Hemorrhage Slices Detection in Brain CT Images

Ruizhe Liu, Chew Lim Tan, Tze Yun Leong
Department of Computer Science, School of Computing, National University of Singapore
{liurz, tancl, leongty}@comp.nus.edu.sg

Cheng Kiang Lee, Boon Chuan Pang, C. C. Tchoyoson Lim
National Neuroscience Institute, Tan Tock Seng Hospital, 11 Jalan Tan Tock Seng, Singapore 308433
{cheng_kiang_lee, boon_chuan_pang, tchoyoson_lim}@nni.com.sg

Qi Tian, Suisheng Tang, Zhuo Zhang
Institute of Infocomm Research, 21 Heng Mui Keng Terrace, Singapore, 119613
{Tian, suisheng, zzhang}@i2r.a-star.edu.sg

Abstract

Multi-slice Computer Tomography (CT) scans are widely used in today's diagnosis of head traumas. It is effective to disclose the bleeding and fractures. In this paper, we present an automated detection of CT scan slices which contain hemorrhages. Our method is robust towards various rotation, displacement and motion blur. Detection of these pathological slices will be useful for further diagnosis and retrieval.

1. Introduction

Multi-slice Computer Tomography (CT) scans are widely used in today's diagnosis of head traumas. It is effective to disclose the bleeding and fractures. Also, it is cheap and thus affordable to public. A huge amount of CT images are produced in modern hospitals. For example, in Singapore, the Neuroradiology Service at the National Neuroscience Institute (NNI), Tan Tock Seng Hospital, performed over a thousand CT scans, with each scan consisting of 20 slices, in the two-year period of 2003 to 2005 as a result of hospital admission for mild head injured patients [1]. Detection of abnormal slices is useful for further processing such as diagnosis and retrieval. The usefulness can be viewed as the following scenarios: (a) Doctors may confirm their diagnosis with the help of computer-aided segmentation and effective retrieval of other similar cases. (b) Medical students may learn the diagnosis by examples retrieved and enhancements of the hemorrhage segmented [2].

In this paper, we present an automated detection of CT scan slices which contain hemorrhages. We will first discuss some related work. Then we will present the detection method for abnormal brain slices. Next we will show and analyze the result of our detection method. Lastly, we will give our conclusion and discuss the future work.

2. Related work

A content-based 3D neuroradiologic image retrieval system is developed at the Robotics Institute of CMU. In the preliminary results of this system, Y.Liu et al. proposed a symmetric detection approach to detect brain lesions [2][3]. The methods will check the symmetry for each slice. If the mid line of the brain shifts, a hemorrhage is considered to be presented. They also assume the pathological brain absent the symmetry property. Thus if some abnormal region appears only at one side, it is considered as a hemorrhage. A similar method was also adapted by T.Hara et al. [4] In their approach, they detect mid line according to the skull contour. Mid line detection was also adapted by T.Chan [5]. However, all of these studies only consider the slices of encephalic region. In real situation, the slices will also include the nasal cavity and sometimes do not follow the sequential order. For example, some slices rescanned will be appended after all slices and some slices even interleave each other. In addition, the mid line detection approach will not work if the trauma is too severe. For example, some severe patients have such a fatal injury that the mid line does not present clearly as shown in figure 3 in the next section. Moreover, if the patient moves his/her head or does not place his/her head in a correct angle, the scanning angle will not be perfect. Thus the image result will not be symmetric even his/her brain is healthy. In the following sections, we will present a method that detects the encephalic slices and hemorrhages without using mid line estimation.

3. The detection method

The detection method consists of two parts. The first part splits the scan slices into encephalic region and nasal cavity region (Figure 1). The second part focuses on the encephalic region and detects the abnormal slices. In both parts, we apply the same method by using wavelet and Haralick texture model.

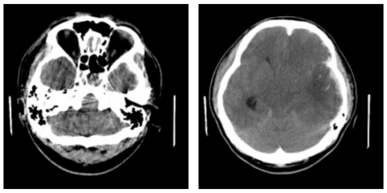


Figure 1. Left: Nasal Cavity; Right: Encephalic region

3.1. Split slices into encephalic region and nasal cavity region.

From Figure 1 we see that the nasal cavity region is much more complex than the brain region. Thus the effective methods used in the brain region may not work dealing with the nasal cavity, for example, some segmentation methods such as simple background removal. Therefore, we will first separate them.

