www.ijecs.in
International Journal Of Engineering And Computer Science ISSN:2319-7242
Volume 6 Issue 6 June 2017, Page No. 21746-21751
Index Copernicus value (2015): 58.10 DOI: 10.18535/ijecs/v6i6.33

A Survival Study on Pattern Recognition for Ischemic Stroke Detection on CT Images

B. Sowmya[1], Dr. P.R.Tamiselvi[2]

1. Research Scholar, Department of Computer Science,
Periyar University, Salem
sowmyabala06@gamail.com
2. Assistant Professor in Computer Science,
Government Arts and Science College, Komarapalayam
selvipr2003@gmail.com

Abstract:

The stroke disease is caused because of the cerebrovascular accident which does not allow the vessels to supply blood to the brain. Occurrence of stroke is due to the burst or blockage of the blood vessel. For efficient diagnosis of ischemic stroke, Computed Tomography (CT) images are used with life support devices. Segmentation is one of the methods through which ischemic stroke region get differentiated from healthy tissues in CT images. However, accurate segmentation of original CT images is not obtained in minimum response time and pattern recognition is not carried out. Our research aims to perform early detection using segmentation and extracts the trivial features through optimality for classifying the ischemic stroke CT images into stroke and non-stroke images. In addition, pattern recognition is carried out for differentiation between strokes and non-strokes model.

Keywords: computed tomography images, ischemic stroke (IS), stroke and non-stroke images, life support devices

1. Introduction

Stroke is third frequent cause of deaths after cardiovascular diseases and cancers. Stroke is frequently resulted in long-term disability or death. Ischemic stroke is described as an event classified by sudden onset of acute focal neurologic deficit attributable to cerebral ischemia after elimination of hemorrhage by CT. Prognosis of ischemic stroke are enhanced when thrombolytic therapy is administered to patients in first three hours. Stroke or cerebrovascular accident is a disease that changes the vessels that provide blood to the brain. The stroke occurs when blood vessel bursts or blockage occurs in blood vessel. Due to the loss of oxygen, nerve cells in affected brain area failed to execute the functions that resulted in the death of brain tissue. Stoke is occurred because of ischemia caused by blockage, or hemorrhage. In ischemic stroke, blood supply to part of brain is reduced resulting in death of the brain tissue in particular region.

2. Literature Review

Early detection of ischemic stroke by image feature characteristics with CAD called Circular Adaptive Region of Interest (CAROI) was presented in [1] with small lesions. The CAROI method analyzed the CT images of the brain using mathematical model incorporating the feature change weighting. Though accurate diagnosis for ischemic stroke with small lesion size was provided, optimality was not addressed. Susceptibility-weighted imaging (SWI) [3] was compared with perfusion-weighted imaging (PWI) to analysis ischemic penumbra detection in stroke patients with acute cerebral infarction. Though patterns were extracted for disease diagnosis, differentiation between stroke and non-stroke were not performed.

Cerebellar ischemic stroke mimic acute peripheral vestibular disorders, a cause for vertigo and hearing loss from cerebellar syndrome was presented in [2]. In [6], beamformer-based reconstruction of signals in source image evaluates the spectral and nonlinear measures in perilesional and healthy cortices. The spectral-based and entropy-based measurements are used to extract the voxel-based comparisons between patients. The correlations between task activation in right hemisphere and left hemisphere are carried out for detecting tissue dysfunction inside individual patients with higher detection rate. Though, early detection of stroke remained a future issue.

An automated method called Mid Line Shift (MLS) [4] to detect ischemic stroke in brain CT images was designed by segmentation, texture features and tracing midline shift algorithm. Computer aided detection system with small ischemic stroke has constructed using MLS method. Feature extraction was carried out using Gray Level Co occurrence Matrix (GLCM) where an early detection of ischemic stroke in brain CT images was made possible. However, the rate and time of detection remained an important issue to be handled. Arterial Spin Labelling (ASL) in the preclinical phase corresponded to pre-clinically latent lesions from Stroke-like Episodes (SE) in [5]. The report indicated that ASL image had greater significance in identifying the preclinical lesions.

