AUTOMATIC DETECTION OF EARLY ISCHEMIC INFARCT ON BRAIN CT

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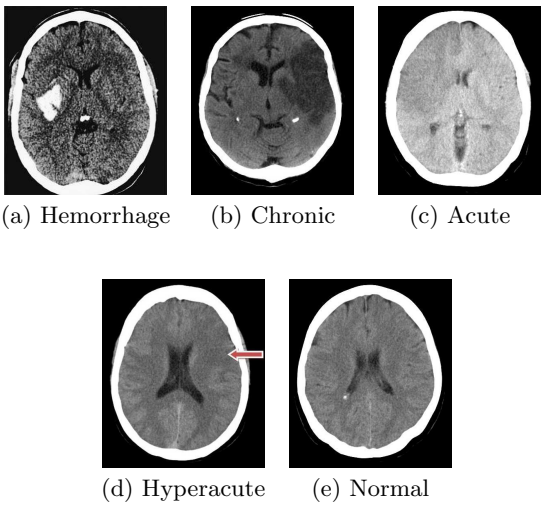
ABSTRACT

Computed Tomography (CT) imaging is affordable and widely used, however due to poor contrast, are not prefrred for early stroke detection. In this paper, we propose a novel method for automatic detection of early ischemic infarct from non-contrast CT images. The method involves enhancement of tissue contrast and classification of brain tissues into gray/white matter followed by contralateral symmetry based abnormality detection. The proposed method has been evaluated on a dataset of 28 patients (370 image slices). The algorithm gives 85.71% recall and 70.27% precision rate in detecting abnormality at slice level.

1. INTRODUCTION

Stroke or "Brain Attack" is increasingly becoming one of the leading causes of death and disability in the world. According to the World Health Organization, 15 million people suffer from stroke, of these 5 million die and another 5 million are permanently disabled. Stroke occurs when blood flow to a region of the brain is affected and may result in death of brain tissue. Strokes can be classified into two major types: Ischemic and Hemorrhagic. Ischemic stroke is caused by blockage in an artery that supplies blood to the brain, resulting in a deficiency in blood flow in a region eventually resulting in an infarct. Hemorrhagic stroke occurs when a blood vessel gets ruptured inside the brain. Ischemic stroke can be further classified into hyper-acute, acute and chronic infarcts depending upon the time from the onset of the symptoms (Figure. 1). About 80% of strokes are ischemic in nature. During ischemic stroke, diminished blood flow initiates a series of events called ischemic cascade that may result in additional, delayed damage to brain cells. Early medical intervention can halt this process and reduce the risk for irreversible complications [14].

Clinicians use both Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) modalities for the detection of stroke. MRI presents a better avenue for detection of hyperacute stroke and as a result not much effort has been directed towards CT images. Detection of infarcts on CT is of interest as CT imaging is faster and more widely available than MR scanners especially in developing economies.



(a) Hemorrhage (b) Chronic (c) Acute

(d) Hyperacute (e) Normal

Figure 1: Images from samples of different stroke cases.

Clinically, the treatment of stroke is only worthwhile within roughly 4-6 hours of onset of symptoms in most cases as this is when the thrombolytic treatment is most effective [14]. During this period, the affected tissues show only subtle hypoattenuation in CT images which can be missed by the radiologists in some cases (Figure. 1(d)). This stage of infarct is known as hyperacute. The perceptual contrasts of the different strokes vary considerably, with the highest being for hemorrhages and least being for the hyperacute infarcts. Sample images for these cases are shown in Figure. 1(a)-1(e)). As seen from these images, the earliest signs of ischemic stroke in CT is blurring of the gray matter-white matter junction mainly due to a gray matter structure becoming isoattenuating to adjacent white matter structures [9] [1]. This loss in differentiation results in asymmetrical distribution of white matter (hypodensense) tissues in left and right hemispheres. We aim to exploit this property by first classifying the tissues into gray/white matter and then comparing their distribution to check for any substantial loss of symmetry. The classification of brain tissue is in itself a challenging task owing to the poor tissue contrast offered by the CT (Figure. 1(e)).

