

STUDY OF NEUROBIOLOGICAL IMAGES BASED ON ONTOLOGIES USED IN SUPER-RESOLUTION ALGORITHMS

Andreea-Mihaela Pintilie¹
Costin-Anton Boiangiu²

ABSTRACT

This paper focuses on the applicability of ontologies in medical image processing area. Techniques for automatically describing medical images in a medical language that doctors can operate with are presented. Super resolution algorithms are also highlighted in order to prove their superiority over usual interpolation methods on medical images. At the end, a set of experimental results regarding ontologies are offered.

KEYWORDS: Neurobiological image, medical image, ontology, super resolution

1. APPLICABILITY OF ONTOLOGIES IN SUPER RESOLUTION ALGORITHMS

Super resolution case studies

The ability to transcend the fundamental resolution limits of sensors using super-resolution algorithms has shown significant progress and capability in the area of photographic imaging. By far, the majority of applications using super-resolution technology have been in the area of photographic imagery for either consumer or defense-type applications. Recently, researchers integrated super-resolution algorithms in different imaging medical applications. In order to improve the super resolution algorithms for medical applications, the researchers took into consideration the differences between the photographic imaging and medical imaging.

Image representation

An image can be represented in various feature spaces, and the FCM algorithm classifies the image by grouping similar data points in the feature space into clusters. This clustering is achieved by iteratively minimizing a cost function that is dependent on the distance of the pixels to the cluster centers in the feature domain. The pixels on an image are highly correlated, i.e. the pixels in the immediate neighborhood possess nearly the same feature data. Therefore, the spatial relationship of neighboring pixels is an important characteristic that can be of great aid in imaging segmentation. General boundary detection techniques have taken advantage of the spatial information for image segmentation. However, the conventional FCM algorithm does not fully utilize this spatial information.

¹ Engineer, Department of Computer Science and Engineering, Faculty of Automatic Control and Computers Science, University "Politehnica" of Bucharest, Splaiul Independenței 313, Bucharest, 060042, Romania, andreea.pintilie@cti.pub.ro

² Associate Professor PhD Eng., Department of Computer Science and Engineering, Faculty of Automatic Control and Computers Science, University "Politehnica" of Bucharest, Splaiul Independenței 313, Bucharest, 060042, Romania, costin.boiangiu@cs.pub.ro

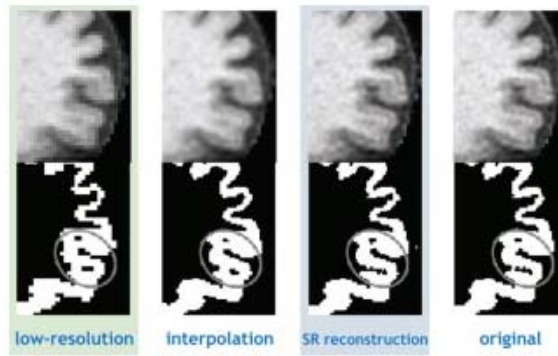


Figure 1: Super resolution steps

Pixel Classification

A noisy pixel might be wrongly classified because of its abnormal feature data, in a standard FCM technique. The method presented in [28] incorporates spatial information, and it altered the membership weighting of each cluster after the cluster's distribution in the neighborhood is considered. This scheme is proposed in order to reduce the effect of noise and to bias the algorithm toward homogeneous clustering.

Medical Image acquisition

Firstly, when a medical image is taken a controlled source of illumination is often used during the image acquisition. The strong illumination often provokes a higher signal-to-noise ratio. [23] In order to prevent tissue damaging, the illumination energy is limited, thereby the SNR is below the SNR of a photographic image.

Secondly, imaging speed is another factor that has to be taken into consideration: in order to avoid patient's movement and therefore minimizing the imaging artifacts associated with patient movement and the acquisition time also has an impact on the patients' comfort.

