FUZZY CONNECTEDNESS IN SEGMENTATION OF MEDICAL IMAGES
A Look at the Pros and Cons

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Abstract: An attempt to recapitulate and conclude numerous experiences with the fuzzy connectedness theory applied to medical image segmentation is made in this paper. The fuzzy connectedness principles introduced in 1996 have been developed and tested in dozens of studies in past 15 years; many advantages, as well as shortcomings have been discovered and described. Some aspects of the method and its applications have been summarized here, including the examples of specific 2D and 3D medical studies with various objects, subjected to fuzzy connected segmentation. Deliberation about the usefulness of multiseeded and multiobject variants is also present. An algorithm optimized for matrix computations-based programming languages is introduced. Finally, 3 fuzzy connectedness-based computer aided diagnosis systems are described and evaluated.

1 INTRODUCTION

There are plenty of areas in the wide world of fuzzy computations. One of them is the fuzzy connectedness (FC) theory, taking advantage of basics of fuzzy logic, sets and relations. Defined as a methodology operating on multidimensional and multifeature sets of ordered and connected data, FC is suited for image processing, in particular for image segmentation. Segmentation is a process of partitioning an image into multiple, separate objects – sets of image points, like pixels or voxels, depending on image dimensionality. The points classified into single objects are strongly connected to each other by some more or less abstract relations, whilst their relations to points constituting other objects have relatively lower values. If the features associated with the points are multivalued (e.g. grayscale images, like in most medical images and volumes, taken from Computed Tomography CT, Magnetic Resonance MR or Ultrasonography USG studies), then the fuzzy computations seem to be perfect in an advanced analysis. For this reason image processing researchers in past decades willingly introduced some fuzziness into their job.

The point of view that can be taken on such a topic is twofold: (1) FC method applied to a specific task of image segmentation or (2) image segmentation performed by a specific tool – FC. Anyway, this paper comprises a broad look at the fuzzy connectedness in the segmentation of medical images. After a short review of FC fundamentals, an analysis of characteristic segmentation subjects is performed, with some notes on FC variants. Then, the dimensionality and computational complexity is taken into consideration. An algorithm optimized for Matlab® applications is proposed. Finally, after a brief presentation of 3 computer aided diagnosis (CAD) systems along with results obtained at the evaluation stage, some conclusions are made.

2 FUZZY CONNECTEDNESS

The idea of fuzzy connectedness relies on performing soft computations in digital spaces. The basic work (Udupa and Samarasekera, 1996) provides definitions of multiple fuzzy relations within topologically ordered dataset C, in particular the fuzzy affinity κ:

$$\kappa = \{((\mathbf{c},\mathbf{d}),\, \mu_\kappa(\mathbf{c},\mathbf{d})) \quad | \quad \mathbf{c},\mathbf{d} \in C \times C\}, \qquad (1)$$

where $\mu_\kappa \in [0,1]$ is the fuzzy affinity membership function, and $\mathbf{c},\mathbf{d}$ are spels (spatial elements) in C. If C is a set of image points, then $\mathbf{c}$ and $\mathbf{d}$ might be treated as pixels or voxels. The value of μ_κ is based on the $\mathbf{c}$ and $\mathbf{d}$ features, like coordinate adjacency, image intensities $I(\mathbf{c}), I(\mathbf{d})$ or local intensity gradients. Fuzzy affinity has to be reflexive: $\mu_\kappa(\mathbf{c},\mathbf{c}) = 1$ and

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symmetric: $\mu_\kappa(\mathbf{c},\mathbf{d}) = \mu_\kappa(\mathbf{d},\mathbf{c})$ for all $\mathbf{c},\mathbf{d} \in C$. It is mostly used in the form of:

$$\mu_\kappa(\mathbf{c},\mathbf{d}) = \mu_\alpha(\mathbf{c},\mathbf{d}) \cdot g(\mu_\phi(\mathbf{c},\mathbf{d}), \mu_\psi(\mathbf{c},\mathbf{d})) \tag{2}$$