There have been a few attempts, both semi and fully auto-

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matic, at enhancing the stroke-affected area in non-contrast CT images to assist radiologists. A bi-orthogonal filter bank based on splines has been proposed in [11] for enhancing the suspected stroke region. This results in enhanced appearance for *acute* infarcts. An extension to *hyperacute* cases is based on data denoising and local contrast enhancement using wavelets [12][10]. Another approach for enhancement of hypo-attenuation uses adaptive median filtering to enhance the gray-white matter interface [8]. The results show impressive performance and have also been validated by radiologists. The above mentioned methods are however only aimed at assisting experts by providing enhanced images. They do not aim at automatic detection of infarct cases.

Both shape and texture information has been used to detect ischemic strokes. In the former category is the work in [7]. Here, a probability measure based on average cohesive rate (a measure of spatial distribution of suspicious pixels around the concerned pixel.) for selected pixels on both sides of the brain is used to assign likelihood of the presence of stroke. Texture is used in [13] for segmentation of stroke by classifying each pixel in the image into two classes.

Recently, an automatic detection approach using contralateral symmetry for detecting various types of stroke was proposed [3]. The symmetry of the two hemispheres is exploited by finding the correlation of their intensity histograms. The fact that hemorrhages and ischemic stroke cause heavy disturbances in the contra-lateral symmetry (CS) is captured using correlation of the intensity histograms. This approach is suited to detecting only acute and chronic infarcts and not hyperacute infarcts as the disturbance in CS is not prominent enough in the last case. Hyperacute cases are of utmost clinical importance as therapy only works when carried out within first few hours.

The purpose of this study is to facilitate treatment of hyperacute stroke by assisting the radiologists through automatic detection of infarction within the first few hours. A method is presented which aims at leveraging the asymmetrical subtle changes that occur during these early times by emphasizing them to help distinguish between normal and abnormal (stroke-affected) tissue. The method is based on a novel approach that utilizes the asymmetry of the hypodense regions (white matter) as an indicator for the presence of stroke. The hypodense regions are identified via a rough segmentation. Notwithstanding the roughness, we show that the fact that tissues in the hypodense regions exhibit similar intensity profile can still be used for symmetry comparison on either side of the symmetry axis.

2. METHOD

In our method, we adopt a two step strategy to first segment the brain tissues into white/gray matter followed by symmetry based evaluation of the distribution of hypodense regions (white matter) in left and right hemispheres of the brain. The segmentation is carried out using Markov Random Field and MAP estimation [5] as it provides an effective way of incorporating spatial information and is generally resistant to noise. In order to aid the segmentation algorithm, the scans are first enhanced to increase the contrast between gray and white matter tissue. Since only soft tissues are of interest, the first step is to extract the brain tissues which lie in the range of white/gray matter (16-50 H.U) which are then enhanced using a method very similar to [4]. A CT slice is decomposed into four frequency sub-bands using Daubechies_9 wavelet to extract the illumination information of the image. The illumination sub-band is then equalized, based on the intensity profile of the same slice with modified window settings using singular value decomposition (SVD). The singular value matrix obtained after SVD contains only the illumination information and hence modifying it results in preserving other important details. In the following section, we provide the details of MRF-MAP segmentation.

2.1 MRF-MAP Model

We assume that images are defined over a finite lattice S = {S_i, 1≤i≤N} where S_i denotes the pixels. For each pixel S_i, the class to which the pixel belongs is specified by a class label, L_i, which is modeled as a discrete random variable L = {L_i, 1≤ L_i ≤M}. We are also given an MRF on these units, defined by a graph G (where the vertices represent the pixels, and the edges represent the label constraints of the neighboring units), and the clique potentials.