Thirdly, the image processing artifacts are much less tolerable in medical images than in photographic applications. Luckily, medical imaging systems operate under highly controlled environments with highly similar objects. Algorithm developers can leverage prior knowledge about the anatomy or biology to improve image quality. [21]

Finally, the majority of medical imaging applications involve creating images from radiation propagation through three-dimensional objects. Thus, while the final images are two-dimensional, they represent some form of projection through a three-dimensional volume.

Low Radiation Digital X-ray Mammography

Super resolution is nowadays used in Low Radiation Digital X-ray Mammography. Today's digital detectors cannot shrink pixel sizes to increase resolution without sacrificing the SNR measurement.[30]

To maximize image resolution, the researchers have explored digitally combining multiple low-dosage images, each containing spatial shifts. The shifts were the result of patient movement, intentional dithering of the detector, vibration in the imaging system, and small movement of the imaging gantry. Providing high resolution imagery required sophisticated, nonlinear reconstruction techniques to address the extremely low SNR of the captured images, but using an improved super resolution algorithm solved the problem. [31]

Optical Coherence Tomography

The invention and utilization of Optical Coherence Tomography (OCT), first reported in [28] in 1991, has had a profound impact on many fields of research, especially ophthalmic sciences. OCT systems provide noninvasive yet high-resolution in-vivo images of retinal structures, which can be used to define imaging biomarkers of the onset and progression of many ophthalmic diseases. By employing an interferometer, several OCT based imaging systems have been developed throughout the years, most notably the time-domain OCT (TDOCT) and ultrahigh resolution OCT (UHROCT).

The advent of the Spectral Domain Optical Coherence Tomography (SDOCT) system has further improved the image quality and acquisition speed. Today, several commercial SDOCT systems are available with similar capabilities and 20-30 kHz A-scan rates.[28]

OWL Ontology

In medicine large-scale ontology domains have been implemented besides UMLS: GALEN, NCI and Medical Entities Dictionary. Though containing huge amounts of useful domain knowledge, most available medical ontologies have been structured under different design principles than those required for Semantic Web applications and therefore cannot be directly integrated in such applications. On one hand most of the available ontologies are not formalized in an appropriate representation language to be shared and reused. On the other hand they have been realized for very concrete tasks and their content is modeled in an ambiguous way.[9]

Ontology in medical images analysis

According to the article [34] a medical image is more than an array of pixels. At least three major distinct components of a medical image can be distinguished:

1. The particular anatomical structure from which the image is taken
2. The array of pixels of measured radiation, hydrogen density, etc.
3. The collection of features each of which is a cluster of pixels with similar pixel values in the pixel array.

The article also states that there are at least four stages of medical image analysis:

1. Clustering pixels into features
2. Analyzing the shape of features and spatial relations between them as they are depicted in the pixel array
3. Mapping features to anatomical structures and relations between features to relations between (parts of) anatomical structures

4. Evaluating the depicted anatomical structure (and parts thereof) as normal or pathological in the sense of canonical anatomy

The first stage of analyzing the image shown in Figure 2(a), is clustering pixels into features like feature 1 and feature 2 as depicted in the drawing shown in Figure 2(b). This process is complex and has the following problems:

1. difficulty of extracting crisp boundaries from the pixel array
2. heterogeneity of pixels that are to be clustered into a single feature



Figure 2: Ontology features classification

In order to cluster the pixels besides using a fuzzy clustering algorithm and a super resolution one to determine the boundaries of the image, the ontology analyses the anatomical structures as a top-down approach to determine which qualitative relations hold between the parts of (normal and pathological) anatomical structures.