The CT scans normally are done sequentially, from bottom upwards. However, there are cases of scanning from the top downwards. Moreover, some rescanning of certain parts is required when the previous attempt failed. Thus, the image sequence may be out of order. Hence, we cannot simply assume that the first slice of encephalic region is next to last nasal cavity slice.

By visual inspection of the two regions, we can see that texture is a good criterion to distinguish them.

Wavelet transform has been widely applied in image processing, especially, texture analysis. In this paper, we use Haar wavelet family in favor of its simplicity and efficiency. The transform can be viewed as transforming a signal from the original space to a new space which is spanned by orthogonal wavelets, which are described by the basis function. Once transformed, we will split the signal into different waves with different frequencies. If we treat the image as a 2D signal, then by wavelet transform, we shall get high frequency components, which corresponds the textures and low frequency components, which corresponds the homogenous intensity field. The former is represented by detail coefficients and the latter is stated in the approximate coefficients. Thus, we are able to operate the texture or the homogeneous field, for example, the hemorrhage in the brain CT scan, by focusing on detail or the approximate coefficients. In this step, we focus on texture analysis, thus we decompose the image four times using Haar wavelet transforms and then reconstruct the signal by only using the detail coefficients and obtain a texture map (Figure 2). More details of the wavelet transform may be found in Refs [6] and [7].

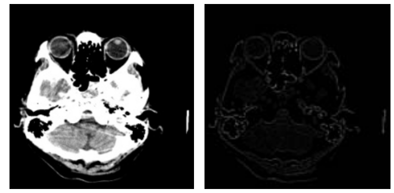


Figure 2. Left: Image; Right: Texture map

Secondly, we calculate the histogram of the intensity distribution and record the arithmetic mean, the standard deviation, the skewness and the kurtosis of the distribution, totally 4 measurements.

Thirdly, we employ a variation of Haralick model texture descriptors [8] and add the 8 values into the feature vector such as entropy, energy, contrast, homogeneity, sum mean, variance, maximum probability and the correlation. The detail calculation may refer to Ref [8].

Thus, the feature vector contains 12 feature values.

To select good features, we employ entropy calculation from information theory. We discard the feature "sum mean" whose entropy is greater than 6, leaving the 11 features for training.

Lastly, we use SVM with a linear kernel to learn the model. The model is also tested and the results will be shown in later section.

3.2. Detect abnormal encephalic slices.

The encephalic region is where the brain locates. The head traumas normally occur in this region. Thus, we will only focus on encephalic slices.

First of all, we define the abnormal brain versus normal brain. As shown in figure 3, the normal brain has a homogenous distribution of gray matter, clear texture on the brain such as fissures, and regular skull-dural outlines. The abnormal brain will have hemorrhage which appears brighter than the gray matter in the image. The hemorrhage occurs in different location will be considered as different types of head traumas. Table 1 and Figure 3 will concisely describe 5 types of hemorrhages we will deal with in this paper such as EDH, SDH, SAH, ICH, and IVH. We define the CT slice which contains hemorrhages as abnormal and CT slices with no hemorrhages as normal.

Table 1. Abnormal definition

Type	Characteristic
EDH	Bulge along inner edge of the skull
SDH	Crescent along the inner edge of skull
SAH	Net-shape along the fissures
ICH	Bright object in the gray matter
IVH	Bright object in the ventricle

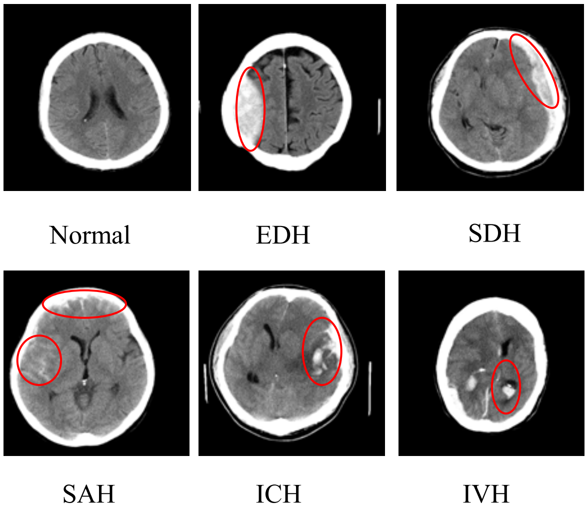


Figure 3. Different types of hemorrhages

Encephalic region are matters inside the skull. Thus the first step is to remove the skull. In CT slices, the skull is the brightest elliptical part (Figure 4). We fit an ellipse to the pixel with intensity above 250. Thus the encephalic region is the region inside this ellipse and has intensity less than 250. (Figure 5)

