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Auto-Windowing of Ischemic Stroke Lesions in Diffusion Weighted Imaging of the Brain

S. Mujumdar and J. Sivaswamy
Centre for Visual Information Technology,
IIIT-H, Hyderabad, India

L.T. Kishore
CARE Hospital,
Hyderabad, India

R. Varma
Krishna Institute of Medical Sciences,
Hyderabad, India

***Abstract*—Diffusion Weighted Magnetic Resonance Imaging (DWI) is routinely used for early detection of cerebral ischemic changes in acute stroke. Fast acquisition with a standard echo-planar imaging technique generally compromises the image signal-to-noise ratio and in-plane resolution resulting in a reduction of the conspicuity and definition of lesions in the acquired data when viewed on a standard 8-bit display. We present a novel method for automatically and adaptively determining the window settings that enhance the contrast of the image relative to the ischemic lesions. The method performs a coarse segmentation of the lesions followed by contrast-to-noise ratio based computation of the optimal window parameters. The proposed method was tested on 24 datasets acquired with different protocols. The contrast improvement of the lesions is validated through a mirror region of interest analysis and by using the contrast improvement ratio metric. The average obtained improvement in contrast ranges from 25% to 60%. Preliminary results of segmentation showed a good reduction in the false positives and improvement in the lesion boundaries. A perception study of the windowed results against 8 radiologists was conducted. Reduction of 14.17% in the mean *response* time of detection was observed. Statistical analysis performed using t-test validates the reduction in mean *response* time to be significant. Results presented in the study show promise in the method.**

***Index Terms*—Diffusion weighted imaging, auto-windowing, acute ischemic stroke, contrast enhancement**

I. Introduction

Early detection of ischemic lesions in the brain helps clinicians to classify the stroke sub-type and plan for treatment. DWI imaging is a standard protocol used for early (within 6 hours of the onset of symptoms) detection of ischemic changes in the brain [2]. DWI encodes the mobility of the water molecules in the brain into sequence of images with varied contrast. In areas of acute stroke, the diffusion process is hindered resulting in a hyper-intense signal in the acquired scan [2].

DWI acquisition is done using the standard echo-planar imaging (EPI) technique. EPI induces a trade-off between signal-to-noise ratio (SNR), time of acquisition and resolution of the acquired image. The clinical practice is to conduct a fast scan ($<$1 min) to gain a quick assessment to enable further detailed and accurate diagnosis [2]. However, EPI compromises the resolution as well as the SNR of acquired scans and affects the precision with which *subtle* lesions can be detected. A solution is to enhance the images to help increase the contrast between the lesions and the normal tissue. This is the focus of the paper.

II. Background

Visibility of abnormalities in images is key to diagnosis and can be improved via a contrast enhancement technique or windowing. At the clinical level, radiologists routinely adjust the window parameters (width and level) to obtain the best overall contrast and brightness before arriving at a diagnosis. This is partly to adapt to their display device and partly tailored to an abnormality of interest. An optimal window setting for DWI, was manually determined for Hypoxic-ischemic encephalopathy and shown to improve diagnosis across patients and scanners [5]. Semi-automated methods have also been utilized towards standardising the display across patients and scanners [8]. Automated methods for determining the window parameters have aimed at global contrast enhancement. Techniques using spatial, anatomical and histogram information [1] as well as pseudo colorisation (of segmented results) [6] have been proposed. In the latter case, different tissue classes for T2 weighted MR images are identified from the histogram and the pseudo-colorisation is done using fuzzy membership functions. The problem of over-enhancement and high complexity of adaptive-histogram equalization is overcome by proposing a local bi-histogram equalization technique in [12] for medical images. A wavelet transform-based approach [10] utilizes a linear function for combining the transform coefficients across scales after thresholding. Alternately, a histogram based method [3], incorporating the gradient and intensity information serves to enhance the white matter lesions while suppressing the background in FLAIR MRI.

Global contrast enhancement may result in loss of local contrast thereby hindering the detectability of small sized lesions and their boundaries in DWI. Such techniques can also result in a non-linear transformation which will change the relative contrast between different tissues which is undesirable. A linear transform which preserves the relative contrast variations while enhancing the data is preferable.