In MRF theory, a configuration refers to a state where each site S_i belongs to a particular label L_i. Our goal is to find the best possible configuration L (L ∈ Ψ_L, where Ψ_L represents the configuration space), which maximizes the posterior probability of L. L can be represented in the form of an energy function as (using [2] [6]),

$$\hat{L} = argmax_{L\in\Psi}\left(\frac{1}{T}\log P\left(S/L\right) + \log P\left(L\right)\right) \quad (1)$$

where $\log P\left(S/L\right)$, $\log P\left(L\right)$ are Gaussian and Gibbs energy respectively, given by,

$$P(S/L) = \prod_{1\le i\le N}\frac{1}{\sqrt{2\pi}\sigma_{L_i}}\exp\left(\frac{-\left(S_i-\mu_{L_i}\right)^2}{2\sigma_{L_i}^2}\right) \quad (2)$$

$$P(L) = \frac{1}{Z}\exp\left(\frac{-1}{T}\sum_{\{S_i,S_j\}\in\Omega}\beta\times V\left(L_{S_i},L_{S_j}\right)\right) \quad (3)$$

where μ_{L_i} is the mean and σ_{L_i}, is the standard deviation of class L_i,T is the temperature, Ω is the set of second order cliques; β (empirically found and fixed as 0.9) is a model parameter controlling the homogeneity of the segmented regions and $V(L_{S_i}, L_{S_j})$ represents the second order clique potential, equal to +1 when neighbouring pixels have same labels and -1 otherwise.

The segmentation process which minimizes the above mentioned energy, requires the initialization of the distribution parameters (mean, variance) of all the label classes. This is done using Otsu segmentation which ensures maximum inter-class variability. The energy function is minimized using Modified Metropolis Dynamics ([2]) as described below.

1. Pick up randomly an initial configuration L0, with iteration k=0 and temperature T=T_a (where T_a is a constant).
2. Pick a global state L' such that: 1≤L'$_i$ ≤M and L'$_i$ ≠ L^k $_i$, 1≤i≤N
3. For each site Si, the local energy E_i(L'), where L' = (L$^k{}_1$,...,L$^k{}_i$,...,L$^k{}_N$) is computed using equation **??**.

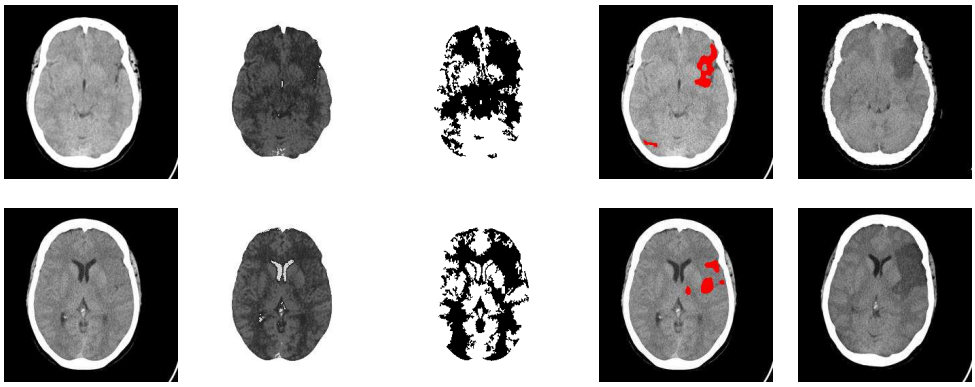

Figure 2: Results of proposed algorithm on 2 hyperacute slices. Columns 1 through 5 show the input image, enhanced image, segmented hypodense tissues, detected abnormal tissues and corresponding follow-up scan.

4. Compute ΔE_i=E_i(L')-E_i(L^k), the new label at site S_i is accepted if if $\Delta E_i \leq 0$ or $\alpha \leq \exp\left(\frac{-\Delta E_i}{T}\right)$
   where $\alpha \in$ (0,1) is a constant.