3.Pattern Recognition For Ischemic Stroke Detection On Ct Images

Computed tomographic (CT) images are used for recognition of abnormal images from normal images for ischemic stroke. Ischemic stroke is described as event classified by sudden onset of acute focal neurologic scarcity presumably attributable to cerebral ischemia after elimination of hemorrhage through CT. CT images has five stages namely, preprocessing, segmentation, brain midline tracing, texture features extraction by gray level co-occurrence matrix and classification. In first step, skull bone components of images are taken out by global thresholding method, noise is suppressed by image filtering and image is improved by max filter. In second process, ischemic stroke region is removed using k-means clustering technique. In third process, midline shift of brain is computed. In fourth process, fourteen texture features are removed by gray level co-occurrence matrix for left and right side of brain. The features derived are employed to train binary classifier that infers whether image has normal brain or an ischemic brain experiencing from brain lesion. In Fifth process, SVM, k-NN, ANN and decision tree classifiers are developed to classify the normal image from the ischemic stroke on CT images.

3.1Cerebellar Ischemic Stroke Syndromes Causing Vertigo and Hearing Loss

Dizziness/vertigo is the symptom in patients with strokes isolated to the cerebellum. Patients with focal cerebellar stroke may complain about isolated vertigo without other symptoms. Cerebellar ischemic stroke is common causes of vascular vertigo. It accompanies with other neurological symptoms or signs. Though, small infarct in cerebellum presents vertigo without other localizing symptoms. By comparing with all other cerebellar stroke syndromes, cerebellar ischemic stroke ranks first that resulted in causes of isolated vascular vertigo. Cerebellar ischemic stroke is essential one for distinguishing the isolated vertigo associated with cerebellar ischemic stroke from benign disorders. Cerebellar ischemic stroke is used with inner ear as therapeutic strategy and prognosis is not same in two conditions. Misdiagnosis of acute stroke leads to the morbidity and mortality. An isolated cerebellar infarction is used as isolated vertigo that results from emboli originating. A proper anticoagulant therapy is required to avoid recurrent emboli that resulting in life-threatening condition.

The frequent pattern of vestibular dysfunction in Anterior Inferior Cerebellar Artery (AICA) territory infarction is mixture of peripheral and central ocular motor or vestibular signs. It is explained with AICA that supplies peripheral vestibular structures like inner ear and vestibule cochlear nerve. AICA infarction leads to the combined peripheral and central vestibular damages besides the hearing loss, facial weakness, limb and facial sensory loss, gait ataxia and cerebellar dysmetria. Acute audio vestibular loss classified through canal paresis to caloric stimulation. AHL on pure tone audiogram is an essential sign for diagnosis of AICA territory cerebellar ischemic stroke.

AICA infarction is recognized with the pattern of neurotological presentations where many pattern of audiovestibular dysfunction is combined loss of auditory and vestibular functions.

3.2 Image Feature Approach for Computer-Aided Detection of Ischemic Stroke

A computer-aided detection (CAD) scheme is used to recognize the identify abnormality where the clinicians overlook and increases the accuracy of disease detection. The mathematical model with CAD has achievement in radiological science. When the average human life span has improved, stroke is the third leading cause of death after heart disease and cancer. Strokes are caused by blockage of blood flow to part of brain supplied through one or more small arteries. It is divided into hemorrhagic and ischemic strokes. A lacunar stroke, subtype of ischemic stroke is not simple to identify, as it manifests small hypodense area of less than 15mm in diameter on Computed Tomography (CT). CT remains preferred choice for patients with acute ischemic stroke as it is accessible, inexpensive, effective and reliable.