The discrimination of subtle ischemic lesions can be confounded by presence of artifacts (for example, susceptibility-related shine through, coil sensitivity, T2 shine through) and acquisition related changes (b1000/b2000) [4]. The practice of acquiring DWI sequences of different b-values produce varied

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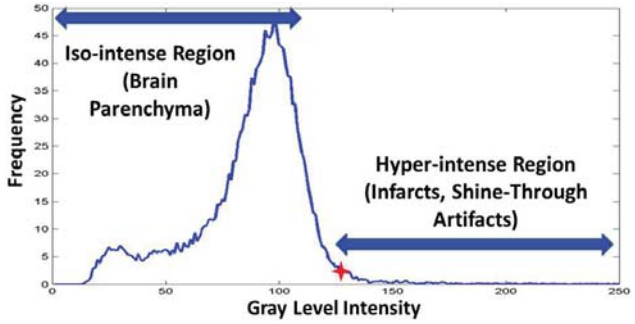

Fig. 1. Regions shown on histogram of a DWI brain volume with background suppressed. Knee-point beyond which infarcts and shine-through artifacts lie, shown in red.

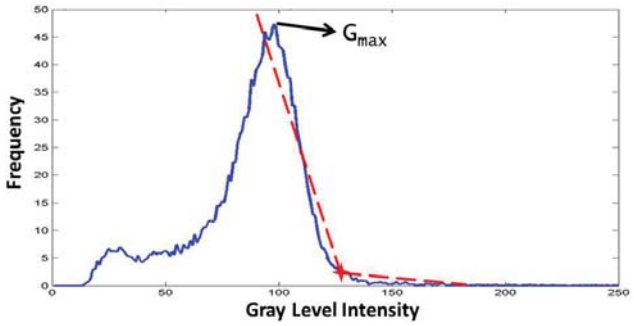

Fig. 2. Knee-point (shown as a red star), global maximum G_{max} and the corresponding line fits.

contrast for the same brain tissue. In this paper, we present an automated windowing technique for DWI scans which adaptively determines the window parameters. The intent is to help improve the discriminability of ischemic lesions. We also report on an investigation carried out on the effectiveness of the proposed algorithm on DWI acquired with different scanners and b-values (b1000 and b2000). A perception study was performed with expert radiologists to validate the algorithm results. A detailed analysis of the perception study results is reported.

III. METHOD

A. Materials

24 DWI volumes of confirmed stroke patients were collected from two local hospitals which had different types of scanners and used different methods of data acquisition. The different b-value data are acquired sequentially on Scanner-1 and simultaneously in Scanner-2. The full data description is provided in Table I. The Apparent Diffusion Coefficient (ADC) maps from Scanner-1 were independently generated for both the b1000 and b2000 data using the Stejskal-Tanner equations: $ADC{=}-(1/b)ln(S/S_0)$, where S_0 is the signal intensity with gradient factor $b{=}0\ s/mm^2$ and S is the signal intensity with gradient factor $b{=}1000\ or\ 2000\ s/mm^2$ [9].

TABLE I
DATA DESCRIPTION.

Scanner	Scanner-1	Scanner-2
Data Sets	16	8
Acquisition	Sequential	Simultaneous
Acquired Data	b=0, b=1000, b=2000, ADC = Post Acquisition	b=0, b=1000, b=2000, ADC = In Acquisition
Voxel Size	0.98×0.98 ×6.32 mm	1.95×1.95 ×7.28 mm
Matrix Size	256×256×22	128×128×20
Pixel Depth	16 bits	12 bits

B. Concept

The auto-windowing problem requires finding two parameters, the optimum window level l_o and width w_o. Since the goal is to improve the discriminability of the ischemic lesions, an approach which achieves local rather than global contrast enhancement is appropriate. Accordingly, we formulate the problem as finding the window setting that maximizes the local contrast for the lesions in a given dataset. Thus, the first step in our approach is to do a coarse segmentation of the lesions from the given DWI dataset. Next, the local contrast is measured for a set of window parameters. The desired *best* window is the one that yields maximum contrast for the lesion(s) relative to the local background. In our work we choose the Contrast-to-Noise Ratio (CNR) as the metric to characterise the local contrast. We now present the proposed auto-windowing method in detail.

