Multimodal Bone Cancer Detection Using Fuzzy Classification and Variational Model

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Abstract. Precise segmentation of bone cancer is an important step for several applications. However, the achievement of this task has proven problematic due to lack of contrast and the non homogeneous intensities in many modalities such as MRI and CT-scans. In this paper we investigate this line of research by introducing a new method for segmenting bone cancer. Our segmentation process involves different steps: a registration step of different image modalities, a fuzzy-possibilistic classification (FPCM) step and a final segmentation step based on a variational model. The registration and the FPCM algorithms are used to locate and to initialize accurately the deformable model that will evolve smoothly to delineate the expected tumor boundaries. Preliminary results show accurate and promising detection of the cancer region.

Keywords: Multimodality image fusion, non-rigid registration, fuzzy classification variational model.

1 Introduction

Accurate segmentation of bone cancer is an important task for several medical applications. For example, it can be helpful for therapy evaluation, treatment planning, modeling of pathological bones, etc. However, this task is a challenging problem because there is a large class of tumor types which vary greatly in size and position, have a variety of shape and appearance properties, have intensities overlapping with normal bone areas, and may deform and defect the surrounding structures. Moreover, the majority of images modalities may contain various amounts of noise and artifacts. Traditionally, bone cancers segmentation is performed manually by marking the tumor regions by a human expert. This process is time-consuming, impractical and non- reproducible. So, a semi or a fully automatic and robust segmentation is highly required in order to generate quickly satisfactory segmentation results. In general, a single medical image modality cannot provide comprehensive and accurate information, so considering more than one acquisition protocols can provide much more useful information about the bone tumor and this can be achieved through image fusion process. Such process is used to derive useful information in order to enhance and taking account

J. Ruiz-Shulcloper and G. Sanniti di Baja (Eds.): CIARP 2013, Part I, LNCS 8258, pp. 174–181, 2013.

the image content by fusing for example computer tomography (CT) image and magnetic resonance imaging (MRI).

Recently, various promising works have studied medical image segmentation, offering a diversity of methods and evaluation criteria [1–5]. However, to the best of our knowledge, only few approaches were proposed in the literature for bone tumor segmentation. Indeed, Frangi et al. in [6] proposed to segment a bone tumor in MR images using a neural network-based classifier approach. Authors used a pharmacokinetic model of the tissue perfusion which can reduce the MR image sequence into three parametric images. A neural network classifier is used to combine temporal and spatial information to determine the tumor region. In [1], a semi-automatic method for gross cancer volume delineation was proposed. It is based on the fusion of pixel intensity from both X-ray, CT and MRI scans. The segmentation process was initialized manually by a physician expert. Statistical shape model has been used also in [3]. In their paper, author proposed an automatic process to segment the Human pelvic bones from CT datasets. Another recently work was proposed in [4] for bone and cartilage segmentation in MRI images of the knee. Their procedure is based mainly on the using of active appearance models (AAM) which is a statistical model of the target shape constructed from manually segmented examples of the Osteoarthritis. Schmid et al. [5] developed a method based on deformable models approach with shape priors to address the segmentation issue of bone structure in MRI. They exploit both prior knowledge and image information for better efficiency. In addition, global shape variation was defined by PCA analysis and local deformation was defined though Markov Random Field (MRF) method.

According to this study, we think that statistical classification, image fusion and active contours are often complementary segmentation strategies. For example, statistical classification can be often successfully applied for a global classification of major anatomical structures, and active contours have been successfully applied to delineate locally the boundary of a particular region. Based on this assumption, we suggest in this paper a new method for bone cancer detection in 2D digitized MRI and CT-scans. This paper is organized as follows. In section 2, we describe the different steps involved in the building of our proposed method for bone cancer segmentation. In section 3, we present and discuss obtained results on different images. Finally, we conclude our paper and point out future research directions.

2 Bone Cancer Segmentation Procedure

We propose a method which operates on MRI and CT scans to segment bone cancer. First, input images are co-registered with a non-rigid deformation algorithm into the same coordinate system, so that we can fuse them properly in the next step. Then, a step of determining a coarse region of the cancer is performed using a fuzzy possibilistic classification method. Finally, a variational model is performed to delineate accurately the bone cancer region. The overall computational steps are illustrated in figure 1.