with μ_α being the functional form of adjacency relation α (e.g. hard 6-neighbourhood in a 3D or 4-neighbourhood in a 2D image) and μ_ϕ, μ_ψ – the intensity-based, and intensity gradient-based parts of the affinity, respectively. Several forms of (2) have been illustrated and discussed in (Saha et al., 2000). Most of the studies prefer the weighted gaussian variant:

$$\mu_\kappa(\mathbf{c},\mathbf{d}) = \mu_\alpha(\mathbf{c},\mathbf{d}) \left(w_1 e^{\frac{\left(\frac{I(\mathbf{c})+I(\mathbf{d})}{2} - m_1\right)^2}{2\sigma_1^2}} + \right.$$
$$\left. + w_2 e^{\frac{(|I(\mathbf{c})-I(\mathbf{d})| - m_2)^2}{2\sigma_2^2}} \right). \tag{3}$$

$m_1, \sigma_1, m_2, \sigma_2$ are parameters of κ related to the intensities of segmented object; they are often computed based on the features of seed points and their neighbours. Weights w_1, w_2 balance the influence of μ_ϕ, μ_ψ, both being positive and $w_1 + w_2 = 1$.

Adjacency relation α causes μ_κ to be nonzero only for pairs of neighbouring spels $\mathbf{c}$ and $\mathbf{d}$. Such a pair is called a link, and the value of $\mu_\kappa(\mathbf{c},\mathbf{d})$ – its strength. Consequently, a path is any sequence of spels $\langle \mathbf{e}_1, \mathbf{e}_2, ..., \mathbf{e}_m \rangle$ such that for any $i \in [1, m-1]$ a pair $\langle \mathbf{e}_i, \mathbf{e}_{i+1} \rangle$ is a link. It is noted p_{cd} if $\mathbf{c} = \mathbf{e}_1$ and $\mathbf{d} = \mathbf{e}_m$. The strength of a path is a strength of its weakest link – the smallest affinity along the path:

$$\mu_N(p_{cd}) = \min_i \{\mu_\kappa(\mathbf{e}_i, \mathbf{e}_{i+1})\} \tag{4}$$

Finally, any image spels $\mathbf{c}$ and $\mathbf{d}$ are fuzzy connected according to relation K. The membership function of fuzzy connectedness $\mu_K(\mathbf{c},\mathbf{d})$ is the strength of the strongest path p_{cd} of all the paths between $\mathbf{c}$ and $\mathbf{d}$, forming a set P_{cd}:

$$\mu_K(\mathbf{c},\mathbf{d}) = \max_{p_{cd} \in P_{cd}} [\mu_N(p_{cd})] \tag{5}$$

FC-based segmentation requires the selection of seed point $\mathbf{o}$ inside an object, and then computation of fuzzy connectivity scene C_o for all spels $\mathbf{c} \in C$:

$$C_o(\mathbf{c}) = \mu_K(\mathbf{o},\mathbf{c}), \tag{6}$$

with the unitary connectivity of a seed point: $C_o(\mathbf{o}) = \mu_K(\mathbf{o},\mathbf{o}) = 1$. The Dijkstra's Algorithm (Carvalho et al., 1999) has been proposed to solve such a specific shortest path problem faster than with the dynamic programming approach (Udupa and Samarasekera, 1996). It is also valid in case of all multi-seeded applications (Saha and Udupa, 2001), where set O of M ($M > 1$) seed points $\mathbf{o}_i$ is indicated, as well as in the relative fuzzy connectedness (RFC) methods (Herman and Carvalho, 2001), (Udupa et al., 2002), (Ciesielski et al., 2007), (Badura and Pietka, 2007), to be discussed later in the paper. Nevertheless, if there is indeed more than a single seed point for the object, the scene C_O for a set O is a fuzzy union:

$$C_O(\mathbf{c}) = \bigcup_{\mathbf{o}_i \in O} C_{\mathbf{o}_i}(\mathbf{c}) = \max_{\mathbf{o}_i \in O} [\mu_K(\mathbf{o}_i, \mathbf{c})]. \tag{7}$$

The final determination of segmented object might be done by the binarisation of scene C_o with threshold $\theta \in [0,1]$, resulting in binary image $O_{\kappa\theta(o)}$:

$$O_{\kappa\theta(o)}(c) = \begin{cases} 1 \Leftrightarrow & C_o(c) \geq \theta \\ 0 & \text{otherwise.} \end{cases} \tag{8}$$

