JOURNAL OF APPLIED
COMPUTER SCIENCE
Vol. 18 No. 2 (2010), pp. 67-78

Active Partition Based Medical Image Understanding with Self-Organised Competitive Spatch Eduction

Michał Pryczek, Arkadiusz Tomczyk, Piotr S. Szczepaniak

Technical University of Łódź
Institute of Information Technology
ul. Wólczańska 215, 90-924 Łódź, Poland
{michalp,tomczyk,piotr}@ics.p.lodz.pl

Abstract. Medical Image Understanding *is a recently defined semantic oriented image recognition task. Its specific requirements, highlighting complex characteristics of recognised objects as well as indispensable use of human-level expert knowledge almost every step of data processing sets new requirements for implemented algorithms. This paper focuses on linguistic image description method, designed to segment low level, semantically coherent image regions and mine adjacency relations among them. Example method results on medical images are presented to specify some methods properties.*
Keywords: *image understanding, image segmentation, active partitions, linguistic.*

1. Introduction

Cognitive Hierarchical Active Partition (CHAP) [1] is a recently developed paradigm of intelligent image recognition and understanding. It places strong emphasis on two aspects, namely the addition of expert knowledge and contextuality of the problem. Hierarchical aspect of this paradigm claims that the dividing of analysis process into subsequent stages of limited scope and well defined knowledge may be the key to meaningful image understanding [2]. It is also implicitly assumed that each stage extends the knowledge base about an analysed image. Typical implementation of such a system is the one in which, starting from the set of pixels of an image, every stage identifies elements increasing semantic complexity, usually by selection of objects from the previous phase or phases. This approach has already been verified in empirical research [1] giving promising results.

In this paper, a prototype *CHAP* based medical image understanding [3, 4] system is presented. In section two self-organising neural networks are used as an intermediate level object identifier model; *Neuronal Group Learning* [5, 6] concept is presented in section 3 as a method that facilitates the use of expert knowledge in a network adaptation process. An additional benefit of applying *NGL* is seamless generation of linguistic description of an image - another source of useful knowledge to be used in subsequent stages [7, 8]. The method is then evaluated in recognition of chambers of ventricular system on *CT* scans of human head. The last section focuses on the summary of the proposed approach.

2. Spatch eduction using neural networks and competitive learning

Cognitive Hierarchical Active Partition based *Image Understanding* techniques are hierarchical methods of object identification/recognition. It differs significantly from traditional aproaches, which employs such techniques as thresholding, region growing and splitting, etc. [9, 10, 11]. Instead of trying to use all available knowledge in one segmentation step, *CHAP* divides the process into organised into hierarchy multiple subsequent steps. Each of the steps addresses different recognition problem, and apart from initial knowledge it can utilise findings of the previuous steps. This reflects possibly fine grained bottom-up recognition process, in which semantic graphical primitives are to be first mined in analysed images, before semantics is ascertained to their subsets. What we call *a graphical primitive*, or *spatial patch (spatch)* can be literally anything from single pixels, through model-based objects like lines or circles, to any set of pixels. This is the last approach that is analysed in the paper presented. What is important, *spatches* may or may not have a direct translation to image's pixel space. Nevertheless, recognised objects are considered to be describable by sets of spatches.

Given a set of *spatches* $\mathcal{P}$ of an image is first identified, object recognition is performed using energy oriented optimisation process, based on the *Adaptive Active Hypercontour* algorithm [2].

2.1. Neural based competitive spatch identification

Let V be a set of of neurons, and let somatic description of each neuron $n \in V$ be defined by a reference point in the image coordinate space $w(n) = (i_n, j_n)$ and one additional real parameter $c(n)$ reflecting a greyscale colour of the pixel from analysed image reflecting neurons reference point. Let than the neurons create a self-organised neural network, operating in a *winner takes all* paradigm [12], which in this case means that the most active neuron for the input is considered to be it's representative. Given that pixels from the image become inputs of the neural network described, every neuron defines a region on an image, formed by the set of pixels for which it wins the competition with other neurons. This region, being a spatch in the context of the previous section, will be denoted as $p(n)$.