C. Coarse Segmentation

We start with the following observations. In the case of an acute stroke,

- Stroke volume $\ll$ Brain volume.
- The infarct appears brighter than the brain tissue.

The first observation is intuitive and the second one is a property of the DWI scan. Let H_v be the volume histogram of the given DWI volume obtained after masking out the background in the image. From our observations the following conclusion can be made: pixels belonging to lesions will give rise to short peaks at the higher end of H_v. This is illustrated in Figure 1. Hence, a simple threshold set at the knee-point after the global maximum in H_v can help select the desired candidates. It is possible to employ a non-linear transformation to find this knee-point accurately, however, a rough method will suffice.

The knee-point is determined by a function which minimizes the error between two line fits which operates as follows: Let G_{max} be the global maximum in H_v. The function iteratively finds a bisection point along the curve after G_{max}. At every iteration, the bisection point divides the curve into two sets of points - curve points lying to the left and to the right of the bisection point. Two lines are fit originating from the bisection point to these set of curve points. The bisection point which minimizes the sum of errors for the two line fits is determined as the knee-point. Figure 2 illustrates the two line fits with minimum error at the knee-point.

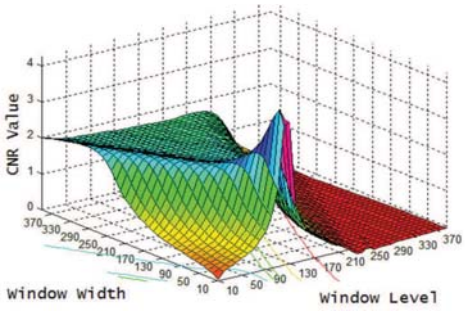

Fig. 3. The CNR surface plot obtained with different window parameters.

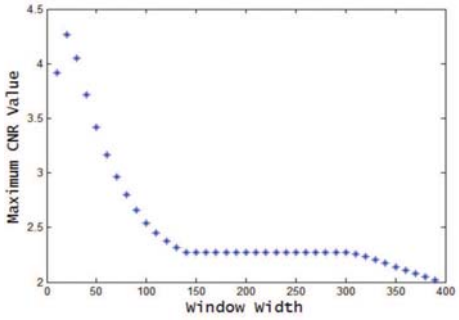

Fig. 4. Maximum CNR values for different window widths.

The given DWI volume data is thresholded at the knee-point and all the pixels having intensities greater than the knee-point are retained. A connected component analysis on these pixels yields a set of coarsely segmented candidate lesions. Connected components with a size less than 5% of the image size were ignored. As seen from Figure 1 the gross anatomy and the intensity distribution of the brain in the DWI scans is relatively similar and hence this method correctly identifies the threshold on all the DWI datasets. The CNR plots for the obtained set of candidate lesions are generated as described in the next section.

D. Generation of CNR plots

For each of the candidate lesions, the CNR is computed as:

$$CNR = \frac{\mu_c - \mu_b}{\sqrt{\left(\sigma_c^2 + \sigma_b^2\right)/2}}$$

where, μ_x and σ_x are the mean and standard deviation of the intensity of region x, respectively; c denotes core region; b denotes background. The candidate lesion is considered as the core region and the surrounding normal brain tissue in a bounding box (with a 3 pixel margin) is considered as the background region. The 'normal' tissue is characterised by ADC values in the following range: $[0.6-1.15]\times10^{-3}mm^2/s$ [9].

Two plots are generated for each volume as shown in Figure 3 & 4. Figure 3 is the plot of $CNR(l,w)$ shown as a surface plot. Figure 4 is the plot of $max\left(CNR(w)\right)$. The interval $[1,N]$, with N being the maximum intensity in the data, was sampled to generate these plots.

$$\mathrm{l} = n\Delta l \quad ; \quad n = 1,2,\ldots \mathrm{N}$$
$$\mathrm{w} = m\Delta w \quad ; \quad m = 1,2,\ldots \mathrm{N}$$

In our implementation, the sampling intervals (Δl and Δw) were fixed at 10. Experiments were done to test the effect of varying the sampling interval on l_o and w_o. A trade-off has been observed between consistency in the obtained window parameters and the computational time with the increase in sampling interval. The desired optimum level l_o is found from $CNR(l,w)$ and is taken to be the value of l corresponding to the highest CNR value. The desired optimum width w_o is chosen such that the variation in $max\left(CNR(w)\right)$ is below a fixed threshold. As seen from Figure 3, $l_o = 120$ and from Figure 4, $w_o = 140$.