2. USE OF OWL ONTOLOGY MODULE IN PROJECT IMPLEMENTATION

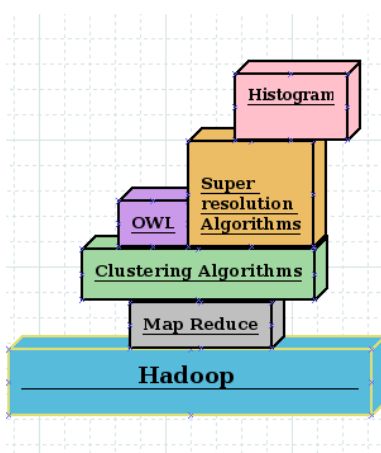


Figure 3: Project structure

OWL Ontology module

The ontology design we used for this project is pretty simple, but we intend to extend it. As stated in the previous chapters, the ontology was designed in order to obtain some representation of the brain and of the tumors located in different parts of the brain. The structure is a hierarchical one, as presented in the following images.

The ontology is not centered on anatomical structures, as in the case of general-use ontology, but rather on radiography entities because a segmentation application makes use of entities which can be determined in radiography. Nevertheless, the parts of the anatomical structures are very useful for refining the segmentation. For instance, more precise coordinates might be added in order to determine the junction points of certain bones or tissues. The main classes are RadiographyEntity and Tumor.

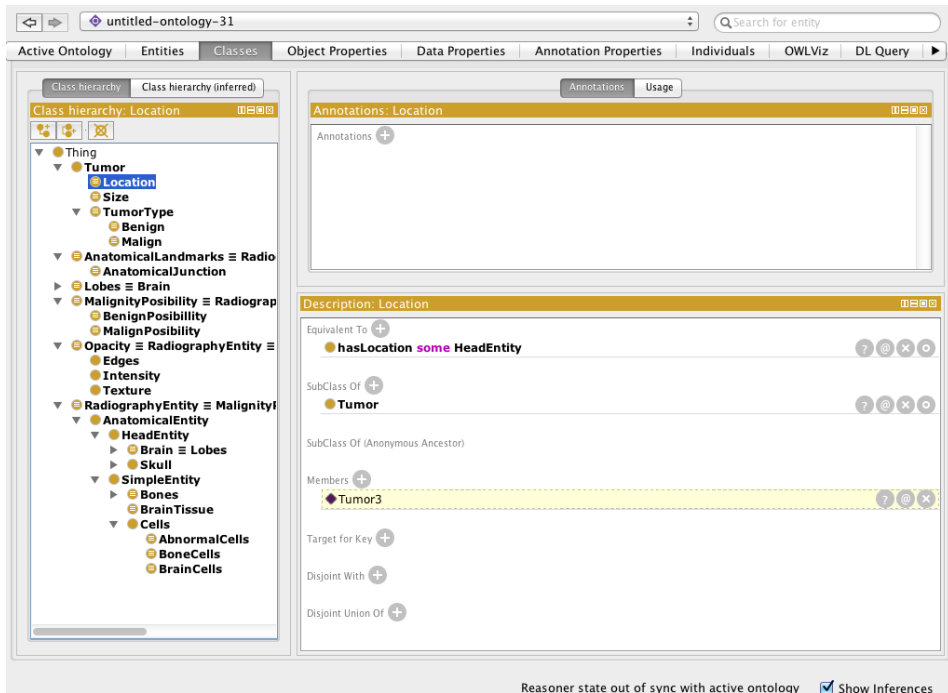


Figure 4: Proposed ontology classes

RadiographyEntity

RadiographyEntity contains the AnatomicalEntity class, at the beginning of the design the Tumor was considered a RadiographyEntity, but the Tumor type must be different from any of the types contained in RadiographyEntity and the location of the Tumor must have as location an anatomical entity. In addition, we started with the idea that the patient has no anatomical abnormality. This way the ontology is modular.

The class was used in order to group entities with the same role. The basic brain parts are mapped on entities from this class. In future implementations, a class like abnormalities must be taken into consideration, because the brain is unique form individual to individual.

SimpleEntity

The SimpleEntity class represents the basic parts that the brain is constituted form. It has restrictions such as: the brain cells and bone cells are disjoint. After reading about the structure and the composition of the brain, we noticed that there are different types of cells

for the skull and for the brain. Even the skull cells differ from one another by density and number of pores. In the present implementation we only took into consideration the number of pores present in the bone.

