Complex problems

Objectives

Solving complex problems - search problems and learning problems. Specification, design and implementation of solving algorithms.

Theoretical aspects

Solving supervised and unsupervised classification problems.
Search algorithms.
Learning algorithms.
Performance evaluation of learning algorithms.

Deadline

Last 3 weeks of the semester.

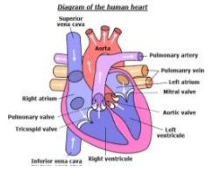
Requirements

Proposed projects:

1. Heart-chamber identification
2. Imaging of atrial fibrosis
3. Image segmentation by complex networks
4. Resource planning
5. Breast cancer detection
6. Intelligent systems for driver assistance

Details are given in what follows.

1. Heart-chamber identification



Objectives

Identification of four chambers of the heart (left atrium, right atrium, left ventricle and right ventricle) in medical images (MRI or CT) by using automated learning methods.

Main idea

We have a set of heart medical images (MRI - magnetic resonance imaging or CT - computed tomography). Some images have been already annotated (classified) with the given four chambers. Identify (by using an automated algorithm - e.g. complex networks) the chambers in the rest of images (by using the model learnt on the first sub-set of images).

TO DO List

1. Select a set S of images (some of them are annotated – for training - - and some of them are not annotated – for testing).
2. Extract a set of features from each image - optional step (if this step is not performed, then the algorithm will work by all pixels/voxels of an image).
3. Learn a classification model by using an automated classification algorithm and the input data (pixels or features of the images).
4. Classify the images without labels (identification of heart chambers) by using the learnt model.

Data and references

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Images

http://segchd.csail.mit.edu/data.html

Existing methods

1. Peng Peng, Karim Lekadir, Ali Gooya, Ling Shao, Steffen E. Petersen, Alejandro F. Frangi, A review of heart chamber segmentation for structural and functional analysis using cardiac magnetic resonance imaging, Magn Reson Mater Phy (2016) 29:155–195
2. Catalina Tobon-Gomez, Jochen Peters, Juergen Weese, Karen Pinto, Rashed Karim, Tobias Schaeffter, Reza Razavi, and Kawal S. Rhode, Left Atrial Segmentation Challenge: A Unified Benchmarking Framework, STACOM 2013, LNCS 8330, pp. 1–13, 2014
3. Catalina Tobon-Gomez et al., Benchmark for algorithms segmenting the left atrium from 3D CT and MRI datasets, IEEE Transactions on Medical Imaging, 2015
4. Bram van Ginneken, Fifty years of computer analysis in chest imaging: rule-

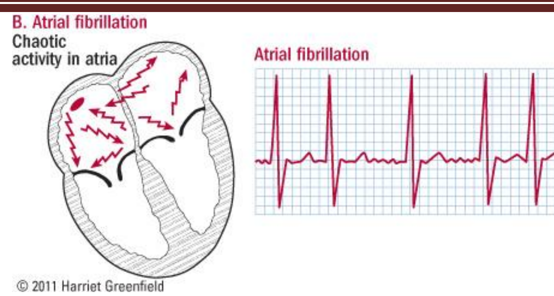
based, Radiol Phys Technol, 2017
5. Lequan Yu, Xin Yang, Jing Qin and Pheng-Ann Heng 3D FractalNet: Dense volumetric segmentation for cardiovascular MRI volumes, 2017
6. Jelmer M. Wolterink, Tim Leiner, Max A. Viergever and Ivana Isgum Dilated convolutional neural networks for cardiovascular MR segmentation in congenital heart disease, 2017
7. Rahil Shahzad, Shan Gao, Qian Tao, Oleh Dzyubachyk and Rob van der Geest, Automated cardiovascular segmentation in patients with congenital heart disease from 3D CMR scans: Combining multi-atlases and level-sets, 2017

Image processing by complex networks

1. Cuadros et al., Segmentation of large images with CNs. In SIBGRAPI 2012 IEEE:24–31.
2. Mourchid et al., A new img. segm. approach using CD algorithms. In ISDA 2015 IEEE:648–653.
3. Mourchid et al., Img. segm. based on CD approach. I. J. of Computer Information Systems and Industrial Management Applications, 8(1):195–204.
4. Nepusz, T., Petróczi, A., Négyessy, L., and Bazsó, F., Fuzzy communities and the concept of bridgeness in CNs. Phys. Rev. E, 77(1):016107

These papers are available at http://www.cs.ubbcluj.ro/~lauras/test/docs/school/UC/2016-2017/projects/HeartChamberSegmentation/

2. Imaging of atrial fibrosis



Objectives

Recognition of atrial fibrosis in medical images (MRI or CT) by using an automated learning method.