Since contrast is a subjective notion the choice of optimal window parameters were made with the following reasoning: Let g_c and g_b denote the gray values of the core and background respectively, for an infarct. Consider the case where $l = g_c$. In this case, the CNR will have a unique peak for this window level, say CNR_p, which will correspond to the smallest w. This can also be observed from Figure 3. Whereas, if $l < g_c$, the visibility of the infarct reduces and the background starts dominating. Beyond some w, the CNR variation is minimal as the lesion is no longer visible (refer Figure 4). Consequently, CNR will still attain a maximum ($< CNR_p$), for some w. Since our aim is to enhance the contrast of the lesions, the width value, above which the contrast of the lesions is not affected significantly, is chosen as the desired w_o.

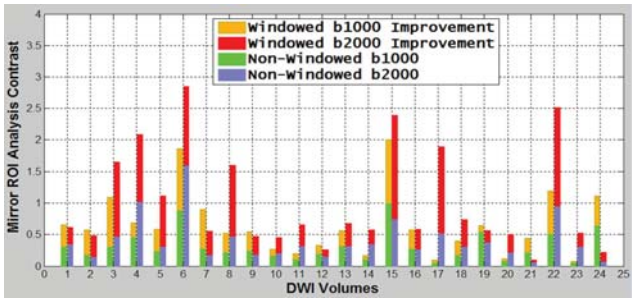

Fig. 5. Results of Mirror ROI Analysis.

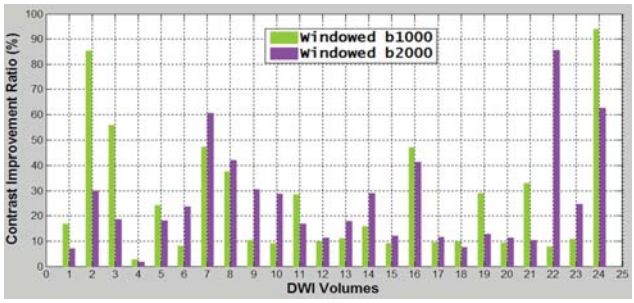

Fig. 6. Contrast Improvement Ratio (%).

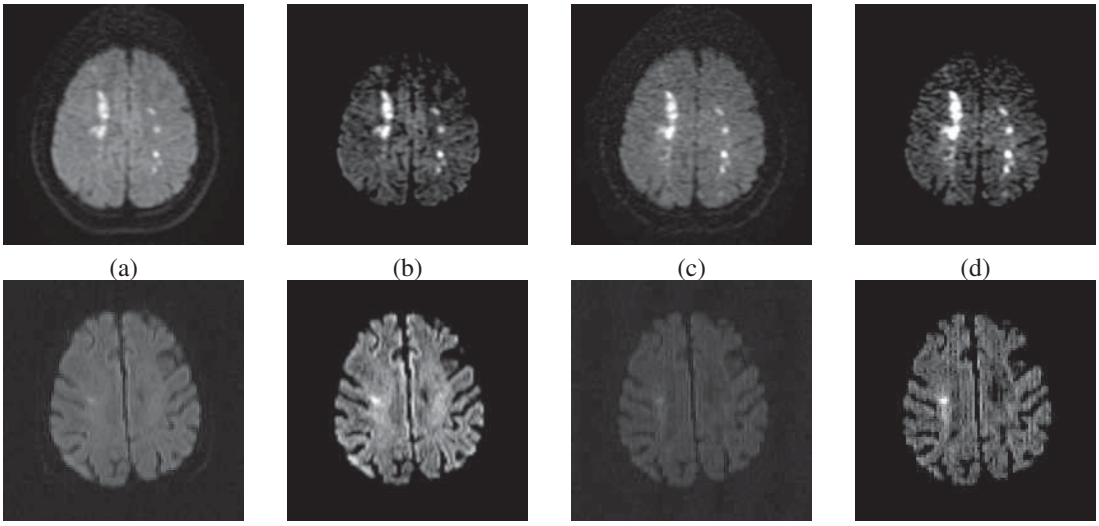

Fig. 7. Results of windowing on sample images from scanner 1 (a,b,c,d) and scanner 2 (e,f,g,h). (a),(e) original b1000 images. (b),(f) windowed b1000 results. (c),(g) original b2000 images. (d),(h) windowed b2000 results.

