Evaluating Intensity Standardization and Inhomogeneity Correction in Magnetic Resonance Images

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Abstract - **Image intensity standardization is a recently developed postprocessing method designed for correcting acquisition-to-acquisition signal intensity variations inherent in MR images [1]. Inhomogeneity correction is a method used to remove the low spatial frequency background non-uniformities that exist in MR images. Both these procedures have important implications for MR medical image segmentation, registration and image analysis. The effects of these post-processing operations on improvement of image quality in isolation has been well documented [1,2,3]. However, the combined effects of these two processes on MR images has not been studied thus far. In this paper, we evaluate the effect of inhomogeneity correction followed by standardization on MR images and vice-versa, in order to determine the best sequence to follow for enhancing image quality. We found that improved standardization was achieved by preceding it with correction, and image inhomogeneity was greatly reduced by standardizing and then corecting.**

I. INTRODUCTION

Image intensity variations due to RF field inhomogeneities may be caused due to a number of different factors, including poor RF coil uniformity, static field inhomogeneity and RF penetration. Most image processing and analysis methods are affected by these variations, especially if quantitative analysis is the final goal [2,3]. In this paper, we use the scale-based technique described by Zhuge et al. [2] to correct background intensity variations in acquired images. Another major difficulty in MR image analysis has been that intensities do not have a fixed meaning, not even within the same protocol, body region, or even for images obtained on the same scanner. For most postprocessing applications, this lack of a standard and quantifiable interpretation of image intensities is a major drawback. In this paper we use a technique devised by Nyul and Udupa [1], which transforms images nonlinearly, so that there is a significant gain in the similarity of the resulting images. In [2] it was found that inhomogeneity correction reduced the normalized standard deviation of the intensity within any, but the same, tissue region in the brain. Nyul and Udupa in [1] found that standardization significantly minimized the variation of the overall mean intensity of the MR images within the same tissue region across studies. Although it has been established that both these techniques are important from the view point of automated quantitative MR image analysis, thus far, their effects have been studied only in isolation. The aim of this study is to find the correct sequence of standardization and correction operations on the image that will produce better overall image quality. In our methodology, we performed two sequences of operations on a database of MR images. the first sequence involved inhomogeneity correction on the image, followed by standardization. In the second sequence, we reversed the steps. The normalized mean intensity (NMI) and normalized standard deviation (NSD) were computed within the white matter (WM) and gray matter (GM) regions of the brain for the results from the two sequences for each data set. The results from the two sequences, were then evaluated for image quality based on the NSD value and the variance of the NMI within the WM and GM.

II. OUR METHODOLOGY

We denote by α_1 the sequence wherein the image is first corrected for inhomogeneity variations and subsequently standardized, and by α_2 the sequence wherein image standardization is followed by intensity correction. We deonte the set of all MRI protocols by $\mathcal{P}$ and the set of body regions by $\mathcal{D}$. We represent a volume image by a pair $\mathcal{V}=(V,g)$, where V is a 3-dimensional array of voxels covering a body region of the particular patient for whom the image data set $\mathcal{V}$ is acquired, and g is a function that assigns an integer intensity value for each $v \in V$. We denote by $\mathcal{V}_{PD}$ the set of all images that can possibly be generated as per a given protocol $P \in \mathcal{P}$ for a given body region $D \in \mathcal{D}$. Before initiating sequence α_1 or α_2, we perform the following operations on the input image $\mathcal{V}_i = (V_i, g_i) \in \mathcal{V}_{PD}$. We first apply inhomogeneity correction to the input image $\mathcal{V}_i$ to suppress any background variations that may be present. The resulting image is denoted by $\mathcal{V}_{ic}$. To $\mathcal{V}_{ic}$ we introduce a known