Main idea

We have a set of heart medical images (MRI - magnetic resonance imaging or CT - computed tomography). Some images have been already annotated (classified) with the given regions of fibrosis. Identify (by using an automated algorithm - e.g. complex networks) the regions of fibrosis in the rest of images (by using the model learnt on the first sub-set of images).

TO DO list

1. Select a set S of images (some of them are annotated – for training - - and some of them are not annotated – for testing).
2. Extract a set of features from each image - optional step (if this step is not performed, then the algorithm will work by all pixels/voxels of an image).
3. Learn a classification model by using an automated classification algorithm and the input data (pixels or features of the images).
4. Classify the images without labels (identification of fibrosis regions) by using the learnt model.

Data and references

Images

http://segchd.csail.mit.edu/data.html

Fibrilation

1. Robert S. Oakes et al., Detection and Quantification of Left Atrial Structural Remodeling With Delayed-Enhancement Magnetic Resonance Imaging in Patients With Atrial Fibrillation (Oakes2009.pdf)
2. Pim Gal and Nassir F. Marrouche, Magnetic resonance imaging of atrial fibrosis: redefining atrial fibrillation to a syndrome, European Heart Journal (2017) 38, 14–19 (Gal2015.pdf)
3. HUBERT COCHET et al., Age, Atrial Fibrillation, and Structural Heart Disease Are the Main Determinants of Left Atrial Fibrosis

Detected by Delayed-Enhanced Magnetic Resonance Imaging in a General Cardiology Population (Cochet2015.pdf)

4. Luca Longobardo et al., Role of imaging in assessment of atrial fibrosis in patients with atrial fibrillation: state-of-the-art review, European Heart Journal – Cardiovascular Imaging (2014) 15, 1–5 (Longobardo2015.pdf)
5. Natalia A. Trayanova, Mathematical Approaches to Understanding and Imaging Atrial Fibrillation, 2014 (Trayanova2014.pdf)
6. Natalia A. Trayanova, Computational Cardiology: The Heart of theMatter, International Scholarly Research Network (Trayanova2012.pdf)
7. Erwan Donal et al., Expert Consensus Document on the role of multi-modality imaging for the evaluation of patients with atrial fibrillation, 2016 (Donal2016.pdf)

Complex networks - community detection in general images

1. Cuadros et al., Segmentation of large images with CNs. In *SIBGRAPI 2012 IEEE:*24–31 (Cuadros 2012.pdf)
2. Mourchid et al., A new img. segm. approach using CD algorithms. In *ISDA 2015 IEEE:*648–653 (Mourchid2015.pdf)
3. Mourchid et al., Img. segm. based on CD approach. *I. J. of Computer Information Systems and Industrial Management Applications*, 8(1):195–204 (Mourchid2016.pdf)

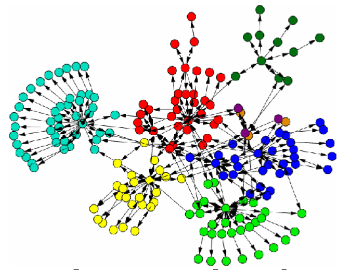
Complex networks - super-pixel in community detection for image processing

1. Cuadros et al., Segmentation of large images with CNs. In *SIBGRAPI 2012 IEEE:*24–31 (Cuadros 2012.pdf)
2. Abin et al., WISECODE, *The Imaging Science J.*, 62(6):327–337. (Abin2011.pdf, Abin2014.pdf)

These papers are available at

http://www.cs.ubbcluj.ro/~lauras/test/docs/school/UC/2016-2017/projects/HeartFibrilation/

3. Image segmentation by using complex networks



Objectives

Image segmentation by using community detection algorithm in complex networks.

Main idea

We have a set of images. Every image is composed by 2 or more regions (Segments). Identify, by using a learning algorithm based on complex networks, these regions.

TO DO list

1. Select a set S of images (some of them are annotated – for training -- and some of them are not annotated – for testing).
2. Extract a set of features from each image - optional step (if this step is not performed, then the algorithm will work by all pixels/voxels of an image).
3. Learn a classification model by using an unsupervised classification algorithm (based on community detection method used in complex networks) and the input data (pixels or features of the images).
4. Classify the images without labels (identification of regions) by using the learnt model.

