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Fuzzy Image Segmentation with Fuzzy Labelled Neural Gas

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Abstract. Processing biological data often requires handling of uncertain and sometimes inconsistent information. Particularly when coping with image segmentation tasks against biomedical background, a clear description of for example tissue borders is often hard to obtain. On the other hand, there are only a few promising segmentation algorithms being able to process fuzzy input data. This paper describes one novel alternative applying the recently introduced Fuzzy Labelled Neural Gas (FLNG) as subsequent classification step to a biologically relevant fuzzy labelling with underlying image feature extraction.

1 Introduction

Biomedical data is often characterised by uncertain and possibly inconsistent information. This holds even more, among others, in the field of biomedical image processing. In the framework described by the present paper, automatic high-throughput segmentation of cross-section images is a crucial step of a rather complex processing chain and the prerequisite of a subsequent three-dimensional modelling.

The objects used in the present paper for fuzzy labelling of biological structures are serial transverse sections of barley grains at different developmental stages. Developing barley grains consist of three genetically different tissue types: the diploid maternal tissues, the filial triploid endosperm, and the diploid embryo. Because of their functionality, cells of a fully differentiated tissue show differences in cell shape and water content and accumulate different compounds. Based on those characteristics, scientists experienced in histology are able to identify and to label differentiated tissues within a given section of a developing grain (segmentation).

However, differentiating cells lack these characteristics. Because differentiation occurs along gradients, especially borders between different tissue types of developing grains often consist of differentiating cells, which cannot be identified as belonging to one or the other tissue type. Positions of those "un-sharp" borders depend on the tissue type under consideration and, additionally, on the developmental stage.

Seeds are sink tissues, i.e. development requires import of assimilates from the photosynthetic active vegetative parts of the plant. Assimilate import is determined by the vascular tissues and regulated by the so-called maternal-filial boundary consisting of nucellar projection and endosperm transfer cells. Type and amount of incoming assimilates change during development and determine in this way differentiation of the filial seed part. The changing assimilate composition is determined by development-specific changes of the maternal-filial boundary resulting from lasting differentiation processes. Especially cells surrounding the vascular bundle and connecting vascular tissues to the nucellar projection show different shape during different developmental stages. Therefore, unequivocal segmentation of this grain part at a given developmental stage is not possible. Thus, fuzzy processing is highly desirable.

In order to incorporate the required fuzzy image segmentation, there are generally a number of alternatives [1]. However, since (training) examples, manually labelled by a biological expert, are generally available and have to be used to transfer the expert knowledge to the automatic solution, the use of supervised methods seems more natural than of unsupervised techniques [2]. Furthermore, neither approaches requiring extensive a-priori knowledge about the areas to be segmented [3] nor morphology based solutions [4] are applicable in the case considered in the present paper. Besides some rule-based techniques, or using fuzzy integrals, or measures of fuzziness (e.g. fuzzy entropy) and image information (e.g. fuzzy divergence) [5], particularly artificial neural network (ANN) based solutions offer promising approaches [6, 7].

Here, similar to many other *crisp* as well as *fuzzy* segmentation methods[1], a two-stage system is applied, where a set of significant features is extracted from the images and then clustered (unsupervised), or, as in this case, classified (supervised). Due to their adaptive behaviour, there are numerous applications of ANNs in this context. However, this mainly concerns only crisp segmentation, although there are some neural network paradigms accepting fuzzy input data [8, 9, 10].

With the recently suggested *Fuzzy Labelled Neural Gas* (*FLNG*) [11] also a prototype-based neural network became available for this purpose now. After briefly introducing an interactive editor to obtain expert labelled training data in the next section, Sect. 3 briefly reviews the FLNG algorithm. Then some results applying the system to biomolecular real-world data are given.

[1]Whereas the term *crisp* commonly refers in this context to segmentation with clear and strict boundaries between different areas, *fuzzy* means a gradual transition between adjacent areas.

2 Providing fuzzy labelled expert data

2.1 A biologically plausible fuzzy label editor

As a first step towards the intended automatic segmentation an adequate and intuitively usable tool is required to support the experts to transfer their a-priori knowledge into a fuzzy machine-readable form. Since segmentation with a biological background is rather based on an assignment of image regions (of arbitrary form) than of single pixels, a graphical 2-D editor was implemented. Despite of assigning each pixel exactly to one of – in this case – 20 model-specific materials, now an adequate vector representation is used characterising user-defined 2-D membership functions for each material. Furthermore, the common practice to normalise the sum over all material membership-values at a certain pixel to 1.0 has been followed as well. A detailed description of this editor can be found in [12].