Most parts of the content inside the skull are the gray matter. To get the hemorrhages, a simple subtraction off the gray matter intensity will give us an image with the background removed and the hemorrhages left. (Figure 6) Please note that this will remove the gray matter only. Thus, it does not examine the mid line shifting. Hence, even the patient moves or leans his/her head, the method will still work.

Again, we decompose the image two times using Haar wavelet transforms and then reconstruct the signal. However, this time we shall not focus on texture, but the homogenous intensity regions, i.e. the hemorrhages. Hence we set the detail coefficient to zero to get the homogeneous intensity map.

Same as the previous part, we construct similar features. We also use entropy to select good ones. This time we discard six values whose entropies are above 6. Finally we use SVM with a linear kernel to classify the normal and abnormal slices.

4. Experiment results

The data we used consists of 493 patients' brain CT scans. CT Slices contains various situations, such as rotation, displacements, and motion blur. (Figure 7) Moreover, not all slices follow the sequential order. Different patients have different scanning starting or ending positions, and different scanning angles. Each patient has 20 to 30 slices. The total number of images is 11011.

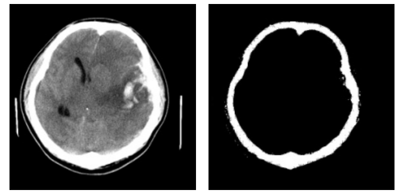


Figure 4. Left: Image; Right: Skull

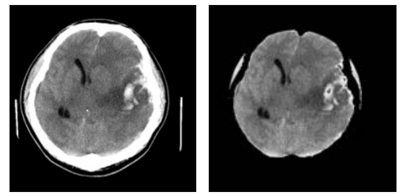


Figure 5. Left: Image; Right: Skull removed

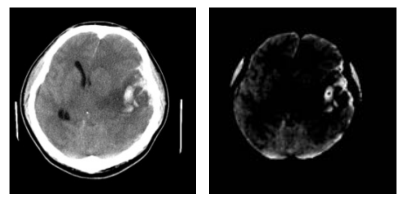


Figure 6. Left: Image; Right: Gray matter removed

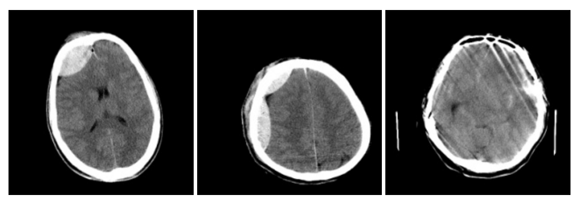


Figure 7. Left: rotation (anti-clockwise); Middle: displacement (towards right bottom) Right: motion blur (diagonal motion)

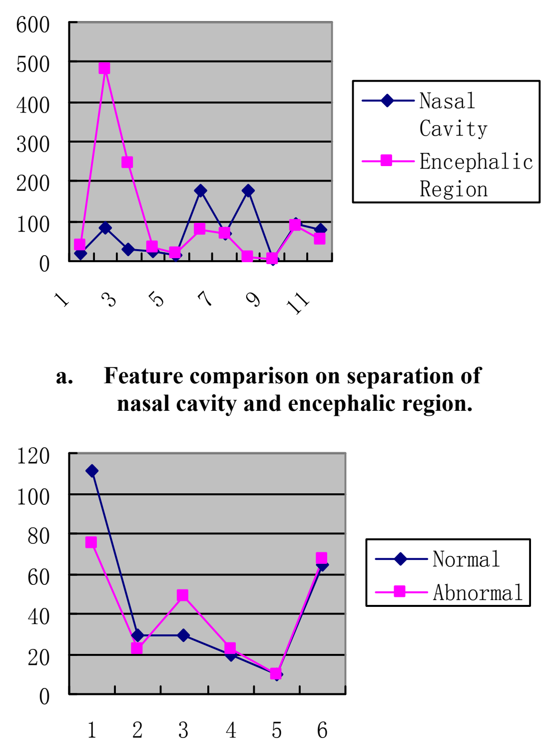
We run our experiment on a PC with 2.33 GHz Pentium 4 CPU using MATLAB. The average runtime per image of the first part is 0.26s. The average runtime per image of the second part is 8.62s with image and text I/O.