The RFC variant uses the second object, treated as a background region with its own seed point $\mathbf{b}$, to determine $O_{\kappa\theta(o)}$ in a rivalry mode. Spel $\mathbf{c} \in C$ belongs to an object according to affinity κ and connectedness K if $\mu_K(\mathbf{o},\mathbf{c}) > \mu_K(\mathbf{b},\mathbf{c})$. The above condition leads to fuzzy connectivity scenes C_o and C_b and their comparison in a form of a "division of spoils".

The list of medical image processing applications, where the FC method has been used is already long, yet still far from completion. Let us notice here just a few segmentation applications: airway trees (Tschirren et al., 2005), multiple sclerosis (Udupa et al., 1997), (Admasu et al., 2003), (Kawa and Pietka, 2008), brain cancer (Moonis et al., 2002), lung cancer (Badura and Pietka, 2008), (Dehmeshki et al., 2008), bone cancer (Czajkowska et al., 2010), angiography (Abrahams et al., 2002), colonoscopy (Udupa et al., 2001). In many cases FC is treated as a part of a wider methodology, mostly used for fine segmentation. The authors of this paper have adapted various models of FC into segmentation of a variety of anatomical structures. Some examples and an analysis presented in the following sections are an attempt to point out areas, where FC provides an effective outcome, mentioning also applications requiring modifications.

3 SUBJECT ANALYSIS

3.1 Solid & Well Circumscribed Tissues

If an anatomical structure to be delineated features an intensity distinctly different than the surrounding regions, most of the well known segmentation methods may show their best. The above rule refers both to: the edge detection (because the edges are sharp enough), and the region-based methods. The FC approach belongs to the latter, as a particular type of

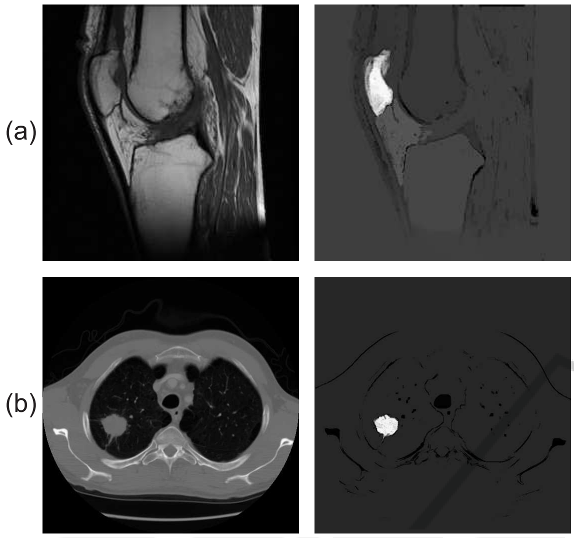

Figure 1: Typical well circumscribed objects (left) and their FC scenes (right). Objects (M – number of seed points): patella in MR, $M = 1$ (a), lung nodule in CT, $M = 1$ (b).

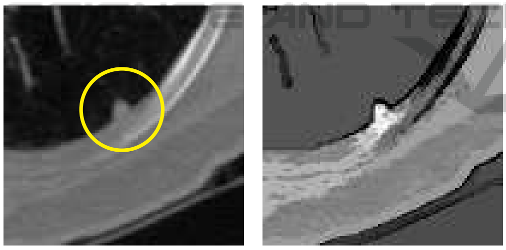

Figure 2: ROI within a thoracic CT with the juxtapleural lung nodule (left) and its FC scene (right).

a region growing algorithm. In cases of clearly visible tissues without significant level of noise (or denoised by some sort of prefiltering) the canonic form of FC usually yields very good results. The selection of threshold θ is quite simple, due to the histogram bimodality of fuzzy connectivity scene C_o. Moreover, such approaches are practically insensitive to the location of a seed point, if only located inside an object. The fuzzy connectivity scenes of a couple of typical structures are illustrated in Figure 1.