An important undisclosed aspect of the neurons presented is their transmission function tr_n. Because the function exerts a significant influence on the shape characteristics of spatches, it should be chosen on the basis of a selected knowledge domain. This paper addresses the problem of *Medical Image Understanding*. Limiting our considerations to the ventricular system recognition we have developed a desired spatch characteristic, on the basis of the following observations:

1. Filled with cerebrospinal fluid, the chambers constituting the ventricular system are darker than the surrounding brain tissues

2. These chambers are compact, usually being elliptical like regions or a sum of elliptical regions.

As a result, a desired characteristic of spatches set $\mathcal{P}$ reflects the properties of Voronoi mosaic with one modification, aiming to utilise colour information. Pixels of a desired colour (defined in a neuron's description), located near a neuron's reference point, should be connected to its spatch. As a result the following transmission function have been used:

$$tr_v(\mathbf{x}) = \exp(-\rho(w(v), \mathbf{x})(1 + |c(n) - image(x)|)) \tag{1}$$

where ρ is distance function and $image(x)$ is greyscale colour value of the pixel from the image having coordinates $\mathbf{x}$.

In addition to this, let us define graph G over set of neurons V. Edges of G define neighbourhood relation that can be used to aid spatches composition into semantically relevant objects - a further phase of the method presented. Graph G as such can also be considered. From now on, in this paper the terms neural network and graph will be used interchangeably.

2.2. Spatch graph adaptation

An actual task performed by the spatches eduction phase can be considered a structural pattern analysis process. For every image analysed, a separate neural network has to be constructed and its parameters have to be adapted through a learning process. The resultant network constitutes a description of an image on the basis of which it has been learning.

In this paper, we use Growing Neural Gas [13] inspired network learning process, which has been modified to reflect Adaptive Active Hypercontour process, presented in a simplified form as follows [14]:

Algorithm 1: Adaptive Active Hypercontour Algorithm

$i \leftarrow 1$
$c_0 \leftarrow$ *initial clasifier*
...
$e_0 \leftarrow E\,(H(c_0))$
while stop condition **do**
    if *β-phase condition* **then**
        `//` α`-phase: subordinate induction algorithm invocation`
        $c_i \leftarrow \kappa^{p(i)}\,(c_{i-1})$
        ...
    else
        enter *β-phase*
    end
    evaluate *stop condition*
    $i \leftarrow i + 1$
end

Two phases of the algorithm can be distinguished. The first one, α-phase, is in fact an invocation of an adaptation method typical of the classifier model applied (in this case Growing Neural Gas). The second one, however, can be considered an unrestricted solution modification, based on additional knowledge about the problem, known properties of the classifier model and the subordinate adaptation method used (here denoted as κ). Please refer to [14] for a detailed description and full algorithm formulation.

In this paper, we use a modified *growing neural gas (GNG)* as the classifier model- a flexible self-organised neural network inference algorithm. However, network adaptation and growth have been separated ; the former one is performed solely in β phase.

Below, we can see that a single α step consists of λ adaptation iterations, each based on one random pixel from an image.

Algorithm 2: adaptation iterator (κ) within α

// $d \in [0,1]$ and $\eta_n, \eta_a : \mathbb{N} \to [-1,1]$ are method parameters
$\mathbf{x} \leftarrow$ random element from pixel coordinate space
$n_1 \leftarrow \arg\max_{v \in V}\ tr_v(\mathbf{x})$
$n_2 \leftarrow \arg\max_{v \in V \setminus \{n_1\}} tr_v(\mathbf{x})$
$error(n_1) \leftarrow error(n_1) + E^{-tr_{n_1}(\mathbf{x})}$
increment the age of all edges emanating from s_1
/* update reference elements of n_1 and it's neighbours in graph G using any Hebbian-like learning */
$w(n_1) \leftarrow (1 - \eta_n) * w(n_1) + \eta_n \mathbf{x}$
for $a \in adj(s_1)$ **do**
    $w(a) \leftarrow (1 - \eta_a) w(a) + \eta_a \mathbf{x}$
    increment $age(edge(n_1, a))$
end
if $n_2 \notin adj(n_1)$ **then**
    add $edge(n_1, n_2)$ to E
    $age(\{n_1, n_2\}) \leftarrow 0$
end
/* remove non-active edges */
for $e \in E$ **do if** $age(e) = a_{max}$ **then** remove e from E
/* remove orphaned nodes */
for $n \in V$ **do if** $deg(n) = 0$ **then** remove n from V

