MRI Measurement of Ischemic Brain Penumbra Using Kohonen's Multi-Parametric Self-Organizing Map (KMP-SOM) Technique

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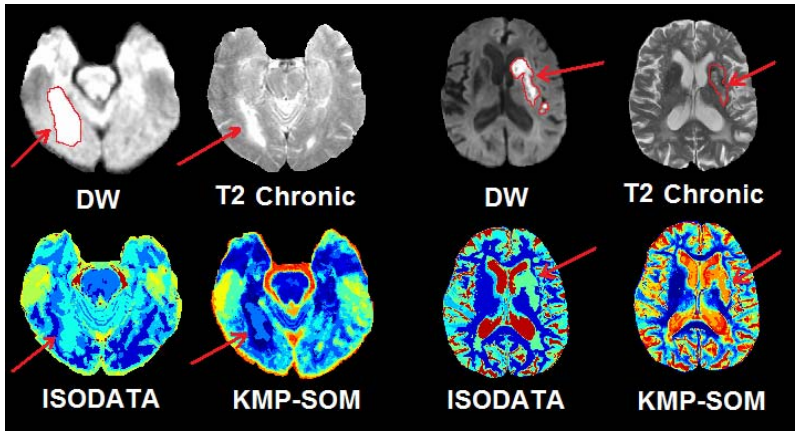
Introduction

Multi-parametric MRI analysis of the ischemic lesions of stroke patients demonstrates inhomogeneities in the degree of ischemic injury and recovery potential [1]. Experimental and clinical studies indicate that the likelihood for progression to infarction in the penumbra of physiologically impaired but potentially salvageable tissue surrounding the central core of focal cerebral ischemia is the most important factor in evaluating treatment efficacy [2]. Thus, a multi-parametric analysis that increases the ability of investigators to detect and characterize ischemic penumbra in the early stages of stroke may have a profound clinical significance.

Kohonen's Multi-Parametric Self Organizing Map (KMP-SOM) technique was used to detect the ischemic penumbra using MR acute information: KMP-SOM generates nodes on a two-dimensional (2-D) lattice in which the distribution of these nodes corresponds to the proximity of their associated node patterns in the signal intensity space. The benefits of this clustering technique are: 1) if started with an adequate number of neurons, it can find distinctive features in the data even if they are less evident (e.g., the lesion periphery); 2) the emerging node patterns are ordered according to their proximity properties in the data space. [4-6]. KMP-SOM's were used to analyze MR acute information (T_1 pre-contrast, T_2, Diffusion-Weighted and proton density) of 7 brain stroke patients. The training dataset consisted of 7 MRI sets with 10 slices from 5 untreated stroke patients and 2 abciximab-treated patients acquired at an average of 16:52 ±4 hours after onset. The co-registered three-month T_2 map was considered to be the gold standard for the tissue fate, and its difference from the DW lesion was used to validate and optimize the KMP-SOM. KMP-SOM results were compared to an unsupervised clustering method (Iterative Self-Organizing Data Analysis Technique – ISODATA) a variant of K-means algorithm. From a statistical viewpoint, the clusters obtained by K-means can be interpreted as the Maximum Likelihood Estimates (MLE) for the cluster means, assuming that each cluster comes from a spherical Normal distribution with different means but identical variance (and zero covariance). K-means and ISODATA work well for images with clusters that are spherical and that have the same variance. However, this is always not true for MR images. [7-8].

Materials and Methods:

Seven patients presenting with acute neurological deficit consistent with stroke, with MRI studies within 24h of onset, were selected. Stroke onset was defined as the last time the patient was known to be without neurological deficit. The severity of the neurological deficit was assessed using the National Institutes of Health Stroke Scale (NIHSS) score at the time of each MRI study. MRI studies were performed at the acute time point (<24 h after stroke onset), and outcome time point (90 days after stroke). Patients were excluded if they had cerebral hemorrhage at the acute time point or a history of prior stroke. MRI studies were acquired on a 1.5-tesla GE Signa MR scanner with echo-planar capability (GE, Milwaukee, Wisc., USA). Each MRI study consisted of axial multi-spin echo T_2-weighted imaging (T2WI), T_1-weighted imaging (T1WI) and diffusion-weighted imaging (DWI) with slice thickness of 6 mm. The field of view (FOV) was 240 × 240 mm. For T1 and T2 imaging, the matrix was 256 × 192 and for DWI 128 × 128. Additional parameters for each study were: (a) T1WI: TR/TE = 600/14 ms; (b) T2WI: TR/TE = 2,800/30, 60, 90, 120 ms; (c) axial DWI was performed using an echo-planar sequence, TR/TE = 10,000/101 ms, b-values = 1,000, 600, 300, 0 s/mm^2, 1 NEX. For each patient, four images (T_1, T_2 –TE90, DWI and PD) at the acute time point were selected to provide the essential input features to the KMP-SOM and ISODATA technique. All acute and chronic images were registered to T_2-TE90 as reference using Eigentool and Smartmorph software [7]. A feature set was generated and sampled from four acute images and put into a KMP-SOM with 5x8 neuron topology structure (learning rate: 0.01) and Best Matching Unit (BMU) neighborhood learning algorithm [6,8]. In training and classification, every node within the BMU's neighborhood (including the BMU) had its weight vector adjusted according to the following equation: $W(t+1)=W(t)+L(t)[V(t)-W(t)]$, where t represents the time-step, V(t) denotes input vector, W(t) denotes old weight and L(t) is a small variable called the learning rate, which decreases with exponentially with time and is a function of neighbor distance [8]. The difference between DWI and T2-Chronic lesions was considered as the penumbra. The power of predicting the core of the T2-chronic pattern in both techniques was used to evaluation their robustness.



Results and Discussion

Two subjects are shown in figure-1. Red arrows point to the lesion penumbras (darker area) and lesion cores in KMP-SOM maps for both patients. Considering the DW and T2 lesions, the KMP-SOM maps have distinguished the penumbra and core of the lesions much better than ISODATA, and the patterns of the core in both patients are more matched with the T2-Chronic lesions in the KMP-SOM compared to ISODATA. We conclude that a KMP-SOM capable of predicting the ischemic penumbra, both in pattern and size, of a stroke from MR acute information can play an important role in describing tissue viability. Since it is strongly related to the clinical outcome, such modeling may play an important role in the assessment of subacute therapeutic interventions, currently of great interest in the treatment of stroke.

References

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