5. Decrease the temperature T(k+1)= a × T(k) (where a = 0.9 is a predefined constant, used to control T and T_a=4) and go to step 2 until the number of modified sites is less than a threshold.

To aid convergence of the algorithm, the entire image is first partitioned into disjoint regions R_n ($1 \leq n \leq 2$). This initial segmentation is carried out by assigning a label to each pixel which generates the least amount of Gaussian energy (using log of equation 2). The tissue segmentation results in a binary map with white matter indicated in black (Figure. 2).

2.2 Infarct Detection

Infarct detection is based on the disturbance in the contralateral symmetry (CS) in the hypodense tissues. To assess this CS, we first determine the orientation of the major axis of skull, by locating the mid sagittal plane, and correct for any tilt. The distribution of white matter (hypodense) tissues in left and right hemisphere is compared in a 3-dimensional neighborhood (which is a $n \times n \times 3$ window, W) of every hypodense pixel by defining a probability measure P,

$$P_{S_i} = \left| \frac{\sum_{W_{S_{iRight}}} S_{iRight} - \sum_{W_{S_{iLeft}}} S_{iLeft}}{3 \times n^2} \right| \qquad (4)$$

where, S_{iRight} and S_{iLeft} refer to corresponding pixel locations. P gives the measure of asymmetry in the distribution of hypodense tissues in the vicinity of the concerned tissue and its counterpart in the other hemisphere. The value P_{S_i}, is the probability that S_i belongs to an infarct region.

The final decision on the presence of infarct is taken by combining the probability maps from the entire volume. A confidence threshold is applied to the probability maps to find the regions which exhibit a significant loss in symmetry in each probability map. Only those regions which show significant overlap in neighboring slices is considered as belonging to infarct whereas those regions which appear in isolation are considered to be artifacts or false positives. The rationale behind the above selection process is that stroke regions are solid tissue structures and occur mostly across multiple slices where as the artifacts are mostly, regions exhibiting localized loss of symmetry and appear in isolated slices due to the slice thickness of CT volume (along axial direction).

3. RESULTS

The above algorithm was tested on a dataset collected from a local hospital, consisting of CT scans of 18 normal and 10 abnormal (6 acute, 4 hyperacute) cases. The dataset has a total of 370 slices (images), out of which 279 are normal, 61 acute and 30 hyperacute. The scans were from patients belonging to various age groups (7,8,13 datasets in the age-groups 0-30, 30-50, 50 and above respectively). This helps in robust testing of the method since natural symmetry is disturbed as the age advances due to increasing amounts of CSF. The results were validated against ground truth data consisting of follow-up CT scans. The results of the entire algorithm are showcased in Figure. 2, with the detected infarct regions displayed in red. Also we show the results of hyperacute stroke detection against follow-up CT scans.

Table. 1 presents the obtained slice level and patient level detection results. The results show a high recall rate for both the normal (94.98%) and abnormal slices (85.71%). The Precision rate of the algorithm is good for normal and not as good for abnormal cases. The main reason for the latter is due to cases in which inherent symmetry in the brain is lost. This occurs mainly due to widening of sulci and ventrical with age. These false positives are mostly suppressed at the final patient-level decision which can be seen by the better patient level results. One problem the algorithm faces is in detection of small infarcts. These are very difficult to detect as the symmetry which exists between left and right hemispheres is very abstract. Increasing the sensitivity to cover these cases increases the overall false positive numbers.

Table 1: Slice Level Results

Ground Truth	Normal		Abnormal	
level	Patient	slice	Patient	slice
Precision	94.44	94.98	90	70.27
Recall	94.44	88.17	90	85.71

4. CONCLUSION

We have presented a scheme based on tissue enhancement and symmetry comparison to detect the presence of ischemic stroke in noncontrast CT images. The method has high recall rate (particularly in case of hyperacute) which is a chief requirement since it ensures that lesser number of infarct cases pass through undetected albeit at the cost of false positives. The performance has scope for improvement with more accurate segmentation of gray/white matter.

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