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Inhomogeneity correction and fat-tissue extraction in MR images of FacioScapuloHumeral muscular Dystrophy

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ABSTRACT

The paper proposes an automatic algorithm for the fat- and muscle-tissue delineation in the Magnetic Resonance Image data of the patient's leg with FacioScapuloHumeral muscular Dystrophy. The algorithm corrects the tissue inhomogeneity with a novel method that produces good results with low computation time and complexity. The estimated bias field is modelled as a multiplicative noise and uses low-pass filtering to obtain smoothness of the form. To reduce the impact of the background low-level intensity on the object high-level intensity, the background is remodified. The inhomogeneity correction method is validated by comparing its results with those of a simulated ground-truth image. In the segmentation procedure, fuzzy c-mean clustering is used. The segmentation results of the automatic algorithm are comparable to the medical-specialist annotations with a similarity index above 0.91, indicating an excellent result of the proposed automatic processing.

1. Introduction

The purpose of the paper is to describe an automatic and time-efficient algorithm for accurate delineation between the fat and muscle tissue in the multi-slice T1-weighted Magnetic Resonance images (MRI) of the human calves as an aid in clinical diagnosis of FacioScapuloHumeral muscular Dystrophy (FSHD) (The FSH-DY Group, 1997; Olsen et al., 2006). FSHD is one of the most common types of muscular dystrophy, with an estimated prevalence of 1:20,000. The FSHD patients often experience pain during exercise, which may be related to "hidden" or asymmetric patterns of the muscle weakness. The fat infiltration tends to affect the perivascular tissues of the perimysium before replacing the vascular muscle fibres and could be used as a marker in analysing of the disease progression (Stramare et al., 2010). MRI of the lower legs may therefore be a helpful tool in assessing the muscle involvement before starting a training program.

The classic adipose measurements have been based on the weight or Body Mass Index (BMI) (Ferrera, 2006). Recently, the MRI-based technologies have emerged as a powerful tool for refined adipose assessment (Broderick et al., 2010; Johnson et al., 2009; Alizai et al., 2012; Elder et al., 2004; Wattjes et al., 2010; Gloor et al., 2011). Imaging can detect not only the fat area, but also its location. However, the area being irregularly shaped and at various location in the body, its manual segmentation is difficult and much time consuming for medical specialists. Hence, automatic algorithms should be helpful.

The MRIs are often corrupted by a common artefact known as a bias field (or inhomogeneity) that strongly affects the computerized analysis (Prescott et al., 2009; Broderick et al., 2010; Urricelqui et al., 2009). Commonly, the presence of a multiplicative inhomogeneity can significantly reduce the image segmentation accuracy (Garcia-Sebastian et al., 2007), hence decreasing the reliability of the subsequent quantitative measurements. The corrupted pixels within the same class cannot be recognized correctly or are even unrecognizable without having the image pre-processed. The segmentation algorithm that is presented in the paper is based on the pixel-intensity assumption and therefore, is focused on the pre-processing to eliminate the inhomogeneity in the tissue classes (Brooks, 2003). Usually, it is difficult to locate and characterize the tissue inhomogeneity automatically. Most of the existing methods (Milles et al., 2007; Hou, 2006) assume that the bias field is smooth compared to the true image with a relatively mild intensity inhomogeneity. This is why the bias-field assessment models use the theory of spline, polygons exponent two, advanced smoothing filters, etc. Unfortunately, to be identified separately, different tissue components require complex mathematical analysis, which can be useless for partial problems and much time consuming in a multi-scale analysis. Furthermore, most approaches rely on the assumption that all the tissue classes are homogeneously distributed in the MR data.

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Frequently, the methods used to correct the inhomogeneity of the human leg MRI are N3 (Sled et al., 1998), BCFCM (Ahmed et al., 2002) and homomorphic filter (Gonzalez and Woods, 2002). These correction methods cannot be generalized for the medical data of just any type. For each type of the medical data, the method with the best performance should be selected individually through a comparative analysis. Prescott et al. (2011) shows that by using the N3 method, the bias field presented in MRI of the human thigh could not be adequately removed. Moreover, the localized correction was unsuccessful and for some data his algorithm performed poorly. Therefore, to improve the correction results for the thigh and calf MRI, we propose a new method for the tissue inhomogeneity correction and compare it with the well-known methods.

The proposed method requires no training phase and its complexity is low. The bias-field is estimated as a multiplicative smoothed intensity map with a Gaussian low-pass filter. To decrease the impact of the low-level background intensity on the higher-level intensity of the object, the background is modified using a 2D polar-coordinate system.