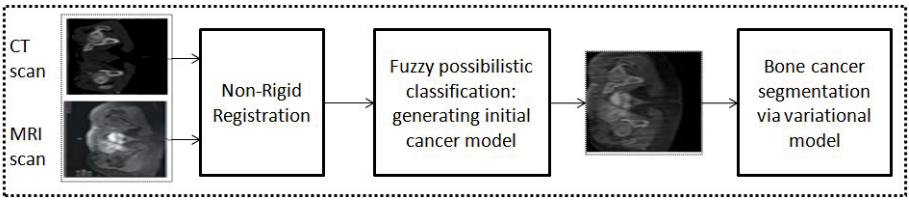


Fig. 1. Proposed method for bone cancer detection

2.1 Non-rigid Multimodal Image Registration

Image registration is the process of aligning two images by computing a geometrical transformation that can match the first image to the second one. Such transformation can be affine, rigid or non-rigid. In this paper, we investigate this line of research by exploiting information of different modalities through a non rigid registration step which is more suitable in our case to match both MRI and CT scans. Over recent years, a number of non-rigid registration techniques have been proposed. Looking at non-linear multi-modal image registration, we choose to apply the registration algorithm proposed in [7, 8] which is based on free-form deformations and cubic B-spline. It has shown to be very robust for multi-modal images even on low quality. More details can be found in their publication.

2.2 Initial Segmentation Using FPCM

Fuzzy classification algorithms have been widely used in medical image analysis due to its ability to model the uncertainty. It is a process of grouping pixels into a fuzzy set [9]. One of the widely used fuzzy algorithms is Fuzzy C-Means (FCM). Indeed, unlike hard clustering algorithms which force pixels to belong to only one class, FCM allows pixels to belong to multiple classes. However, FCM fails to deal with main properties in images given that neighbor pixels are strongly correlated, which results in poor segmentation. To address this problem and to improve the performance of the FCM algorithm in noisy environment, the possibilistic c-means (PCM) clustering [10], has been shown to be more robust as compared with FCM. Nevertheless, PCM also has the disadvantages in its sensitivity to initialization and easily leading to coincident clustering. To overcome this problem, a new mixed Fuzzy Possibilistic C-Means Algorithm (FPCM) was proposed [11]. By combining FCM and PCM, PFCM can simultaneously produce membership, possibilities and the cluster centers for each cluster. It can provide a better insight into how regions are distributed. Moreover, it can solve the noise sensitivity defect of Fuzzy C-Means algorithm and overcomes the problem of coincident clusters of possibilistic C-means algorithm. These desirable properties of FPCM make it suitable to be a basic model of our entire procedure. So, we adopt in our study FPCM in order to classify the target image into appropriate classes. According to Pal et al. [11] that he proposed to use membership

values, as well as typicality values, looking for a better clustering algorithm, this problem is equivalent to an optimization objective function given as follows:

$$F_{PCM} = \sum_{i=1}^{C}\sum_{k=1}^{N}(a\mu_{ik}^{m} + bt_{ik}^{n}) * \|z_k - \upsilon_i\|^2 + \sum_{i=1}^{c} r_i \sum_{k=1}^{N}(1 - t_{ik})^n$$

Subject to the constraints $\sum_{i=1}^{C} \mu_{ik} = 1 \quad \forall\, k; \quad \mu_{ik} \geq 0, \quad t_{ik} \leq 1$ and the constants a, b>0 and n>1.

The parameters a and b define the relative importance between the membership values and the typicality values. μ_{ik} defines the absolutes importance of the membership values and t_{ik} defines the absolutes importance of the typicality values. While detailed proofs are not included, the interested reader can refer to citations and detailed descriptions in the publication [11].

Based on the possibility theory, input images (MRI and CT) are fused in three steps. First, information are modeled in order to manage ambiguous and imperfection information. Second, these information are combined and aggregated though a fusion operator. Such operator must avoid the redundancies and exploit the complementarities between the MR and CT images. Third, a decision step in which the resulted image is classified by taken into account a decision rule such as the maximum of possibility. In other word, each pixel is assigned to an appropriate tissue/structure according to its greatest membership (maximum of possibility). The fusion procedure can be summarized as follows:

1. Information modeling:
   For each pixel in {MRI, CT}:
   We compute the FPCM (for this pixel), i.e the membership degree for both images (MRI and CT).
2. Possibilistic fusion:
   Through FOP operator, we aggregate each class of MRI with the same one of CT.
3. Decision :
   Image is finally classified based on the maximum of possibility rule.

2.3 Variational Model for Cancer Region Detection

Although the FPCM algorithm has been proposed as robust when estimating the cluster center of the image and yields good results when we have high contrast between soft tissues, it fails to segment complex medical images and results in "poor" segmentation when more noise are involved. For these reasons, we propose to perform our developed variational level-set model which is applied successfully in our previous works for 3D brain segmentation [2, 12]. We present in the following briefly this model.

