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Multi-Atlas Segmentation with Improved Pair-Wise Dependency Estimation in Joint Label Fusion

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ABSTRACT: Multi-atlas segmentation is a best way of segmenting object of interest in medical images. In multi-atlas segmentation multiple segmented images of object of interest called atlases are registered to a target medical image. Then these images are combined using label fusion. Among the label fusion methods, local weighted voting methods assigning weights to the regions in target image based on atlas and target intensity similarity are well used. In these methods the weights are calculated independently for each atlas but the limitation is different atlases produce similar label errors. In this paper the proposed method assigns weights based on the pair wise dependency between atlases. This dependency between atlases is termed as the joint probability of two atlases making a label error at a region. The probability is measured by the intensity similarity measure between the atlas and target image. The intensity similarity measure is calculated based on the gradient correlation values between atlas and target images. This method is applied on medical MR image of brain. The different parts in the axial cut of the brain MR image are segmented.

KEYWORDS: Multi-atlas Segmentation; Label Fusion; Image Registration

I. INTRODUCTION

Atlas based segmentation use a prior knowledge about the shape of the segmented structure in a simple way, by using a pre-segmented image called atlas as a reference that guides the segmentation. This technique is more advantageous when compared to other segmentation techniques, such as level sets or watersheds. This process can be applied to wide range of image modalities and segmentations [1], [2], [3].

In principle, a single atlas image is sufficient for segmenting target images. However, by using multiple atlas images for segmenting target image can yield better results. The major advantage of multi atlas segmentation is the error produced by single atlas can be diminished by the fusion of remaining atlases.When there is more number of atlases to be used then the computational cost is increased as a proportion to the number of atlases used. However it is also to be considered, that is the atlases used may be different with target image we should consider the age, pathology etc. we should use the atlases which are coinciding with the candidate segmentation for the segmentation of the target image. Theses atlases are to be used for propagation of labels and segmenting the object of interest in the target image. These atlases will produce the better segmentation results. Instead of selecting one manually labelled image as an atlas, the atlas is constructed from a more number of images. From a given set of reference images, information from several reference images can be combined into an average atlas or [4], [5], if probability values for each particular location are included, this is called as probabilistic atlas[6],[7]. However to have more advantage from the multiple atlases, each atlas is to be registered to the target image to be segmented and then formed segmentations are combined by a label fusion method to produce the final segmentation.

There are mainly two fusion strategies one is global fusion strategy and the other is local fusion strategy. The global fusion strategy assigns a global weight to the each segmentation of the target image by each atlas. This global weight is calculated based on the parameter called segmentation accuracy[8], [9].Finally fusion is done region by region. The local fusion strategy assigns the weights to each region in the segmentation of the target image by each atlas. The local weights are spatially varied in the segmentation of target image. These local weights are assigned based on the local similarity measure. These local fusion strategies are most successful[10], [11]. In this paper we used the local fusion strategy with new approach. Here also the final segmentation is done region by region.

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II. RELATED WORK

In the local weighted voting method, the weights are calculated and assigned region by region. The labels in the each atlas image are propagated to the target image. Every atlas is registered to the target image and produces a particular segmentation. Mainly the errors in the multi atlas based segmentation are due to the registration error. Each atlas will produce different weights to the regions in the target image. Each atlas will produce label errors. Label error means the difference between the labels of each atlas and the target segmented image. In this local weighted voting method the weights are calculated independently for each atlas. The different atlases may produce similar label errors. Suppose if we have an atlas which is repeated twice, the total weight given in the final segmentation will be increased as a proportion to the number of times the atlas is repeated. So it will be difficult to correct the error produced by the repeated atlas.

The majority voting label fusion methods give voting to the atlas globally or locally by matching. It leaves the information from the less matched atlas[12]. This method is also less efficient to the problem of repeating atlases because the atlas repeated will be included only if it is matched best with the target image or else it is eliminated from the set. This method is applicable when the atlas set has atlases similar to the target image. In this paper a label fusion strategy that reduces problem raised by having the repeated atlas in the atlases set without leaving properties of voting. In this method the weights are calculated based on the minimizing of the expected total error of the present segmentation related to final segmentation.It requires the joint probability of the pair of atlases producing the similar segmentation error at a particular region [13]. It is estimated based on the intensity similarity. In this method the weights are minimized for the repeated atlas. The weight minimization is depended on a pair wise dependency of the atlases.