Effectiveness of the tissue-inhomogeneity correction can be determined by having the segmentation results comparatively analysed (Garcia-Sebastian et al., 2007; Siyal and Yu, 2005). Therefore, the Zijdenbos Similarity Index (ZSI) (Zijdenbos et al., 1994) was used to examine similarity of the automatic segmentation results with the medical-specialist annotations. The coefficient of variations λ (Boyes et al., 2008) – that was used to numerically measure the tissue inhomogeneity – was compared to the coefficient of variations of other methods. Finally, the additive noise was reduced by using a bilateral filter (Bhonsle et al., 2012). Preprocessing for each 2D slice was performed separately.

The tissue inhomogeneity having been corrected, the fat tissue can now be extracted. Some of the several segmentation methods used for this purpose (Prescott et al., 2011; Wang et al., 2007) propose to delineate the fat tissue area with a simple histogram (the pixel number versus the signal intensity) thresholding obtained manually by analysing the histogram. Mathematically more complex methods use automatic threshold calculation, such as fuzzy-logic techniques. They follow connectivity rules for grouping pixels in homogeneous regions. In the presented application, the most frequently used in the human-leg analysis (Kang et al., 2011; Broderick et al., 2010; Peijie et al., 2010; Alkan, 2011; Positano et al., 2009), the fuzzy c-mean clustering (FCM) method was applied. The 4-class clustering (4-class FCM) was performed for each slice to obtain an adaptive threshold for the fat and muscle delineation.

2. Materials

In our analysing of the muscular dystrophy, 108 T1-weighted MRIs of ten patients were used. The T1-weighted images were chosen for providing us with the information of fat distribution. MRIs were captured by employing the 1.5T GE Medical System. Imaging was performed by using a T1-weighted axial slice (TR = 4 ms and TE = 20 ms sequence times) placed over the lower body with a separation of 10 mm between slices. Conversion to the 2D grayscale images (512×512 pixels) was performed using the program MRIcro. Images of the leg below the knee (calf) were chosen for containing the muscle structure of the research interest.

MRIs highlight the variations in the human tissue through different intensities of the grayscale. The T1-weighted MRIs of each FSHD patient contain the skin, bone (bone marrow and cortical bone), muscle tissue and fat tissue. Anatomically (Broderick et al., 2010; Urricelqui et al., 2009), the human calf consists of two bones (fibula and tibia) that appear in the T1-weighted MRI scan with the highest intensity (close to white) for the bone marrow and with the lowest intensity for the cortical bone (close to black). The muscle tissue appears as a medium grayscale intensity. The intensity levels of the fat tissue of the FSHD patients are similar to those of the bone marrow. The fat tissue is located within and around the muscle tissue. Finally, the skin tissue surrounds the outer fat tissue and its intensity is similar to that of the muscle tissue.

3. Description of the proposed algorithm

In our research, all the algorithmic stages were performed for the 2D slices and were verified by a medical specialist. The parameters used in pre-processing were assessed once and remained unchanged for all the used data. Our algorithm consists of four stages: (i) calf-region registration; (ii) background removal; (iii) inhomogeneity correction and (iv) segmentation.

3.1. Calf-region registration

In the registration procedure, was separated the input MRI into sub-images with either the left or right calf only, so that they could be processed independently. Three intensity profiles were computed for the input MRI. The intensity profiles were evaluated first on the x-axis to estimate the initial separation and then on the y-axis to retrieve the two regions of interest containing either the left or right calf only. The x-axis profile was obtained by summarizing the pixel intensities in columns. A relatively small threshold (for a normalized image it is 0.05) was used on this profile. The obtained non-zero regions indicate the initial object positions and are then used to obtain the two sub-images. Further, for each sub-image its intensity profile on the y-axis was calculated to obtain the region of interest by thresholding.

3.2. Background removal

The most common solution to remove the background is direct thresholding an image. However, if the inhomogeneity is strong, thresholding cannot be applied. In such case, one may use the region-growing procedure to group pixels based on predefined criteria. Combining the region-growing procedure with morphological filtering proposed in Wei et al. (2008) guarantees the background noise to be completely reduced.

In our approach, the region is formed from a set of points having their properties similar to those of the seed points. The calves lie in the central region of the image and their boundaries are closed. Moreover, the noise values on the background are of a lower intensity than the values on the calf boundaries. Therefore, the seed pixels were selected on the four image corners. The intensity difference between the neighbour pixels is used as the criterion for region growing. Region growing is followed by morphological opening to reduce small artefacts from the background. By the removing the background, an object mask is generated for further processing.

3.3. Inhomogeneity correction

One of the main goals of the image pre-processing is to increase the segmentation-step efficiency by increasing the image quality to obtain more accurate results. The input – image equation is shown in (1), where $\hat{I}(X)$ is the acquired image, $B(X)$ is the multiplicative non-uniformity or multiplicative bias component, $I(X)$ is the true image without bias, and $N(X)$ is the additive noise or additive bias component supposed to be the additive zero-mean Gaussian noise. The goal of the inhomogeneity or the bias-correction procedure is to estimate $I(X)$.

$$\hat{I}(X) = I(X)B(X) + N(X), \quad X \in R^2 \tag{1}$$