By investigating relevant features, we plot features of two sample pairs randomly chosen from the entire dataset to compare. We scale the feature values to make the plot presentable. Each pair corresponds to one step. The result is shown in Figure 8. Some features are quite different. For example, the 3rd feature energy has a low value in the normal slice and a high value in abnormal one. This is because after removing the gray matter, abnormal slice will still have a hemorrhage region but the normal one will be mostly blank thus resulting in relatively lesser energy.

The test of encephalic slices separation use ten-fold cross validation. The results are shown in Table 2.

The experiment of the abnormal slice detection has results shown in Table3.

From the results, we can see that the recall of both experiments is as high as 90 percents. The first experiment is as high as 96 percents' accuracy but the second one drops to 80. In medical application, the recall rate is concerned to be more important than the accuracy. This is because the computer acts as an assistant for doctors. We would rather like to treat the normal people as patients to do further medical diagnosis, than miss the actual patients who are wrongly considered as normal. This is because the latter case may have risks of deteriorations of patients' diseases or even deaths. Hence, we prefer false positive than negative.



a. Feature comparison on separation of nasal cavity and encephalic region.

b. Feature comparison on normal/abnormal slices

Figure 8. Feature comparison

Table 2. Encephalic slices separation result

Precision	Recall
96.27%	89.48%

Table 3. Abnormal slices detection result

Precision	Recall
80.32%	88.22%

5. Conclusion

In this paper, we present a method using machine learning approach to detect abnormal slices. It consists of two parts. The first part automatically splits the scan slices into encephalic region and nasal cavity region. The second part focuses on the encephalic region and detects the abnormal slices. The method is robust towards image rotation, displacement and motion blur. Testing on over 10 thousands CT scans, the splitting accuracy and recall reaches 96% and 89% respectively. The detection has accuracy 80% and recall 88%.

In the future, we will do further study based on the abnormal slices detected. We will build in 3D information and develop a 3D segmentation and retrieval system of brain trauma CT images.

Acknowledgment

This research is supported in part by NUS FRC grant R252-000-290-112 and MOE ARC grant R-252-000-349-112

References

[1] B.C.Pang and H.Yin, Analysis of clinical criterion for "talk and deteriorate" following minor head injury using different data mining tools, *Journal of Neurotrauma National Neurotrauma Society,* Gainesville, Florida, USA, in press.

[2] Y.Liu, W.E.Rothfus and T.Kanade. Content-based 3D Neuroradiologic Image Retrieval: Preliminary Results, *IEEE Content-based video and image retrieval workshop associated with CVPR97*, June, 1997.

[3] Y.Liu, N.A.Lazar, W.E.Rothfus, F.Dellaert, A.Moore, J.Schneider, and T.Kanade, Semantic-based Biomedical Image Indexing and Retrieval, *Trends and Advances in Content-Based Image and Video Retrieval*, Shapiro, Kriege, and Veltkamp, ed. February, 2004.

[4] T.Hara, N.Matoba, X.Zhou, S.Yokoi, H.Aizawa, H.Fujita, K.Sakashita and T.Matsuoka, Automated Detection of Extradural and Subdural Hematoma for Content-enhanced CT Images in Emergency Medical Care, Proceeding of SPIE, 2007.

[5] T.Chan, Computer aided detection of small acute intracranial hemorrhage on computer tomography of brain, *Computerized Medical Imaging and Graphics* 07(4-5): 285-298, June-July, 2007.

[6] S.G.Mallat. A theory for multiresolution signal decomposition: the wavelet representation. *IEEE Trans. Patt. Anal. Mach. Intell.* 89(11): 674-693.

[7] C.K.Chui. *An Introduction to Wavelets*. Academic Press Inc. New York. 1992.

[8] R.M.Haralick, K.Shanmugam, and I.Dinstein. Textural Features for Image Classification. *IEEE Transactions on Systems, Man and Cybernetics*, 1973; Smc-3(6): 610-621.