CAD scheme operated on CT images in Digital Imaging and Communication in Medicine (DICOM) or bitmap format. The CT images were attained from radiology department with all preserved health information. For identifying the abnormality in brain, the bony skull and scanning artifact are to be taken out. It includes the automatic segmentation of cranial content of the brain, elimination of skull and alignment of brain to best symmetric position. CT signs of stroke are complex one for identifying the first 24 hour of ischemic stroke onset. Brain contains anterior, middle and posterior cerebral artery (ACA, MCA and PCA) territory and basal ganglia. Circular Adaptive Region of Interest (CAROI) method identifies the region with subtle variation in intensity at ACA, MCA and PCA territory.

Stroke causes profound disturbances to cognition and it is a leading cause of adult disability. One of the debilitating cognitive impairments is aphasia. It causes the damage to language networks in the left hemisphere. When the stroke-induced cortical lesions are stable, language recovery precede the processes of reorganization and neural plasticity taking place in structurally intact brain tissue.

3.3 Susceptibility-Weighted Imaging and Perfusion-Weighted Magnetic Resonance Imaging in Acute Ischemic Stroke

Imaging techniques are employed to identify the ischemic penumbra like single-photon emission computed tomography (SPECT), positron emission tomography (PET) and perfusion-weighted imaging (PWI). The techniques need the radionucleotides or contrast agents that are used in less clinical application. Susceptibility-weighted imaging (SWI) is new high-resolution magnetic resonance imaging (MRI) method used for identifying the penumbra in stroke patients. SWI failed to need administration of radionucleotides or contrast agents. In addition, it employs the paramagnetic susceptibility effects for studying the metabolic changes in hypoperfused brain tissues. SWI identifies the paramagnetic susceptibility difference between deoxygenated and oxygenated hemoglobin (Hb) that reproduces the oxygen extraction fraction (OEF) of brain tissues. In ischemic stroke, minimal cerebral perfusion pressure results in development of Hb/HbO ratio through rising OEF. SWI presents better information on metabolic variation in the ischemic brain area for detection of the ischemic penumbra for stroke patients in starting stage.

4. Parameters To Compare Pattern Recognition For Ischemic Stroke Detection On Ct Images

In order to compare the pattern recognition for ischemic stroke detection, number of CT images can be taken to perform the experiment. Various parameters are used for pattern recognition for ischemic stroke detection on CT images.

4.1 Pattern Recognition Time

Pattern recognition time is defined as the time taken for pattern recognition in CT images. It is also defined as the difference of ending time and starting time of pattern recognition on CT images. It is measured in terms of milliseconds (ms).

$$Pattern\ Recognition\ Time$$
$$= Ending\ time$$
$$- Starting\ time\ of\ patern\ recognition\ on\ CT\ images$$

When lower pattern recognition time, the method is said to be more efficient.

The pattern recognition time comparison was used on existing Cerebellar Ischemic Stroke Syndromes scheme, Computer-Aided Detection (CAD) Scheme and Susceptibility-weighted imaging (SWI) with perfusion-weighted imaging (PWI).

The Cerebellar Ischemic Stroke Syndromes scheme provides better performance in terms of pattern recognition time as compared to other methods. When the number of CT images gets increased, the pattern recognition time also gets increased correspondingly.

4.2 Segmentation Accuracy

Segmentation accuracy is defined as the ratio of number of correctly segmented images to the total number of CT images. It is measured in terms of percentage (%)

$$Segmentation\ Accuracy$$
$$= \frac{Number\ of\ correctly\ segmented\ images}{Total\ number\ of\ images}$$

When higher the segmentation accuracy, the method is said to be more efficient.

The segmentation accuracy comparison takes place on existing Cerebellar Ischemic Stroke Syndromes scheme, Computer-Aided Detection (CAD) Scheme and Susceptibility-weighted imaging (SWI) with perfusion-weighted imaging (PWI).

From the study, we infer that the Computer-Aided Detection (CAD) Scheme provides better performance in terms of segmentation accuracy as compared to other methods. When the number of CT images gets increased, the segmentation accuracy also gets increased correspondingly.