As in all the region growing applications there is a danger of a ”leak” if there are any ”bridges” between the object and a region with similar intensity. Such a problem is visible in case of pleura-connected lung nodules, where the employment of some preprocessing methods is indispensable (Figure 2).

3.2 Soft Tissues

The fuzziness brought in by the method seems to be more interesting in difficult cases. Already (Udupa and Samarasekera, 1996) point out the FC’s good performance in the presence of object-independent ”intensity ramps”, mainly due to an enhancement provided by the gradient-based affinity component μ_ψ (Figure 3a). Another, yet more frequent example is a segmentation of regions with slight intensity differences, which corresponds to e.g. the abdominal structures in the CT studies (Figure 3b).

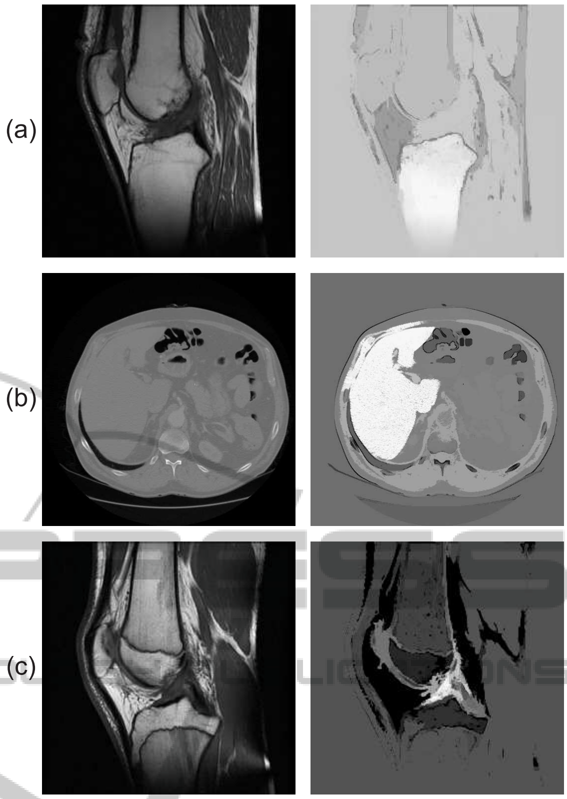

Figure 3: Typical objects more difficult to delineate (left) and their FC scenes (right): tibia in MR, $M = 2$ (a), liver in CT, $M = 1$ (b), anterior cruciate ligament in MR, $M = 2$ (c).

In all cases mentioned above it is advisable to obtain a larger number of seed points, since it leads to more reliable values of affinity parameters m and σ. Besides, the computations (growth) of a fuzzy connectivity scene start from many points. If the processing stages preceding the FC analysis are trustworthy enough, they might even produce full binary masks corresponding to the core of an object, passed as sets of seed points to the FC.

Because of the blurred edges between the structures and therefore less evident slopes in the fuzzy connectivity scene, the relative FC modes are always recommended here, despite their greater time consumption. Figure 3c shows the anterior cruciate ligament in a MR slice well separated from the bone, fat and muscle regions, yet hardly distinguishable from articular capsule fluids and tissues. Treating the lat-

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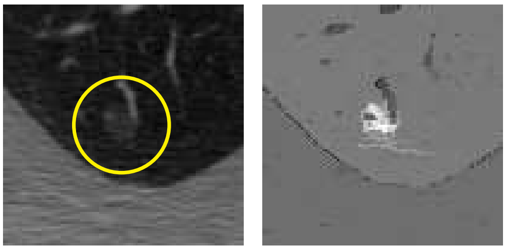

Figure 4: ROI within a thoracic CT with the low intensity lung nodule (left) and its FC scene (right).

ter as a background region with its own seed points and fuzzy connectivity scene and giving permission for a ”battle for pixels” usually increases the method performance.

3.3 Homogeneous vs Inhomogeneous Regions

Homogeneity of a segmentation subject is a separate issue, although it refers mainly to the previous section. The noise present in the images brings more problems within the regions, where the intensities of adjacent structures differ slightly. In the FC approaches it might lead to leaks or more or less significant ”holes” within the fuzzy connectivity scene region corresponding to an object. Note the liver in Figure 3b: the inhomogeneity is even more apparent in the fuzzy connectivity scene than in the original slice. The image data for the FC analysis should be prepared, e.g. by the anisotropic diffusion (Perona and Malik, 1990), and additionally postprocessed e.g. using the mathematical morphology (Gonzalez and Woods, 2002).