The β**-phase** of the method presented is responsible for extending a set of neurons. For this purpose, neuron n which has the biggest accumulated error is selected and duplicated, which results in the addition of a new neuron n‘ to V. In the subsequent adaptation phases, the neurons start to differentiate, dividing the original area into two parts, which increases region analysis granularity. The accumulated error of both neurons is set to half of original value. After duplication accumulated errors of all neurons are decreased by being multiplied by a constant parameter $d \in [0, 1)$.

3. Neuronal Group Learning

Kohonen-inspired self-organised neural networks are thought to optimise quantisation of input space. This task is only partially compatible with spatch identification. One of the main problems encountered while performing research in this topic is instability of generated spatches caused by image noise. Given an exemplary winning neuron n, even small change in the position of its reference point $w(n)$ might lead to a significant change in value $c(n)$. As transmission function computed using formula 1 gives emphasise on the colour of analysed pixel (which is the desired property) its small alteration may lead to an unpredictable modification in current patching $\mathcal{P}$.

A simple modification of the method, leading to inclusion of $c(n)$ into somatic description of neuron n does not give the expected improvement, as in most cases in leads to equalisation of all colour parameters, depending on the properties of the image.

3.1. Alteration of the α-phase

Neuronal Group Learning concept, first described in [6] enables us to enforce the desired behaviour in a novel and effective way. This concept allows neurons to cooperate during network adaptation. *NGL* assumes that neurons are labelled, leading to their clustering into *neuronal groups*. Neurons from the same *NG* can collaborate during network adaptation. In the method presented, the scope of *NGL* has been limited to two predefined neural groups- one aiming to claim dark areas of image (with somatic colour set to black) and the other aiming to claim brighter regions (with colour value set to RGB(70,70,70)). The colour values assigned do not ever change during network adaptation, ensuring greater patching stability. Actual *NGL* strategy is applied during winning neuron’s neighbourhood adaptation.

Spatching behaviour analysis leads to strong antagonistic definition of both *NGs*. A standard learning rule aims to equalise the distribution of neurons throughout active regions, whereas the specificity of image recognition task emphasises a more detailed analysis of regions of interest. What is more, in the approach presented, it is expected that neurons will be present only in the areas matching the group definition. As a result, it is desired that neurons of "black" group be pushed into dark areas of the picture, and neurons of "white" group be pushed out of these regions. This antagonism of defined *NGs* leads us to apply a strategy in which neighbours of the same group, as the winner, are attracted to the processed input, and neighbours belonging to a different group are repelled.

The strategy applied leads to the expected behaviour, in which subgraphs g of graph G patching colour coherent regions become connected and contain neurons of the same neuronal group.

3.2. Alteration of the β-phase

Apart from the modification presented above, an additional step in beta phase is added. Let $p(n)$ be spatch related to neuron n. This is, in fact, a finite set of points in the pixel coordinate space. This step aims to place n in its centre of competence $O(n)$, here computed using the following formula:

$$O(n) = \sum\nolimits_{x \in p(n)} x tr_n(x) \tag{2}$$

In the final step of the network adaptation, this strategy leads to a situation in which most neurons are placed close to a geometric centre of claimed patch, resulting in smoother and more natural borders between patches.

4. Experimental results

The method presented was evaluated in the task of recognition and segmentation of chambers of ventricular system. Heading towards implementation of a hierarchical object retrieval model, the image spatching has to be performed. From the actual recognition point of view, the solution is the resultant graph $G = (V_G, E_G)$, which is a kind of linguistic description of an image. The graph defines the patching of analysed image, here denoted as $\mathcal{P}^G = \{p(v) : v \in V_G\}$. This set is treated as analysed object set of subsequent in hierarchy object recognition method, which in this case id Adaptive Actihe Hypercontour method. Edges of the gram form a supplementary knowledge used to ease *AAH* process.

