size of 512x512x150, and the 3D CNN in the second stage was very quick and could handle a subject inside 1 second.

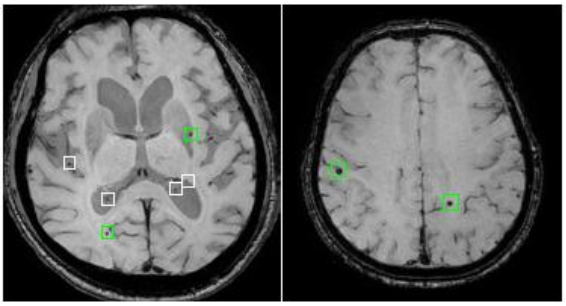

Fig 10. Examples of True CMBs detection
(Green rectangles)

V. CONCLUSION

In this paper, a two-stage cascaded framework for CMBs detection was introduced. The proposed framework is used to reduce its computational cost and improve the detection performance. This framework followed by the use of a shape descriptor based on features called Hierarchical centroids. The first (screening) stage removes the non-CMBs regions and screening potential candidates. In this stage we develop the 3D FCN strategy eliminates the number of redundant convolutional computations, and hence dramatically speeds up the detection procedure. The second (discrimination) stage focuses on the candidates and remove the difficult false positive which are similar to the CMBs. In this stage we take up 3D CNN to identify

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified
Vol. 5, Issue 10, October 2016

the true CMBs while applying the HCSD. The proposed framework can be effectively adjusted to other detection and segmentation tasks and support the use of 3D CNNs on volumetric medical data.

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