HeadEntity

The HeadEntity represents the level above the SimpleEntity. Instead of using HeadEntity any other composed structure such as thorax or rib cage. Besides the fact that the composition of each element can be established and inference rules can be applied in order to generate the structure of related elements, the spatial relations between objects were also taken into consideration.

OpacityEntity

It is important to make a clear distinction between anatomical objects or tumor objects and the opacities visible on radiographs like edges, intensity and texture. In defining the opacity class we took into consideration the fact that these opacities are proper to each radiographic image and after reading about the x-rays image interpretation we managed to define the attributes: edges, intensity and texture. Moreover, these attributes are also very important in image segmentation.

MalignityPossibility

The malignity possibility represents the class where the percentage of a tumor of being malign or benign is expressed. If a tumor could not be classified as malign or benign, then it can be in a certain percentage malign or benign.

Lobes

The class, as the name states, represents the lobes of the brain. The lobes are also parts of right or left hemisphere.

Anatomical Landmarks

The landmarks are of great importance for image segmentation algorithms. Based on them, the entire junction between the cranial structures can be determined.

Tumor

Important subclasses for image segmentation are the location and the size of the tumor. After establishing the location and the size of the tumor, with the help of a radiologist certain conclusions might be drawn such as: the possibility for a tumor to become malign or to grow and the influence of the tumor on the cognitive and behavioral process. In the present ontology the assumptions about the malignity of a tumor were made based on the size of the tumor.

Relations

The relations are grouped in spatial relations, consistence relations and malignity relations.

The spatial relations have the role to design the brain map and usually are expressed by words like: toLeft, toRight, above, etc. or for establish the intersection point: isIntersectionPoint.

The consistence relations are used in order to create the anatomical hierarchy previously presented: hasCells, hasBones, consitsOf, etc.

The malignity relations refer to the malignity of a tumor.

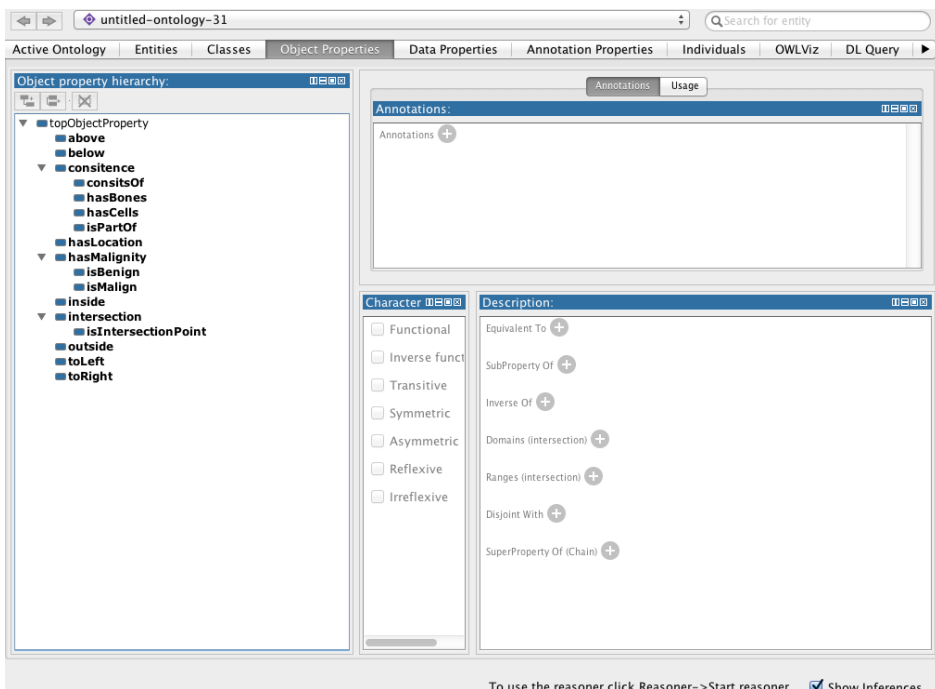


Figure 5: Proposed ontology relations

3. EXPERIMENTAL RESULTS

Data properties

The data properties were used in order to establish certain intervals e.g. for a malign tumor or for the opacity properties like texture type and edges type, the size of the tumor, the lobes position in a certain hemisphere etc.