One of the fundamental properties of patches sets obtained using *NGL* based self-organised competitive neural network learning is their informativeness. Areas are not only colour coherent, but also have smooth borders resulting from precise filling of coherent regions in an analysed image.

This is significant progress compared to the previously presented circle graph description [1] in the following aspects.

- Spatch is adapted to be of a'priori defined semantics, which may be considered experts knowledge parametrising a method to a specific task. (Here, we search for dark regions, as this is a photometric property of cerebrospinal fluid on CT images.)
- All pixels from the analysed image are members of some spatch - in the case of a circle graph, detailed description requires the use of a smaller minimal circle radius, leading to a significant increase in analysed object count
- The set of edges is inferred to reflect semantic adjacency, not only a geometric one, as it was the case in the previously analysed linguistic descriptions.

Figures 1 and 2 depicts linguistic description of the same images using a cirle graph and a NGL-inferred neural-based spatches. These descriptions have been found using 10-20 iterations of main algorithm, with $\lambda = 1000$ adaptations followed be neuron centering and network growth. Strong dependency on network initialisation has been observed, which can be considered a weak point of the method. Nevertheless, this problem can be easily overcome by over-initialisation, as *GNGs* network pruning mechanism and NGL-empowered somatic adaptation will either remove unnecessary neurons, or move them to desired areas.

5. Conclusions

This paper presents novel method for identification of semantically sound low level image fragments. Apart from region segmentation, the method catches adjacency relations between them. Both this aspects, sided by introduced *neuronal group* information, constitutes linguistic description of an image. This characteristic places the method presented somewhere between segmentation and structural recognition methods, serving as flexible and easy to use middle ground, relieving potential user from conforming to sometimes strict constraints of structural pattern recognition algorithms. Through careful tuning of parameters, this method