Data and references

Images

https://www2.eecs.berkeley.edu/Research/Projects/CS/vision/bsds/

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Complex networks and community detection algorithms

1. Fast Greedy: Clauset et al., Finding com. struct. in very large networks. *Phys. Rev. E*, 70:1–6, 2004
2. Lovain: Blondel et al., Fast unfolding of communities in large networks, *J. of statistical mechanics: theory and experiment*, 10, 2008
3. Newman-Fast algorithm: Newmann, M. E. J., Fast algorithm for detecting com. struct. in networks. *Phys. Rev. E*, 69:1–12.
4. Label Propagation: Raghavan et al., Near linear time algorithm to detect com. struct. in large-scale networks. *Phys. Rev. E*, 76:036106
5. Infomap: Rosvall, M. and Bergstrom, C. T., An information-

theoretic framework for resolving com. struct. in CNs. *Proc. of the Nat. Acad. of Science*s, 104(18):7327–7331.

Hierarchical communities

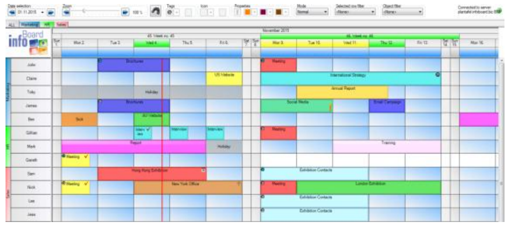
1. Girvan, M. and Newman, M. E., Community structure in social and biological networks. *Proc. of the Nat. Acad. of Science*s, *99(12):7821–7826*
2. Newmann, M. E. J., Fast algorithm for detecting com. struct. in networks. *Phys. Rev. E*, 69:1–12.
3. Arenas et al, Analysis of the struct.of CNs at dif. resol.n levels. *New J. of Physics*, 10(5):053039.
4. Lancichinetti et al., Detecting the overlapping and hierarchical com. struct. in CNs. *New J. of Physics*, 11(3):033015.
5. Ronhovde, P. and Nussinov, Z. (2009). Multiresolution CD for megascale networks by information-based replica correlations. *Phys. Rev. E*, 80(1):016109
6. Sales-Pardo et al., Extracting the hierarchical organization of complex systems. *Proc. of the Nat. Acad. of Science*s, 104(39):15224–15229.

Community detection in general images

1. Cuadros et al., Segmentation of large images with CNs. In *SIBGRAPI 2012 IEEE:*24–31 (Cuadros 2012.pdf)
2. Mourchid et al., A new img. segm. approach using CD algorithms. In *ISDA 2015 IEEE:*648–653 (Mourchid2015.pdf)
3. Mourchid et al., Img. segm. based on CD approach. *I. J. of Computer Information Systems and Industrial Management Applications*, 8(1):195–204 (Mourchid2016.pdf)

These papers are available at
http://www.cs.ubbcluj.ro/~lauras/test/docs/school/UC/2016-2017/projects/ImgSegmentByComplexNetworks/

4. Task planning



Objectives

Planning of resources by using optimisation algorithms.

Main idea

There are some tasks, each of them having a starting time and an ending time. There are a set of employees, also, that have to execute all the given tasks. Each employee can execute one task in a given period. Determine a minimum number of employees such as all the tasks to be performed.

TO DO list

1. Process and store the input data.
2. Developing of an optimisation algorithm.

Data and references

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Resources

http://people.brunel.ac.uk/~mastjjb/jeb/orlib/files/

Existing methods

1. Jorne Van den Bergh, Jeroen Beliën, Philippe De Bruecker, Erik Demeulemeester,Liesje De Boeck, Personnel scheduling: A literature review, European Journal of Operational Research 226 (2013) 367–385
2. M. Krishnamoorthy, A.T. Ernst, D. Baatar, Algorithms for large scale Shift Minimisation Personnel Task Scheduling Problems, European Journal of Operational Research 219 (2012) 34–48
3. Pieter Smet, Greet Vanden Berghe, A matheuristic approach to the shift minimisation personnel task scheduling problem, Practice and Theory of Automated Timetabling (PATAT 2012), 29-31 August 2012, Son, Norway
4. PieterSmet, AndreasT.Ernst, GreetVandenBerghe, Heuristic decomposition approaches for an integrated task scheduling and personnel rostering problem, Computers & Operations Research 76 (2016), 60–72

These papers are available at http://www.cs.ubbcluj.ro/~lauras/test/docs/school/UC/2016-2017/projects/taskPlanning/

5. Breast cancer identification

Objectives

Breast cancer recognition in images.

Main idea

We have a set of breast images (mammographies). Some of the images have been already annotated (labelled) as images with cancer. Identify, by using a learning algorithm, the correct labels of the rest of images.