Unlike the traditional parametric active contours-based methods, geometric level set-based methods are considered an appropriate framework for merging heterogeneous information that provide a consistent geometrical representation

suitable for image analysis. Moreover, level-sets do not depend on the parameterizations of the contour/surface and have become popular thanks to its ability to handle complex geometries and topological changes. These advantages make level-set very attractive and flexible in shape modeling and image segmentation. According to Sethian [13], the implicit level set function can be evolved by solving the following PDE (partial differential equations):

$$\frac{\partial \phi}{\partial t} = F.|\nabla \phi| \tag{1}$$

Where F is a scalar velocity (speed) function depending on the local geometric properties (i.e. curvature) and on the external parameters related to the input data (i.e. image gradient). The construction of a speed function is crucial in applying the level set method. Our intention in this work is to exploit the advantage of the cooperation of different information in the same evolution equation. So, we propose basically to constrain our variational model by both boundary and regional information. Recently, we have proposed a new formulation [2, 12] for the evolution of the variational model which is expressed as:

$$\frac{\partial \psi}{\partial t} = [\alpha_r F_{region}(I) + \alpha_b F_{boundary}(I)]|\nabla \psi| \tag{2}$$

$F_{boundary}$ causes the evolving of the front to be more strongly attracted to image edges. It is expressed as :

$$F_{boundary}(I) = sign(F_{boundary}).\frac{c+k}{1+|\nabla I|} \tag{3}$$

$$sign(F_{boundary}) = \begin{cases} +1\ if & F_{region} < 0 \\ -1\ otherwise & \end{cases} \tag{4}$$

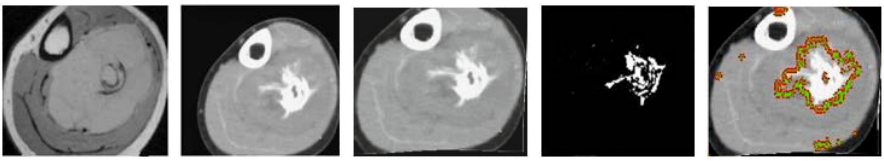
F_{region} controls the evolution of the model and segments the cancer region based on the following equation:

$$F_{region}(I) = \begin{cases} I - (m_T - \epsilon_T) \text{ if } I < m_T \\ (m_T + \epsilon_T) - I \text{ otherwise} \end{cases} \tag{5}$$

Where ϵ_T is a constant parameter, and m_T is the mean value of the bone cancer region. This value is calculated on the estimated region after the classification step. ϵ_T controls the brightness of the region to be segmented and define a range of greyscale values that could be considered inside the expected region of interest. More technical details are found in the papers [2, 12].

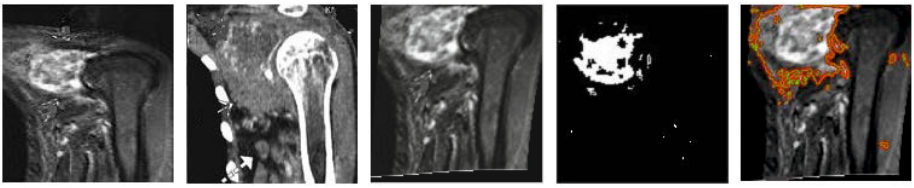
3 Experimental Results

We focus in this work only on the detection of the bon tumor boundaries from 2D images (CT and MRI). We have validated qualitatively the performance of the proposed method on several couple of MRI and CT scan images. Figures 2 c, 3 c, 4 c, and 5 c show the result of the non-rigid registration. In this study, images



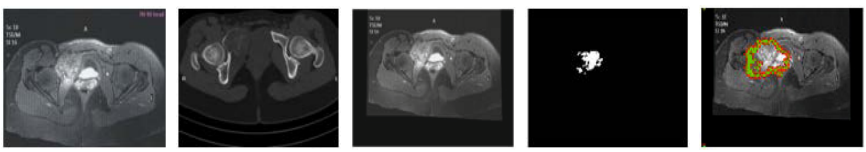
(a) (b) (c) (d) (e)

Fig. 2. (a) T2 weighted MR image of lower leg , (b) CT image of lower leg, (c) registered image (d) initial region of the tumor region (PFCM classification result), (e) Final segmented tumor region



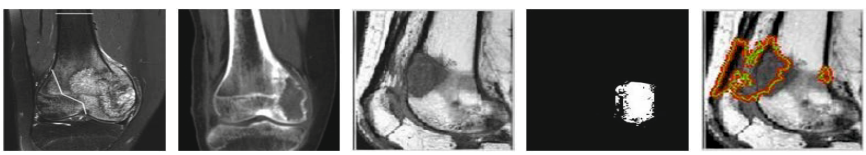
(a) (b) (c) (d) (e)