An even more clear example is illustrated in Figure 4, including an inhomogeneous, vascular lung nodule with very low intensity. The vessel is separated well enough; the lung parenchyma, however, is not. Thresholding the scene could make binary object $O_{\kappa\theta(o)}$ torn or expanded. It is a perfect case to employ the RFC with a seed point somewhere within the parenchyma and determine the boundary between the object and the background by comparing two scenes. Compare this boundary-setting mechanism to the watershed algorithm (Gonzalez and Woods, 2002).

3.4 Multiseeded and Multiobject Approaches

As mentioned above, the performance of FC algorithms improves with an increasing number of seed points (as in each seeded segmentation method). Usually, the seed points indicate the core of an object. With many seed points, the mean distance from the seed to the object boundaries shorten, which avoids a potential undersegmentation mechanism. On the other hand, the determination of fuzzy affinity function parameters (m, σ in (3)), often relies on the features of seed points and their neighbours. In case of a multiseeded approach such a way of computations makes the parameters better representatives of an object, due to averaging phenomenons. However, the parameters can be estimated using clustering methods (e.g. Fuzzy c-Means or Gaussian Mixture Models).

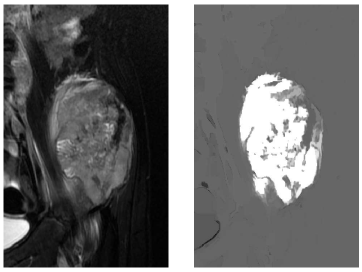

Figure 5: ROI within an abdominal MR slice with the Ewing’s sarcoma (left) and its FC scene (right).

The manual indication of multiple seed points is rarely performed, because the segmentation approaches should rather be as automatised as possible. However, ”indication” might be understood as ”getting as a result of some preprocessing operation”, which actually allows full automatisation. Several such solutions have been designed in our research, e.g. automatic selection of multiple seed points spread within an object via an evolutionary algorithm (Badura and Pietka, 2007) or passing the presegmentation-made binary masks as sets of seed points (Kawa and Pietka, 2008), (Czajkowska et al., 2010). The exemplary fuzzy connectivity scene resulting from the latter is presented in Figure 5, where the object region (a Ewing’s sarcoma) is mostly white, which relates to the connectivity level at 1.0.

If many adjacent objects have to be determined, the multiobject FC (Herman and Carvalho, 2001) might be employed, with at least one seed per each of the M objects. After getting the M fuzzy connectivity scenes a defuzzifying decision is made, about the membership of each point: it is attached to the object with the strongest connectivity value. In particular, if two objects are taken into consideration, the method is called relative fuzzy connectedness. At least one seed is sown in the object, and at least one – in the background. In our research this mode has been used a lot of times, many of them involving object-multiseeded approaches, as described above.

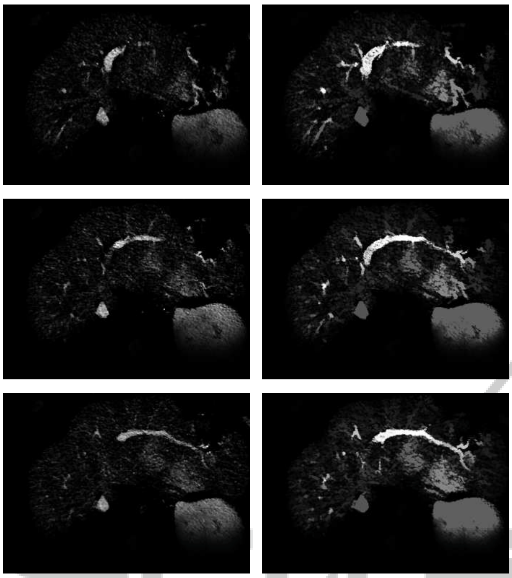

Figure 6: ROI within prefiltered abdominal CT volume with liver vasculature (left) and corresponding FC scene (right).