4.3 Peak-Signal-to-Noise Ratio (PSNR)

PSNR is the ratio between the maximum power of an original image and the power of corrupting by compressing that changes the reliability of its demonstration. It is expressed in terms of logarithmic decibel scale. PSNR is described through mean squared error (*MSE*). Given a noise-free $p \times q$ monochrome image I_m and its image approximation *A*, *MSE* is defined as:

$$MSE = \frac{1}{pq}\sum_{i=0}^{p-1}\sum_{j=0}^{q-1}[I_m(i,j) - A(i,j)]^2$$

The PSNR (in dB) is defined as:

$$PSNR = 10.\log_{10}\left(\frac{M^2}{MSE}\right)$$

$$= 20.\log_{10}\frac{M}{\sqrt{MSE}}$$

$$PSNR = 20.\log_{10}(M) - 10.\log_{10}(MSE)$$

Where,

I_m = the matrix data of our original image

A = the matrix data of our degraded image in question

p = the numbers of rows of pixels of the images

q = the number of columns of pixels of the image

i = the index of p^{th} row and j = the index of q^{th} column

$M = 2^B - 1$, B= Number of bits

The Peak-Signal-to-Noise Ratio comparison takes place on existing Cerebellar Ischemic Stroke Syndromes scheme, Computer-Aided Detection (CAD) Scheme and Susceptibility-weighted imaging (SWI) with perfusion-weighted imaging (PWI).

From the study, we infer that the Susceptibility-weighted imaging (SWI) with perfusion-weighted imaging (PWI) provides better performance in terms of Peak-Signal-to-Noise Ratio as compared to other methods. When the number of CT images gets increased, the Peak-Signal-to-Noise Ratio also gets increased correspondingly.

5. Discussion On Limitation Of Pattern Recognition For Ischemic Stroke Detection On Ct Images

During Cerebellar ischemic stroke, mimic acute peripheral vestibular disorders identifies vertigo and hearing loss from cerebellar syndrome. Acute Hearing Loss (AHL) of a vascular cause is connected with cerebellar infarction in territory of Anterior Inferior Cerebellar Artery (AICA). The method with the recovery of caloric induced vestibular response still remained unclear. SWI compares perfusion-weighted Imaging (PWI) system to investigate ischemic penumbra detection in stroke patients with acute cerebral infarction. SWI is non-traumatic imaging technique which presents cerebral blood flow information with acute infarction. SWI assess the survival of damaged brain tissue and showed intra-arterial thrombolytic therapy. SWI describes the thrombus in affected artery with essential information for selecting and developing therapies with acute cerebral infarction. Patterns are extracted for disease diagnosis, differentiation between stroke and non-stroke are not performed.

Computer-Aided Detection (CAD) method identifies early stage of ischemic stroke with small lesions by image feature characteristics called CAROI. CAROI method analyzes the Computed Tomography (CT) images of brain using mathematical model incorporating the feature change weighting. Both emergency physicians and radiology residents presents large development in sensitivity and specificity when using CAD. CAROI approach provides perfect diagnosis for ischemic stroke with small lesion size is not addressed.

5.1 Related Works

An ischemic stroke (IS) in Active Cancer (AC) showed exact features in [9] that supported for active malignancies in development of stroke. Various patterns were identified and found that pancreatic, lung and liver cancer that are susceptible to IS. The infarct pattern was found to be associated with proximal source like stroke aetiology was actually less often diagnosed in patients with AC than NAC. The objective of study presented in [8] was to determine the patterns required or extracted for diagnosis of acute ischemic stroke. Perfusion Computed Tomography (PCT) and Computed Tomography Angiography (CTA) were applied that resulted in the increased rate of sensitivity of Non-contrast Computed Tomography (NCT) in early diagnosis of acute ischemic stroke. High Throughput Quantitative Polymerase Chain Reactions (HT-qPCR) [7] was designed in three prior gene expression profiling. However, essential factors like location and appearance render laborious task compromises the time for stroke detection.