The proposed method is validated through two different means (i) quantitative and qualitative assessment of lesion contrast improvement (ii) perception study analysis with experts. The validation of the results is presented in the further sections.

IV. Assessment and Results

The assessment aimed at determining the effectiveness of the proposed auto-windowing method across the following independent parameters: multiple scanners and multiple diffusion weighting (b1000 and b2000). We report on two different types of assessments - a mirror region of interest analysis and contrast improvement ratio. The former was done to determine the quantitative improvement in contrast of the lesions relative to the normal brain tissue in the anatomically similar region [11]. Given a lesion, it was flipped about the mid-line and the corresponding mirror region in the contra-lateral hemisphere was found. For a given dataset, the mid-line was manually detected and the contrast and the percentage improvement in contrast were computed as,

$$C_M = \frac{|\sum_i^n \mu_i - \sum_i^n \tilde{\mu}_i|}{\sum_i^n \tilde{\mu}_i} \; ; \; C_{MI} = 100 \times \frac{(C_{M_W} - C_{M_{NW}})}{C_{M_{NW}}}$$

where, μ and $\tilde{\mu}$ are the mean intensity values of a lesion and its mirrored region respectively and n is the number of lesions. Here, C_{M_W} and $C_{M_{NW}}$ are the C_M values for windowed data and non-windowed data respectively. This metric, in essence, captures the improvement in the lesion contrast, relative to the anatomically similar background brain tissue as represented by the mirrored region. This can also be viewed as a measure of contrast enhancement in a global sense where the improvement in contrast of the lesion is measured against the normal brain tissue globally, represented by the mirrored region.

Additionally, a contrast improvement ratio (C_{IR}) [3] was also computed to quantify the results of local contrast enhancement. The C_{IR} is defined as,

$$C_{IR} = 100 \times \frac{\sum_i^n \mid c_i - \hat{c}_i \mid^2}{\sum_i^n c_i} \quad ; \quad c_l = \frac{|\mu_c - \mu_b|}{|\mu_c + \mu_b|}$$

where, c and $\hat{c}$ represent the local contrast without and with windowing respectively and n is the number of lesions. The local contrast c_l is defined based on the mean values of the lesion (μ_c) and its local background (μ_b). The normal brain tissue present in the bounding box with a 3 pixel margin around the lesion is used to define the lesion's local background.

The results of quantitative evaluation of C_{IR} are presented in Figure 6. The average values of C_{IR} were found to be (25.82%, 25.59%) for (b1000, b2000) respectively. The C_M values for data with and without auto-windowing are plotted in Figure 5 for both b1000 and b2000 datasets. The average C_{MI} values were found to be (34.35%, 59.71%) for (b1000, b2000) respectively. The mean values of C_{MI} and C_{IR} were computed across the scanner and the values were found to be as shown in Table II. From the results we can infer that windowing is more effective to data obtained from scanner-2 relative to scanner-1. The voxel size, matrix size and the pixel depth of the data obtained from scanner-1 is higher relative to that of the scanner-2. Thus, the data from scanner-2 has poorer contrast and noisier relative to data from scanner-1. Hence the improvement in local and the global contrast after windowing as measured by C_{IR} and C_{MI} respectively is more in data from scanner-2 relative to scanner-1.