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background variation $\mathcal{V}_a$. In our study, we used multiplicative Gaussian variations. The resulting image was obtained as $\mathcal{V}_{ica}=\beta\mathcal{V}_a\mathcal{V}_{ic}$. We used the variable β to control the percentage of total non-uniformity introduced into $\mathcal{V}_{ic}$. In sequence α_1, we first performed correction on the image volume $\mathcal{V}_{ica}$ to obtain $\mathcal{V}_{icac}$. Next we performed standardization on this image, which gave us $\mathcal{V}_{icacs}$. For the training step of the standardization procedure [1], we used a set of $\mathcal{V}_{icac}$ such that $\mathcal{V}_i \in \mathcal{V}_{PD}$. In the second sequence α_2, we first performed standardization on $\mathcal{V}_{ica}$ to obtain $\mathcal{V}_{icas}$. A set of $\mathcal{V}_{ica}$ was used during the training phase. This was followed by correction to give $\mathcal{V}_{icasc}$. Having obtained $\mathcal{V}_{icasc}$ and $\mathcal{V}_{icacs}$, we used fuzzy connectedness [4] to segment the brain region in our data sets into white matter and gray matter. Any errors in segmentation as determined visually by an expert were corrected. Next, we computed the normalized mean intensity (NMI) and standard deviation (NSD) for segmented white matter (WM) and gray matter (WM) regions for $\mathcal{V}_{icacs}$, $\mathcal{V}_{icasc}$ and $\mathcal{V}_{icas}$ in each of the twelve patient data sets. We also computed the standard deviation of the NMI (σ_{NMI}) over all the 12 data sets for both WM and GM. We then performed a paired t-test on the NSD values obtained for $\mathcal{V}_{icacs}$, $\mathcal{V}_{icasc}$ and $\mathcal{V}_{icas}$ for WM and GM.

III. RESULTS

Tables 1,2 and 3 show the σ_{NMI} and mean NSD values for twelve patient data sets for segmented WM and GM regions using proton density weighted images for a multiplicative Gaussian background with β=0.25, β=0.3 and β=0.5 respectively. In table 4, we list the p-values for the paired t-test on the NSD values for the 3 pairs among $\mathcal{V}_{icacs}$, $\mathcal{V}_{icasc}$ and $\mathcal{V}_{icas}$ for the case β=0.25.

TABLE 1

	$\mathcal{V}_{icas}$		$\mathcal{V}_{icacs}$		$\mathcal{V}_{icasc}$	
	WM	GM	WM	GM	WM	GM
σ_{NMI}	.0291	.0290	.0274	.0283	.0291	.032
NSD	.0455	.0452	.0452	.0447	.0438	.043

IV. CONCLUSIONS

In this paper, we have described a methodology for determining the effects of standardization on correction and vice-versa, in order to find the best sequence to be followed on an MR image from the perspective of quantitative image analysis. In the first step, we performed correction on the image followed by standardization, and in the second step, we reversed the processes. The results obtained from the two sequences were compared with one another and with the result obtained by only standardizing the image. The results seem to agree with our intuitive reasoning behind both the standardization and correction procedures. To evaluate the results of standardization, we computed σ_{NMI} for $\mathcal{V}_{icacs}$, $\mathcal{V}_{icasc}$ and $\mathcal{V}_{icas}$. It was found that in all cases, $\mathcal{V}_{icacs}$ had the smallest σ_{NMI}, implying that correction before standardization, produces better standardization results than just standardization or standardization followed by correction. Further, we found that in most cases σ_{NMI} for $\mathcal{V}_{icas}$ was better than $\mathcal{V}_{icasc}$. This is because correction introduces a small bias into the images. For evaluating, inhomogeneity correction, we examined NSD values for $\mathcal{V}_{icacs}$, $\mathcal{V}_{icasc}$ and $\mathcal{V}_{icas}$. We found that $\mathcal{V}_{icasc}$ outperformed $\mathcal{V}_{icas}$ and $\mathcal{V}_{icacs}$, except at high values of β, when the values were fairly similar. We found no statistically significant difference between the NSD values for $\mathcal{V}_{icas}$ and $\mathcal{V}_{icacs}$ at lower values of β. In conclusion, we believe that when standardization is the final goal, it should be preceded by correction (i.e. α_1). On the other hand the results of correction are improved by performing standardization first (i.e. α_2). In general, the results of both α_1 and α_2 for standardization and correction respectively, were better than just standardization alone.

TABLE 2

	$\mathcal{V}_{icas}$		$\mathcal{V}_{icacs}$		$\mathcal{V}_{icasc}$	
	WM	GM	WM	GM	WM	GM
σ_{NMI}	.0290	.0289	.0251	.025	.0306	.033
NSD	.0455	.0452	.0453	.044	.0446	.044

TABLE 3

	$\mathcal{V}_{icas}$		$\mathcal{V}_{icacs}$		$\mathcal{V}_{icasc}$	
	WM	GM	WM	GM	WM	GM
σ_{NMI}	.1129	.109	.1063	.105	.1118	.111
NSD	.0668	.055	.0597	.053	.0592	.053

TABLE 4

	WM	GM
$\mathcal{V}_{icas}$ - $\mathcal{V}_{icacs}$	.2866	.2749
$\mathcal{V}_{icas}$ - $\mathcal{V}_{icasc}$	.0433	.0840
$\mathcal{V}_{icacs}$ - $\mathcal{V}_{icasc}$	.0031	.0075

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