3.5 Dimensionality Analysis

The challenge presented by the FC in the image domain is connected with the digital space dimensionality. In the 3D analysis, a number of possible paths is much higher than in the 2D space and analysis time increases. In our works both, 2D and 3D modes of the FC have been performed in multiple, independent researches. Depending on the segmentation subject, various hard adjacency relations α have been employed: 4- or 8-neighbourhood in 2D as well as 6-, 18- and 26-neighbourhood in 3D. The rule is clear in all the dimensions: the smaller (closer) the neighbourhood for fuzzy affinity κ is: (1) the lower the mean value of fuzzy connectivity scene is, (2) the lower the possibility of a ”leak” occurrence is, (3) the faster the computations are. You may find any of these features more important than the other. We mostly prefer smaller neighbourhoods, since they produce good results in reasonable time.

A similar remark does not have to be made referring to the μ_κ form. It practically does not depend on the image dimensionality, since equations (1)-(8) take into consideration two points, independently of how many coordinates they have. So, we did not make any particular distinction between 2D and 3D μ_κ-s.

The practical application in a 3D space may also be complicated by the inhomogeneous dimensions of a voxel (a cuboid instead of a cube). Mainly, an interpolation is to be performed in the Z-direction to ensure the FC not to discriminate any axis. However, we tried to analyse the FC within uninterpolated volumes, achieving proper segmentation results.

A few consecutive slices of the fuzzy connectivity scene for a 3D segmentation of liver vasculature are presented in Figure 6.

Due to the increased computation time, testing various FC-based methods in the 3D medical images is harder than in 2D. A robust and fast implementation is necessary that could be easily deployed in various image segmentation tasks and integrated with our prototyping environment (currently Matlab). In the following section an algorithm optimized for such conditions is presented.

4 MATLAB OPTIMIZED FC ALGORITHM

In Matlab the standard FC method (Udupa and Samarasekera, 1996), as well as the Dijkstra’s search algorithm-based version (Carvalho et al., 1999) can both be implemented. Both these approaches are far from optimal for direct use in Matlab, as they operate iteratively on the separate image points.

Matlab is a weakly-typed, interpreted language optimized for the matrix computation. In Matlab, an algorithm implemented by means of standard for loops and indexing can be much slower than the same algorithm implemented by operations on the whole matrices. The process of optimization, that replaces slow element-wise operations by fast matrix-based ones is in Matlab known as vectorization.

As images are represented as 3D matrices (tables) with a basic type of floating point or integer number, the vectorized implementation can significantly speed processing. The algorithm presented below uses the basic 3D manipulation functions available: `circshift`, `padarray` and the matrix-wise `min/max` operations. It can process any number of seed points in parallel, providing all of them has been chosen within a single processed object. Using the precomputed affinity tables (step 4), the operations are sped up, but if the memory is a critical factor, the affinity tables can also be recomputed in each iteration.

1. Chose the hard adjacency relation α.
2. Decompose α to the series of shifts s denoting neighbouring elements (e.g. a 2D 4-connectivity consists of: (1) one to the left, (2) one to the right, (3) one to the bottom and (4) one to the top).
3. Preprocess the original image by padding rows, columns and layers as not to permit for wrapping the original values in the later steps.
4. Precompute the fuzzy affinity values for each neighbourhood member (one table T_s containing

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the affinity values for each α-connected member; e.g. 4 tables if 4-connectivity has been chosen; e.g. T_1 for the *one to the left*).

5. By using circular shift of the precomputed fuzzy affinity tables ensure, that the element of a new $T_s(\mathbf{c})$ denotes the affinity of original spel $\mathbf{c}$ with respect to the s-th neighbour; e.g. for a pixel $\mathbf{c} = (c_x, c_y)$ $T_1(c_x, c_y)$ contains $\mu_\kappa(\mathbf{c}, \mathbf{d})$ with respect to the left pixel $\mathbf{d} = (c_x - 1, c_y)$.
6. Prepare zeroed matrix C_o and set all the elements matching the seed point locations to ones.
7. `repeat`

```
repeat
  for each Ts
    TEMP = min(Co, Ts);[1]
    Co = max(Co, TEMP);[2]
  end
while Co changes
```

where `min` and `max` are the element-wise matrix operations.