Next, we note from Figure 5, that the C_M values are high for both windowed and non-windowed b2000 data in most of the cases. Such a trend is to be expected since b2000 offers higher contrast of the lesions relative to the b1000 data [7]. In our dataset, it was found that there was only one volume where the lesions occurred in contra-lateral locations in the

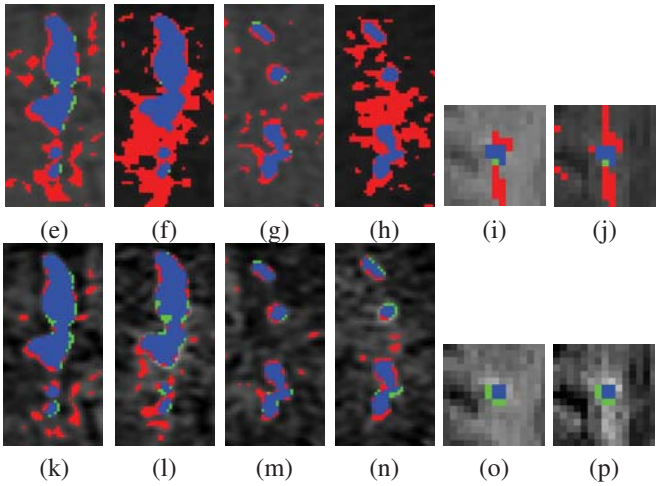

Fig. 8. Segmented lesions of data from Scanner 1 and 2. (e)-(j) Segmented results of images in Figure 7(a), 7(c), 7(e), 7(g) (Before Windowing). (k)-(p) Segmented results of images in Figure 7(b), 7(d), 7(f), 7(h) (After Windowing). Blue:TP, Red:FP and Green:FN.

same slice (shown in Figure 7(a)).

Overall, the quantitative assessment of the proposed method indicates that the method results in a significant improvement in the contrast of the lesion relative to global brain tissue background *and* relative to the local background. It is also noteworthy that the reported results are obtained over datasets with different acquisition protocols. This demonstrates the robustness of the method.

Sample windowed results with the original data are shown in Figure 7. It can be observed that the detectability and the extent of the lesion boundaries is improved as well as the background noise is suppressed in the auto-windowed results which offers much more discrimination between the lesions and the normal brain tissue.

In order to further validate the gain in local contrast and assess the gain which can be expected in segmentation with the proposed windowing approach, the coarse segmentation method described in section III-C was employed on the windowed data and the results were compared with the ground truth obtained from experts (neuro-radiologists). Sample colour coded segmented results are shown in Figure 8. The colour code is as follows: blue, red and green pixels indicate true-positive (TP), false-positive (FP) and false-negative (FN) pixels respectively. The results show that windowing helps in a) reducing the FPs significantly and b) capturing the true extent of the lesions. Future work will include further improvement and an in-depth validation of the segmentation results.

V. Perception Study and Results

The proposed windowing scheme generates results where the lesions appear bright and can easily be distinguished thus increasing the discriminability of the lesions. However, in order to assess the clinical significance of such results, a validation from the expert radiologists was required. In view of this, a perception study was conducted with the hypothesis that the response time (RT) in identifying the number of lesions in a presented slice of a DWI dataset is less in case of windowed result as opposed to the case of an original image. The experiment was conducted with different radiologists with varied years of experience. In this section, the proposed experiment that was done as part of the perception study and analysis of the obtained results of the experiment is presented.

TABLE II
Quantitative Comparison of Results Across Scanners.

Scanner	C_{MI}		C_{IR}	
	b1000	b2000	b1000	b2000
Scanner1	23.59%	53.51%	21.39%	25.13%
Scanner2	39.73%	62.82%	34.67%	25.82%

A. Experiment Setting

The objective of the experiment was to note the RT of the radiologists in identifying if the presented slice of DWI is normal or abnormal.

1) Stimuli: The stimuli used for the experiment was a set of windowed and original DWI slices. This set comprised of normal and stroke slices with different sized lesions, of different b-values and obtained from two different scanners. The categorical distribution of the slices is shown in Figure 9. For each category 4 slices were chosen (2 from each scanner) therefore amounting to a total of 64 slices.

2) Participants: 8 radiologists from Z hospital, with varied years of experience participated in the experiment. The radiologists were broadly classified into two groups of *Experts* and *Learners* as shown in table III.

3) Method: Each of the radiologists was randomly presented with the stimuli and the RT of classifying the presented slice as normal or abnormal (binary output) was noted. The expectation of the experiment was reduction in the mean RT for classification of windowed data against that of the normal data.

4) Experiment Environment: The RT of the radiologists were accurately noted using the DirectRT software which is designed for cognitive and perception tasks that require millisecond precision. The experiment was set up in the hospital environment on the monitor regularly used by the radiologists for analysing patient data in order to avoid introducing bias in the measured RT due to different monitor settings (resolution, contrast, brightness settings). The participants were presented with few samples slices to get them acquainted with the functioning of the software.