5.2 Future Direction

The future direction of the work is to detect the ischemic stroke on computed tomography (CT) images using segmentation at early stage and extracts trivial features through optimality for classifying the ischemic stroke CT images into stroke and non-stroke images. The pattern recognition for ischemic stroke detection on CT images is to perform effective differentiation of strokes and non-strokes images.

6. CONCLUSION

A comparison of different techniques for pattern recognition for ischemic stroke detection on CT images is carried out. In the present environment, there are many risks undergone for segmenting and classifying the strokes and non-strokes CT images. From the survey, essential factors such as location and appearance render laborious task, compromising the time for stroke detection. The early detection of stroke remained a key problem. The rate and time of detection remained an important issue to be handled. The wide range of experiments on existing techniques calculates the comparative results of the various techniques of pattern recognition for ischemic stroke detection on CT images and its limitations. Finally from the result, the research work can be carried out with segmentation and classifier approach for attaining the effective pattern recognition for ischemic stroke detection on CT images.

References

[1] Fuk-hay Tang, Douglas K. S. Ng, Daniel H. K. Chow, “An image feature approach for computer-aided detection of ischemic stroke”, Computers in Biology and Medicine, Elsevier, Volume 41, Issue 7, July 2011, Pages 529–536

[2] Hyun-Ah Kim & Hyon-Ah Yi & Hyung Lee, “Recent Advances in Cerebellar Ischemic Stroke Syndromes Causing Vertigo and Hearing Loss”, Cerebellum, Springer, Volume 15, Issue 6, December 2016, Pages 781–788

[3] Song Luo, Lijuan Yang and Lijin Wang, “Comparison of susceptibility-weighted and perfusion-weighted magnetic resonance imaging in the detection of penumbra in acute ischemic stroke”, Journal of Neuroradiology, Elsevier, Volume 42, Issue 5, October 2015, Pages 255–260

[4] N. Hema Rajini and R. Bhavani, “Computer aided detection of ischemic stroke using segmentation and texture features”, Measurement, Elsevier, Volume 46, Issue 6, July 2013, Pages 1865–1874

[5] Masamichi Ikawa, Makoto Yoneda, Tomoko Muramatsu, Akiko Matsunaga, Tetsuya Tsujikawa, Tatsuya Yamamoto, Nobuyuki Kosaka, Kazuyuki Kinoshita, Osamu Yamamura, Tadanori Hamano, Yasunari Nakamoto, Hirohiko Kimura, “Detection of preclinically latent hyperperfusion due to stroke-like episodes by arterial spin-labeling perfusion MRI in MELAS patients”, Mitochondrion, Elsevier, Volume 13, Issue 6, November 2013, Pages 676–680

[6] Ron K.O. Chua, Allen R. Braune and Jed A. Meltzer, “MEG-based detection and localization of perilesional dysfunction in chronic stroke”, NeuroImage: Clinical, Elsevier, Volume 8, 2015, Pages 157–169

[7] Mateusz G. Adamski, Yan Li, ErinWagner, Hua Yua, Chloe Seales-Bailey, Steven A. Soper, Michael Murphy, Alison E. Baird, “Expression profile based gene clusters for ischemic stroke detection”, Genomics, Elsevier, Volume 104, Issue 3, September 2014, Pages 163–169

[8] Ahmed Deif, Mohamed Shaker b, Abeer Abdelzaher Ibrahim, “Added value of CT perfusion and CT angiography in detection of early ischemic stroke: Comparison with noncontrast CT”, The Egyptian Journal of Radiology andNuclear Medicine, Elsevier, Volume 46, Issue 4, December 2015, Pages 1111–1118

[9] Markus Kneihs, Christian Enzinger, Gerit Wunsch, Michael Khali, Valeriu Culea, Tadeja Urbanic-Purkart, Franz Payer, Kurt Niederkorn, Franz Fazekas, Thomas Gattringer, “Poor short-term outcome in patients with ischaemic stroke and active cancer”, Journal of Neurology, Springer, Volume 263, Issue 1, January 2016, Pages 150–156