Fig. 3. (a) T1 weighted MR image of the left shoulder, (b) CT image for lower leg, (c) registered image (d) initial region of the tumor region (PFCM classification result), (e) Final segmented tumor region



(a) (b) (c) (d) (e)

Fig. 4. (a) T1 weighted MR image of pelvic, (b) CT image of pelvic, (c) registered image (d) initial region of the tumor region (PFCM classification result), (e) Final segmented tumor region



(a) (b) (c) (d) (e)

Fig. 5. (a) T1 weighted MR image of osteosarcoma-femur, (b) CT image of osteosarcoma-femur, (c) registered image (d) initial region of the tumor region (PFCM classification result), (e) Final segmented tumor region

are classified into four classes and one of them is assigned for the bone cancer region. This classification is performed using PFCM algorithm which provides an initial coarse pathological region presented in figures 2 d, 3 d, 4 d, and 5 d. Finally, our variational model is performed on the previous output to give a final segmented region shown in the last result for each row in same figures. Once isolated, the detected cancer can be further processed for example for surface measurement. According to obtained preliminary results, we found our method is able to give acceptable results. This is due principally to the potential use of both FPCM-based clustering, data fusion process and variational model for segmentation of multimodal images.

4 Conclusion and Future Work

We have presented a method for 2D bone cancer segmentation using multimodal images possibilistic fuzzy classification and active contour model. The entire process of our method is automatic except the selection of one pixel after the classification step which is needed to extract the initial tumor area. According to the obtained encouraging results, the main conclusion of this work is that the combination of the possibilistic fuzzy classification and the variational model in a sequential manner is suitable for such problem. Our future research in bone cancer segmentation consists in the quantitative evaluation of our results against a ground truth. It would be also very interesting to investigate a prior knowledge to improve results and to make the process fully automatic. Moreover, we will concentrate on the detection of three-dimensionally (3D) bone cancer.

References

1. Fitton, I., et al.: Semi-automatic delineation using weighted ct-mri registered images for radiotherapy of nasopharyngeal cancer. The International Journal of Medical Physics Research and Practice 38, 4662–4666 (2011)
2. Bourouis, S., Hamrouni, K.: 3d segmentation of mri brain using level set and unsupervised classification. International Journal in Image and Graphics (IJIG) 10(1), 135–154 (2010)
3. Seim, H., et al.: Automatic segmentation of the pelvic bones from ct data based on a statistical shape model. In: Eurographics Workshop on Visual Computing for Biomedicine, pp. 224–230 (2008)
4. Vincent, G., Wolstenholme, C., Scott, I., Bowes, M.: Fully automatic segmentation of the knee joint using active appearance models. In: Proc. Medical Image Analysis for the Clinic (2010)
5. Jrme Schmid, N.M.T.: Fully automatic segmentation of the knee joint using active appearance models. Med. Image Comput. Comput. Assist. Interv. 11, 119–126 (2008)
6. Frangi, A., et al.: Bone tumor segmentation from mr perfusion images with neural networks using multi-scale pharmacokinetic features. In: Image and Vision Computing, pp. 679–690 (2001)
7. Myronenko, A., Song, X.: Intensity-based image registration by minimizing residual complexity. IEEE Trans. on Medical Imaging 29, 1882–1891 (2010)

8. Myronenko, A., Song, X., Carreira-perpinán, M.A.: Free-form nonrigid image registration using generalized elastic nets. In: IEEE Conf. of Computer Vision and Pattern Recognition, pp. 1–8 (2007)
9. Zadeh, L.A.: Fuzzy sets. Information and Control 8, 338–353 (1965)
10. Krishnapuram, R., Keller, J.: A possibilistic approach to clustering. IEEE Trans. Fuzzy Syst. 1(2), 98–110 (1993)
11. Pal, N.R., Pal, S.K., Keller, J.M., Bezdek, J.C.: A possibilistic fuzzy c-means clustering algorithm. IEEE Transactions on Fuzzy Systems 13(4), 517–530 (2005)
12. Bourouis, S., Hamrouni, K.: Fully automatic brain tumor segmentation based on multi-modality mri and level-set. Journal of Ubiquitous Systems and Pervasive Networks 3(2), 47–54 (2011)
13. Sethian, J.: Level Set Methods and Fast Marching Methods: Evolving Interfaces in Geometry, Fluid Mechanics, Computer Vision, and Materials Science, 2nd edn. Cambridge University Press (1999)