III. PROPOSED ALGORITHM

A.*MULTI ATLAS BASED SEGMENTATION:*

In the multi atlas segmentation let F_t be the target image to be segmented. $A_1, A_2, \ldots, A_n$ be the n atlases. $A_1 = (F_1, S_1), A_2 = (F_2, S_2) \ldots A_n = (F_n, S_n)$ in which F_i and S_i denote the ith wrapped atlas image and the respective manual segmentation of the atlas, obtained by performing deformable image registration to the target image.Each atlas produces a candidate segmentation of target image. Each of these candidate segmentations contains some segmentation errors. Label fusion combines all of these candidate segmentations and produce final segmentation with more segmentation accuracy. The majority voting method assumes that the errors produced by the use of different atlases are not similar and reduce label errors.It simply counts the votes for eachlabel from each wrapped atlas and chooses the label receivingthe high votes to produce the final segmentation$\hat{S}_T$:

$$\hat{S}_T(x) = \underset{l=\{1\ldots L\}}{argmax} \sum_{i=1}^{n} S_i^l(x), \qquad (1)$$

Where$l$, is an index through number of labels and L is the total number of labels, $x$pass through image pixels.$S_i^l(x)$Is the vote for the label l produced by the ith atlas, defined by

$$S_i^l(x) = \begin{cases} 1 & if\ S_i(x) = l; \\ 0 & otherwise. \end{cases} \qquad (2)$$

The label fusion accuracy can be improved by assigning weights locally based on the local appearance similarity. It assigns higher weights to the more accurate segmentations. The votes received by the label l is

$$\hat{S}_T^l = \sum_{i=1}^{n} w_i(x) S_i^l(x), \qquad (3)$$

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Where $w_i(x)$ is a local weight assigned to the ith atlas, with$\sum_{i=1}^{n} w_i(x) = 1$. The weights are estimated based on the local image similarity under the assumption that similar segmentations are proportional to similar appearances. Summed Square Distance and Gaussian weighting model are used the weights can be estimated by

$$w_i(x) = \frac{1}{Z(x)} e^{-\sum_{y\epsilon N(x)} \frac{[F_T(y)-F_i(y)]^2}{\sigma}}, \quad (4)$$

Where $N(x)$ defines a neighborhood around x.$Z(x)$is a normalization constant. By estimating based on the local appearance dissimilarity, the inverse distance weighting is as follows

$$w_i(x) = \frac{1}{Z(x)} [\sum_{y\epsilon N(x)} (F_T(y) - F_i(y))^2]^{-\beta} \quad (5)$$

In above two equations σ and β are parameters that control weight distribution. In above methods they assign the weights independently for each atlas. Here theβ is chosen to be 1. These methods do not concentrate on the label errors which are produced by different atlases are related. By this, the weights can be assigned proportional to the dependency of atlases. It is done as follows.

B. *JOINT LABEL FUSION:*

The each region in the target image is labelled and also the regions are labelled by the atlas. Here the binary segmentation is considered for simplicity of calculations. The segmentation errors are modelled as follows

$$S_T(x) = S_i(x) + \delta^i(x), \quad (6)$$

Where $\delta^i(x)$ is the label difference of atlas and target image at the region x. Let $\bar{S}$(x) is a consensus segmentation obtained by the weighted voting.

$$\bar{S}(x) = \sum_{i=1}^{n} w_i(x) S_i(x), (7)$$

Where $w_i(x)$ are spatially varying weights. Here we should find the weights that reduce the total expected errorbetween $\bar{S}$(x)and $S_T(x)$, given by

$$E_{\delta^1(x),\dots,\delta^n(x)}[(S_T(x) - \bar{S}(x))^2 | F_T, F_1, \dots, F_n]$$

$$= \sum_{i=1}^{n} \sum_{j=1}^{n} w_i(x) w_j(x) E_{\delta^i(x)\delta^j(x)}[\delta^i(x)\delta^j(x) | F_T F_1, \dots, F_n]$$

$$= w_x^t M_x w_x, \quad (8)$$

Where $w_x = [w_1(x);\ w_2(x); \dots; w_n(x)]$ and t is the transpose. $M_x$is the pair wise dependency matrix

$$M_x(i,j) = E_{\delta^i(x)\delta^j(x)}[\delta^i(x)\delta^j(x) | F_T F_1, \dots, F_n] \quad (9)$$

Here the $M_x(i,j)$ estimates how the two atlases are dependent to produce the segmentation error for the target image. For achieving the better label fusion the weights are assigned such that the label difference is minimized

$$w_x^* = \underset{w_x}{argmin}\, w_x^t M_x w_x, \text{ Subject to } \sum_{i=1}^{n} w_x(i) = 1 \quad (10)$$

By using the Lagrange multipliers we minimize weights as follows

$$w_x = \frac{M_x^{-1} 1_n}{1_n^t M_x^{-1} 1_n}, \quad (11)$$

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The pair wise dependency matrix M_x is estimated based on the joint probability of pair of atlases producing an error at a region. This probability is calculated based on the intensity similarity measure, which is calculated between target image and the atlas. Here two atlases are considered, so we should calculate the intensity similarity measure independently for each atlas. In this approach we use the gradient correlation coefficients for the estimation of the intensity similarity measure.