In the end, a probability or membership function based annotation of each pixel to a number of or even all classes is obtained. This makes up the first part of the ANN training data set.

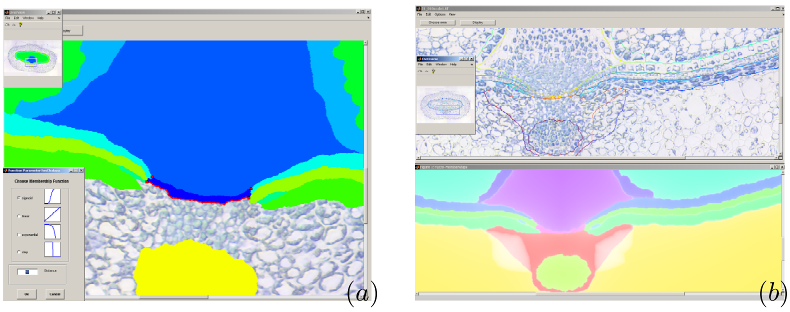

Fig. 1: Exemplary screenshots of fuzzy manual segmentation of a corresponding cross-section image with the specifically implemented graphical 2-D editor: a) Fuzzification at the border between areas with constant membership values. In a preceding step border segments were identified by control points. Then step by step at each segment a smooth transition can be defined separately for each material. b) Additional to the editor's main window (showing the underlying colour-coded regions only) the current state of fuzzy segmentation can be surveyed in a special monitoring window.

2.2 Extracting suitable image features

In order to obtain significant input data, feature vectors describing especially the texture properties of each material in the context of its neighbourhood have to be extracted from the original images. Due to the high degree of complexity of the underlying image material – characterised by several constraints such as incomplete expert knowledge, subjectiveness and often hardly distinguishable materials – the segmentation was based on a pixel-wise classification.

For the proof of concept the focus was not yet on an exhausting search for the optimal features for the application of the FLNG classifier to our particular image data. Instead, for simplification and comparison reasons an existing feature set was first utilised, which was formerly successfully used for several crisp ANN classifiers. This initial feature vector holds 170 properties concerning colour, geometry and symmetry (such as Cartesian and polar coordinates, distance to centroid, absolute angle to symmetry axis) and particularly texture according to varying neighbourhoods (such as Gaussian filters, histogram based features). All features were z-score-transformed to normalise the attributes.

3 Fuzzy classification using FLNG

Fuzzy labelled neural gas (FLNG) is an extension of the well-known prototype based vector quantization neural gas algorithm [13]. It belongs to gradient descent supervised learning schemes [11, 14]. Here, the data $\mathbf{v} \in \mathcal{D} \subseteq \mathbb{R}^d$ are equipped with class labels, which are fuzzy: for each class k we have the possibilistic assignment $x_k \in [0,1]$ collected in the label vector $\mathbf{x} = (x_1, \ldots, x_{N_c})$ as described in Sect 2.1. N_c is the number of possible classes – in the present case up to 20. The prototypes $\mathbf{w}_i \in \mathbb{R}^d$, $i \in A$, now are featured with fuzzy labels $\mathbf{y}^i = \left(y_1^i, \ldots, y_{N_c}^i\right)$, too. Further, we assume an arbitrary differentiable, maybe parameterized, quadratic distance measure $\xi_\lambda(\mathbf{v}, \mathbf{w}_i)$ in the data space with parameters $\lambda = (\lambda_1, \ldots, \lambda_m)$. The cost function of the algorithm is defined as a balanced combination of the cost function E_{NG} of NG and an additional term E_{FL} according to the classification accuracy:

$$E_{FLNG} = (1-\beta) E_{NG} + \beta E_{FL}. \tag{1}$$

Thereby,

$$E_{NG} = \frac{1}{2C(\sigma)} \sum_j \int P(\mathbf{v}) h_\sigma(\mathbf{v}, \mathbf{w}_j) \xi_\lambda\left(\mathbf{v}, \mathbf{w}_j\right) d\mathbf{v} \tag{2}$$

is the cost function of NG with a rank based neighborhood function $h_\sigma(\mathbf{v}, \mathbf{w}_j)$ and E_{FL} is defined as

$$E_{FL} = \frac{1}{2} \sum_j \int P(\mathbf{v}) g_\gamma(\xi_\lambda(\mathbf{v}, \mathbf{w}_i)) \left(\mathbf{x} - \mathbf{y}_j\right)^2 d\mathbf{v} \tag{3}$$

where $g_\gamma\left(\mathbf{v}, \mathbf{w}_j\right)$ is a Gaussian kernel describing a neighborhood range in the data space

$$g_\gamma\left(\mathbf{v}, \mathbf{w}_j\right) = \exp\left(-\frac{\xi_\lambda(\mathbf{v}, \mathbf{w}_i)}{2\gamma^2}\right). \tag{4}$$