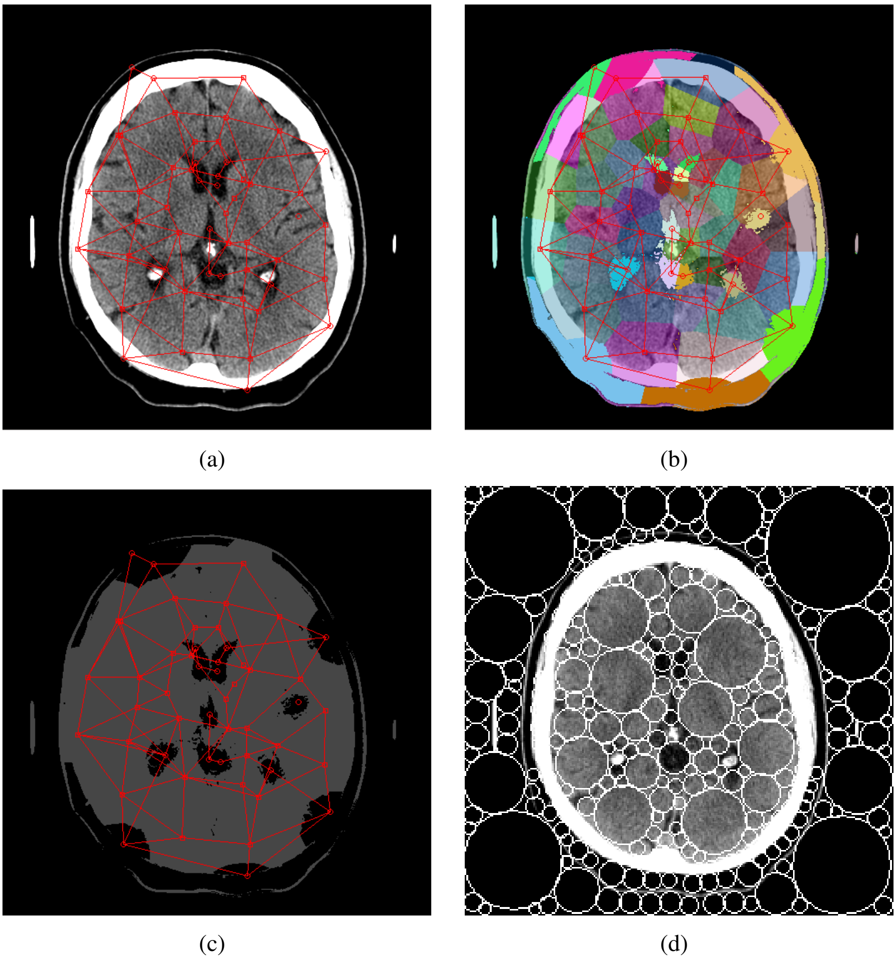

Figure 1. Image linguistic spatching: (a) - original image and G, (b) - spatch mosaic, (c) - neural groups' areas, (d) - circular description

can easily incorporate experts knowledge about expected region properties, making method adaptable to variety of tasks, with *Medical Image Understanding* as an important example. Significant knowledge gain, encoded in description graph G, as well as neuron labelling can easily be used by semantic and context oriented recognition methods, such as *Active Partitions* or *Conditional Random Fields* which makes it easy to use as a part of greater, hierarchical processes, like *CHAP*. Al-

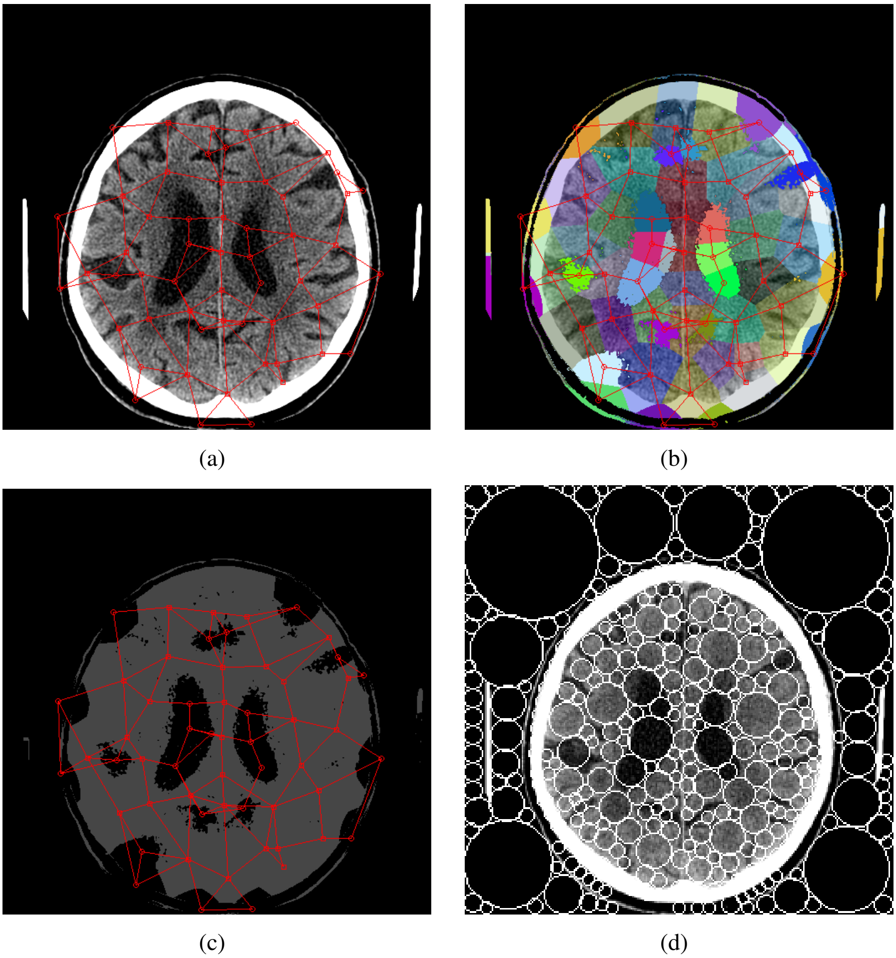

Figure 2. Image linguistic spatching: (a) - original image and G, (b) - spatch mosaic, (c) - neural groups' areas, (d) - circular description

though additional work is required to make the method non-interactive, more dependable and predictable, presented results are very promising, inspiring new applications and further extensions with development of context aware *NGL* strategies as an example.