TO DO list

1. Select a set S of images (some of them are annotated – for training -- and some of them are not annotated – for testing).
2. Extract a set of features from each image - optional step (if this step is not performed, then the algorithm will work by all pixels/voxels of an image).
3. Learn a classification model by using an automated classification algorithm and the input data (pixels or features of the images).

Data and references

Images

MIAS http://www.mammoimage.org/databases/
BCDR http://bcdr.inegi.up.pt/
DDSM http://marathon.csee.usf.edu/Mammography/Database.html

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Learning algorithms

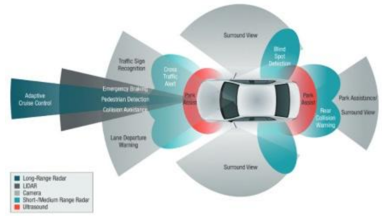
1. Daniel C. Moura · Miguel A. Guevara López, An evaluation of image descriptors combined with clinical data for breast cancer diagnosis, Int J CARS, 2013 (Moura2013.pdf)
2. John Arevalo, Fabio A. González, Raúl Ramos-Pollán, Jose L. Oliveira and Arevalo, J., González, F. A., Ramos-Pollán, R., Oliveira, J. L., & Lopez, M. A. G. (2015, August). Convolutional neural networks for mammography mass lesion classification. In *Engineering in Medicine and Biology Society (EMBC), 2015 37th Annual International Conference of the IEEE* (pp. 797-800). IEEE (Arevalo2015.pdf)
3. Arevalo, J., González, F. A., Ramos-Pollán, R., Oliveira, J. L., & Lopez, M. A. G. (2016). Representation learning for mammography mass lesion

classification with convolutional neural networks. *Computer methods and programs in biomedicine*, *127*, 248-257. (Arevalo2016.pdf)

4. Bekker, A. J., Shalhon, M., Greenspan, H., & Goldberger, J. (2016). Multi-View Probabilistic Classification of Breast Microcalcifications. *IEEE Transactions on medical imaging*, *35*(2), 645-653.(Bekker2016.pdf)
5. Wang, J., Yang, X., Cai, H., Tan, W., Jin, C., & Li, L. (2016). Discrimination of breast cancer with microcalcifications on mammography by deep learning. *Scientific reports*, *6*. (Wang2016.pdf)
6. Moura, D. C., López, M. A. G., Cunha, P., de Posada, N. G., Pollan, R. R., Ramos, I., ... & Fernandes, T. C. (2013, November). Benchmarking Datasets for Breast Cancer Computer-Aided Diagnosis (CADx). In *Iberoamerican Congress on Pattern Recognition* (pp. 326-333). Springer Berlin Heidelberg. (Moura2013_2.pdf)
7. Fratean S., Diosam L., (2015). Descriptors fusion and genetic programming for breast cancer detection, Studia Universitaria, 2015 (Fratean2015.pdf).
8. Nogueira, M. A., Abreu, P. H., Martins, P., Machado, P., Duarte, H., & Santos, J. Image descriptors in radiology images: a systematic review. *Artificial Intelligence Review*, 1-29. 2016 (Nogueira2016.pdf).
9. Abbas, Q. (2016). DeepCAD: A Computer-Aided Diagnosis System for Mammographic Masses Using Deep Invariant Features. *Computers*, *5*(4), 28. (Abbas2016.pdf)

These papers are available at
http://www.cs.ubbcluj.ro/~lauras/test/docs/school/UC/2016-2017/projects/BreastCancer/

6. Intelligent systems for driver assistance



Objectives

Obstacle identification in traffic images by using learning algorithms.

Main idea

We have a set of traffic images with different objects (cars, animals, signs, pedestrians). Learn to identify the obstacles in these images.

TO DO list

1. Select a data set.
2. Extract features from images.
3. Learn a classification model.
4. Test the learnt model on new images.

Data and references

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Images

INRIA http://pascal.inrialpes.fr/data/human/

Daimler http://www.lookingatpeople.com/download-daimler-stereo-ped-det-benchmark/index.html

Caltech http://vision.caltech.edu/Image_Datasets/CaltechPedestrians/index.html

Learning algorithms

http://www.pedestrian-detection.com/

http://www.gavrila.net/Publications/door2door01.pdf

http://ebookbrowse.com/survey-of-pedestrian-detection-for-advanced-driver-assistance-pdf-d264642098

http://www.vision.caltech.edu/publications/dollarCVPR09pedestrians.pdf