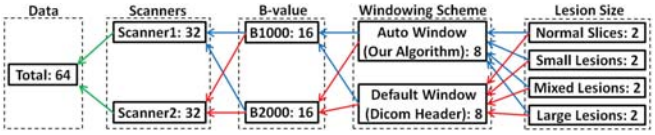

Fig. 9. Categorical distribution of the stimuli for the perception study. For each sub-category the number of slices is shown.

TABLE III
EFFECT OF WINDOWING ON OBSERVERS WITH DIFFERENT EXPERTISE LEVELS.

Category	Radiologist	Years of Experience	Reduction in Mean RT (%)	P-value (t-test Outcome)
Experts	E1	29	17.22	0.000657
	E2	20	14.11	0.019214
	E3	17	11.17	0.000846
Learners	L1	4	15.32	0.010151
	L2	4	14.12	0.014375
	L3	3	11.18	0.025503
	L4	2	8.10	0.015574
	L5	0.6	11.47	0.042163

TABLE IV
EFFECT OF WINDOWING ON DETECTING LESIONS OF DIFFERENT SIZES.

Category	Radiologist	Percentage Change in RT			
		Small	Mixed	Large	Normal
Experts	E1	-17.85	-30.48	-13.60	+1.22
	E2	-18.47	-2.34	-29.06	+0.45
	E3	-16.24	-23.75	-9.11	+0.26
	Mean	**-17.52**	**-18.86**	**-17.26**	**+0.64**
Learners	L1	-36.43	-22.75	+3.02	-9.10
	L2	-33.14	-16.88	-14.25	+6.04
	L3	-23.33	-25.20	-6.69	-0.43
	L4	-7.50	+6.42	-11.09	-16.56
	L5	+5.63	-16.45	-4.95	-22.72
	Mean	**-18.95**	**-14.97**	**-6.79**	**-8.55**

B. Results of Perception Study

First, we examine the response time for decision making by an observer. Table III gives the results of the RT obtained for different radiologists. The t-test was used to ascertain the statistical significance of the obtained results. The p-value listed in Table III characterizes the significance, with a $p < 0.05$ indicating a high degree of statistical significance. The mean RTs can be seen to be reduced by 14.17% & 12.04% for *Experts* and *Learners* respectively. Thus the analysis strongly contributes to the initial expectation. It is noteworthy that there is no observable trend in the RTs across expertise levels.

Next, we studied the effect of windowing and size of lesions on the RT. The results of such an analysis are presented in Table IV. The (-) sign indicates a reduction while a (+) sign indicates increase in RT with windowing. Overall, it is apparent that windowing serves to reduce the RT for the learner group for slices with smaller lesions more than mixed or larger ones. Detection of small-sized lesions in the data is crucial and the most difficult task in abnormality detection and hence these results are attractive. In contrast, the reduction in RT does not seem to depend much on the lesion size for the expert group. An interesting outcome is the trend observed for normal slices across expertise levels. *Experts* took marginally more time to analyse normal slices after windowing. Whereas the average RT is reduced for the *Learners*. The normal data in the stimuli contained slices with shine-through artifacts. Thus reduction in RT validates the utility of windowing for the *Learners*. The cautious decision making of the *Experts* in ruling out artifacts, enhanced after windowing could possibly lead to the marginal increase in the RT.

VI. CONCLUSIONS

A novel automated windowing technique was presented for diffusion weighted MRI. The technique was shown to significantly improve the contrast of ischemic stroke lesions present in the DWI scan. The proposed method is effective for different b-valued DWI scans (b1000 and b2000) and robust to data acquired from different scanners with different acquisition processes. The qualitative and quantitative results reported in this study show promise in the proposed method. Improvement in the lesion definition suggests the effectiveness of the approach as pre-processing step for contrast enhancement in a segmentation framework. The perception study performed with expert radiologists and detailed analysis of the results indicates the effectiveness of the algorithm for clinical usage from the radiologist's point of view. The presented results and the extensive evaluation validates the method and it may play an important role in diagnosis of ischemic stroke in clinical trials.

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