Akcnowledgements

This work has been supported by the Ministry of Science and Higher Education, Republic of Poland, under the project number N 519 007 32/0978; decision No. 0978/T02/2007/32.

Authors would like to express their gratitude to Mr Piotr Grzelak, MD from the Department of Radiology and Diagnostic Imaging of Barlicki University Hospital in Lodz for making brain images available and sharing his medical knowledge.

References

[1] Tomczyk, A., Pryczek, M., Walczak, S., Jojczyk, K., and Szczepaniak, P. S., *Spatch Based Active Partitions with Linguistically Formulated Energy*, Journal of Applied Computer Science, Vol. 18, No. 1, 2010, pp. 87–115.

[2] Tomczyk, A. and Szczepaniak, P. S., *Contribution of Active Contour Approach to Image Understanding*, In: Proceedings of IEEE International Workshop on Imaging Systems and Techniques – IST 2007, May 4–5, 2007, Krakow, Poland, 2007.

[3] Tadeusiewicz, R. and Ogiela, M., *Medical Image Understanding Technology*, Vol. 156 of *Studies in Fuzziness and Soft Computing*, Springer-Verlag, Berlin, Heidelberg, New York, 2004.

[4] Tadeusiewicz, R. and Ogiela, M. R., *Medical pattern understanding based on cognitive linguistic formalisms and computational intelligence methods*, In: Proceedings of the International Joint Conference on Neural Networks, IJCNN 2008, part of the IEEE World Congress on Computational Intelligence, WCCI 2008, Hong Kong, China, June 1-6, 2008, IEEE, 2008, pp. 1728–1732.

[5] Edelman, G. M., *Neural Darwinism: The Theory of Neuronal Group Selection*, Basic Books, New York, 1987.

[6] Pryczek, M., *Neuronal Groups and Interrelations*, In: Proceedings of the International Multiconference on Computer Science and Information Technology, October 20–22, 2008. Wisła, Poland, edited by T. P.-P. M. Ganzha, M. Paprzycki, Vol. 3, 2008, pp. 221–227.

[7] Tadeusiewicz, R., Ogiela, M., and Szczepaniak, P., *Notes on a Linguistic Description as the Basis for Automatic Image Understanding*, Int. J. Appl. Math. Comput. Sci., Vol. 19, No. 1, 2009, pp. 143–150.

[8] Ogiela, L., Ogiela, M. R., and Tadeusiewicz, R., *Mathematical Linguistics in Cognitive Medical Image Interpretation Systems*, J. Math. Imaging Vis., Vol. 34, No. 3, 2009, pp. 328–340.

[9] Gonzalez, R. and Woods, R., *Digital Image Processing*, Prentice-Hall Inc., New Jersey, 2002.

[10] Sonka, M., Hlavec, V., and Boyle, R., *Image Processing, Analysis and Machine Vision*, Chapman and Hall, Cambridge, 1994.

[11] Davies, E. R., *Machine Vision, Theory, Algorithms, Practicalities*, Elsevier, Morgan Kaufmann, San Francisco, 2005.

[12] Haykin, S., *Neural Networks: A Comprechensive Foundation*, Macmillan College Publishing Company, New York, 1994.

[13] Fritzke, B., *A Growing Neural Gas Network Learns Topologies*, In: Advances in Neural Information Processing Systems 7, [NIPS Conference, Denver, Colorado, USA, 1994], edited by G. Tesauro, D. S. Touretzky, and T. K. Leen, Vol. 7, MIT Press, 1994, pp. 625–632.

[14] Pryczek, M., *Supervised Object Classification Using Adaptive Active Hypercontours with Growing Neural Gas Representation*, Journal of Applied Computer Science, Vol. 16, No. 2, 2008, pp. 69–80.