This can be further sped up if the FC is to be used in the segmentation by thresholding. Each T_s matrix can be thresholded and `min/max` can be replaced by the logical `and/or` operations, respectively. Our experiences show that the proposed implementation shortens the computation time compared to the classic Dijkstra search algorithm by a few times.

5 RESULTS

As mentioned above, in most applications the FC analysis is used as a part of a wider methodology. It is, however, usually the critical part of the segmentation step. It is also the case in our research. Let us point out 3 of our CAD applications with a brief description and a results summary.

5.1 Multiple Sclerosis CAD

A 2D relative FC has been used in a Multiple Sclerosis (MS) CAD system (Kawa and Pietka, 2008). The FC is used in the second step of segmentation in the MR FLAIR images (when location of plaques has already been established). The MS plaques are visible in the MR as small, confluent lesions. Due to a low spatial resolution and small differences in a signal level, it is not always clear, also to the radiologists, where a boundary of a separate lesion is located. Using the FC permits to set the continuous border between a normal and affected tissue. The FC analysis is initiated in regions surrounding previously segmented lesions, with a standard affinity and automatically estimated parameters. The results are verified using gold standard images obtained by the experienced radiologist. The mean sensitivity for various test sets varies from 83% to 91%.

[1] zero for elements, that have not been reached yet, tested path strength otherwise.

[2] update, if tested path strength is best so far.

5.2 Lung Nodule CAD

A 3D FC in a modified relative mode stands for a main segmentation stage (Badura and Pietka, 2007), (Badura and Pietka, 2008). It is preceded by the presegmentation (including the manual selection of two seed points, determination of the primary binary masks for the objects and automatic selection of the sets of seed points) and followed by postprocessing stage (the vessel removal and correction procedures). The Lung Image Database Consortium (LIDC) database, containing 23 cases of various pulmonary nodules, has been used for evaluation (note Figures 1b, 2 and 4). The CT studies have been described by the voxel probability maps, obtained in the multistage delineation process, involving experienced radiologists. At the evaluation stage all cases have been segmented with the various pairs of manually indicated seed points. The mean sensitivities obtained in the study were 99.94% for the voxels, whose values in the probability map were equal to 1.0 and 90.94%, when their values exceeded 0.5. The mean false positive rate was 0.39%.

5.3 Bone Cancer CAD

A 3D relative FC on the basis of a gaussian mixture model has been used in the Bone Cancer CAD (Czajkowska et al., 2010). The database consists of 71 examinations of 48 patients with various types of bone lesions (tumour and tumour-like), grouped into 8 classes, i.a. Osteosarcomas, Ewing's sarcomas (Figure 5) and Chondrosarcomas. A total of 118 different MR series have been analysed (T1 contrast enhanced, T2 with fat saturation, STIR and PD). The evaluation stage consists of two parts: the model-based and the radiologist opinion-based verification. The model-based step has been performed on the basis of 24 series. The models have been prepared using segmentation results verified by the radiologist in order to create additional, synthetic volumes. The mean sensitivity yielded using the model-based evaluation was 96.05% with specificity at 98.74%. The second verification step has been performed based on the radiologist opinion. Here, the algorithm worked correctly in 74.5% of 118 cases.

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6 CONCLUSIONS

In the computer aided diagnosis, the image segmentation is often used as a first step in an automated case analysis. As such, it benefits from the fuzzy notion provided by the fuzzy connectedness. After 15 years since being announced the fuzzy connectedness-based algorithms appeared in multiple segmentation applications and programming environments (e.g. note the specified FC filters in the ITK – Insight Toolkit – environment). The properly defined connectedness between points within objects is helpful in achieving precise and reliable delineation of the structures. Sometimes the FC analysis is sufficient as a standalone segmentation method; other times it provides just the most accurate part of a larger process. The spatial relations and fuzziness used in the segmentation step permit better resemblance to the processing performed by the human brain and perceptual system. In our work the fuzzy connectedness proved to be a powerfull tool; we can conclude, that its fuzziness improves flexibility of the segmentation process.

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