The gradient correlation is done by using the sobel operator. Horizontal sobel operator and vertical sobel operators are applied on the atlas and the target image. Sobel masks are applied to the each of the atlases and target image. The vertical sobel operator and horizontal sobel operator are applied to produce the horizontal and vertical gradients. Hence the horizontal gradient image and vertical gradient image of target and atlas is formed. Now the normalized cross correlation coefficients of horizontal gradients of target and atlas are found andcross correlation coefficients of vertical gradients oftarget and atlas is also found. The final gradient correlation is the sum of the both vertical and horizontal normalized cross correlation coefficients. It is shown as follows

$$GC = \frac{\sum_{x,y}(\partial_x F_T)(\partial_x F_i)}{\sqrt{\sum_{x,y}(\partial_x F_T)^2}\sqrt{\sum_{x,y}(\partial_x F_i)^2}} + \frac{\sum_{x,y}(\partial_y F_T)(\partial_y F_i)}{\sqrt{\sum_{x,y}(\partial_y F_T)^2}\sqrt{\sum_{x,y}(\partial_y F_i)^2}} \quad , \qquad (12)$$

$$\partial_x F_T = \frac{\partial F_T(x,y)}{\partial x} \text{ , it is the Horizontal gradient}$$

$$\partial_y F_T = \frac{\partial F_T(x,y)}{\partial y} \text{ , it is the Vertical gradient}$$

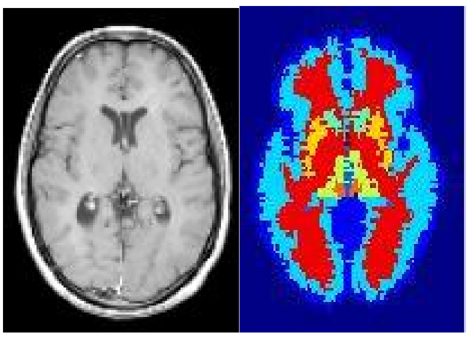
Based on these gradient correlation values the labels in the atlas are transferred to the target image. The label error is found by the label difference in the target image and the atlas image. For the second atlas also the same gradient correlation values are found and based on this the label error is found. By these label errors the probability of the segmentation error at the region is found for each atlas. From the probabilities of each atlas image the joint probability of the two atlases. The joint probability is just the multiplication of both probabilities. From the joint probabilities the pair wise dependency matrix M_x is estimated.

$$M_x(i,j) = \mathrm{P}\,(\delta^i(x)\delta^j(x) = 1 | F_T, F_1, F_2). \qquad (13)$$

Here $\delta^i(x)$ is the label difference of target image and ith atlas. Based on this pair wise dependency matrix the weights are minimized from equation (11).

IV. RESULTS

The experiment is conducted on the brain MR images. The segmentation on the axial cut of brain MR Image is done in this method. This method is done in the matlab. The images are taken from diacom website. Each color indicates the different part in the brain.



a)InputImage b)Atlas Image

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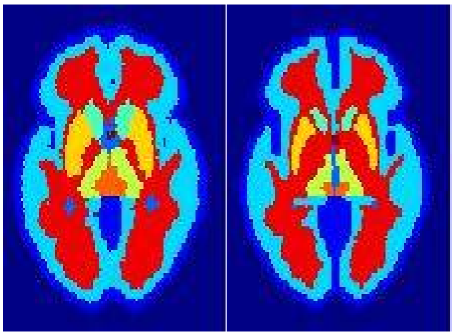

c)LWJoint d)LWproposed

The segmentation accuracy is determined by the Dice Similarity Coefficient (DSC). The DSC is the given by DSC = $2*(S_i \cap S_o) / (|S_i| + |S_o|)$. Here S_i is the reference segmentation and S_o is the output segmentation. Here ∩ means the number of regions overlapped between the reference segmented image and output segmented image and|| represents the number of regions in the segmented part. The values of dsc are in the following table.

Table1. Dice Similarity Coefficient

Fusion Method	DSC
LWJoint	0.83
LWproposed	0.90

V. CONCLUSION

From the results it is shown that the proposed algorithm performs better in the segmentation.Hence a better way of weighted voting label fusion method is proposed.In this method, by using the local intensity similarities we calculated the pair wise dependency between atlases. This method mainly concentrates on this pair wise dependency matrix estimation. By using the better intensity similarity measure, the estimation of the pair wise dependency matrix is accurate and the weights calculated are accurate.Better representing atlases are to be considered for the better segmentation accuracy. Different weights are assigned to the different atlases locally. Based on these weights the combination of these atlases is done. The computational complexity increases when there are more number of atlases are used as a proportion to the number of atlases. We should consider the more similar atlases with the target image.

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