Note that the kernel g_γ depends on the prototype locations, such that E_{FL} is influenced by both $\mathbf{w}_i$ and $\mathbf{y}$. Formal derivation yields

$$\frac{\partial E_{FLNG}}{\partial \mathbf{w}_k} = (1-\beta) \frac{\partial E_{NG}}{\partial \mathbf{w}_k} + \beta \frac{\partial E_{FL}}{\partial \mathbf{w}_k} \text{ and } \frac{\partial E_{FLNG}}{\partial \mathbf{y}_k} = \beta \frac{\partial E_{FL}}{\partial \mathbf{y}_k} \tag{5}$$

which yields

$$\triangle \mathbf{w}_i = -\epsilon h_\sigma \left(\mathbf{v}, \mathbf{w}_i\right) \frac{\partial \xi_\lambda \left(\mathbf{v}, \mathbf{w}_i\right)}{\partial \mathbf{w}_i} + \frac{\beta}{4\gamma^2} g_\gamma \left(\mathbf{v}, \mathbf{w}_i\right) \frac{\partial \xi_\lambda \left(\mathbf{v}, \mathbf{w}_i\right)}{\partial \mathbf{w}_i} \left(\mathbf{x} - \mathbf{y}_i\right)^2 \quad (6)$$

and

$$\triangle \mathbf{y}_i = \epsilon_l \beta g_\gamma \left(\mathbf{v}, \mathbf{w}_i\right) \left(\mathbf{x} - \mathbf{y}_i\right) \quad (7)$$

as learning rules. The respective gradient yields

$$\triangle \lambda_k = \frac{\partial \xi_\lambda \left(\mathbf{v}, \mathbf{w}_j\right)}{\partial \lambda_k} \left(\frac{(1-\beta)}{2C\left(\sigma\right)} h_\sigma \left(\mathbf{v}, \mathbf{w}_j\right) - \frac{\beta}{4\gamma^2} g_\gamma \left(\mathbf{v}, \mathbf{w}_j\right) \left(\mathbf{x} - \mathbf{y}_j\right)^2 \right) \quad (8)$$

for adaptation. Further details can be found in [11].

4 Results

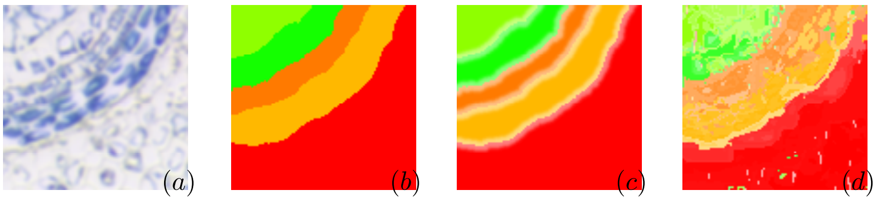

Fig. 2: Corresponding cutouts of images of the same cross-section illustrating the results of an automatic fuzzy classification: a) Original colour image, b) Manually crisply segmented image, c) Manually fuzzily segmented image (see Sect. 2.1), d) Automatic classification using FLNG based on c).

The used FLNG approach (50 prototypes, γ exponentially decreasing from 50/2 down to 0.01) is a fuzzy classifier, which involves also statistical information about the data distribution into the classification decision controlled by the balance parameter $\beta = 0.6$. Therefore, the method is not fully comparable to pure (crisp) classifiers. As to be seen in Fig. 2, the result in the given fuzzy classification task is a combination of the given manually obtained fuzzy classification (c) and the structural image properties of the original colour image (a), which are coded in the feature vectors.

5 Summary

Biomedical data often requires not just *interpretation* but also *processing* in a *fuzzy* way. This paper demonstrated the processing chain of fuzzy data *preparation* and *feature classification* using FLNG by means of a fuzzy image segmentation task. This self-contained fuzzy approach yields a much better biological plausibility of the image segmentation within particular image areas.

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