Individuals

Test

The ontology accepts individuals like the one presented in the "Individuals" section. An individual can be added as a class type, or by using some rules that define the class. As an

example, in order to add a facial bone, this can be added either as a direct type of facial bones or as:

- (isPartOf some Bones)
- and (consistsOf only BoneCells)
- and (hasBones only FacialBonesCells)
- and (hasPores some integer[< 1])

Results

The ontology is very useful when trying to determine the intersection points between two entities and when trying to establish a "map" of the human brain, in order to decide the gravity of the tumor.

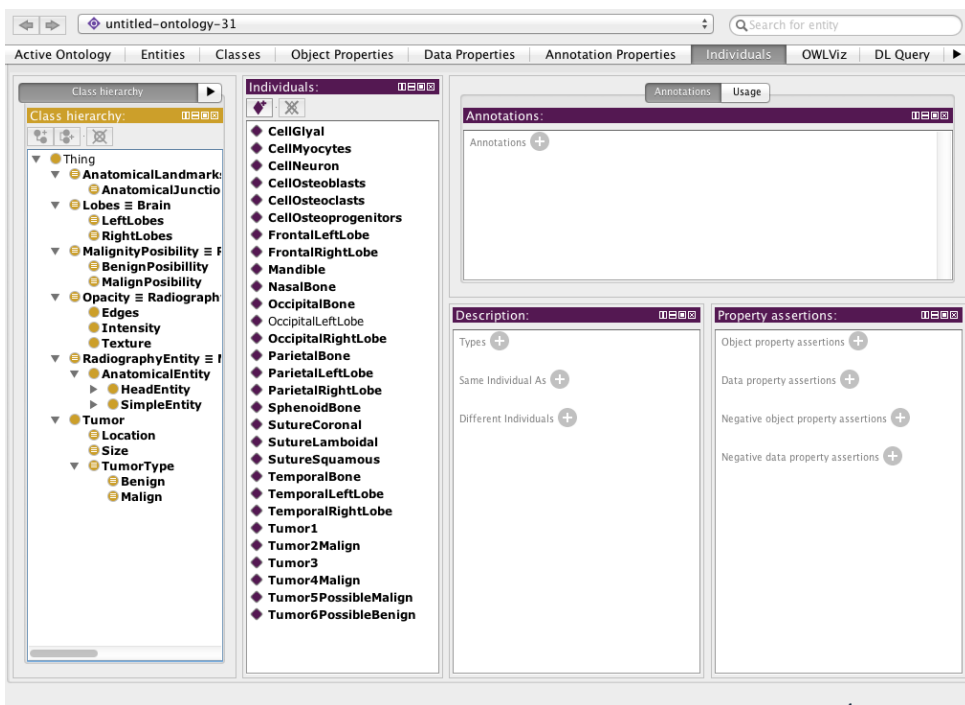


Figure 6: Ontology data set and results

4. REFERENCES

- [1] Jean-Pierre Schober, Thorsten Hermes, Otthein Herzog "Content-based Image Retrieval by Ontology-based Object Recognition", *KI-2004 Workshop on Applications of Description Logics*.
- [2] Paul M. Thompson "Bioinformatic and brain imaging: recent advances and neuroscience applications" Ph. D, 2002.
- [3] Dameron O Modlisation, "Representation et partage de connaissances anatomiques sur le cortex cerebral", These de doctorat d'Universite, Universite de Rennes 1 2003.
- [4] Paul M. Thompson "Bioinformatics and brain imaging: recent advances and neuroscience applications" 2002.

- [5] Thompson PM et al. "Brain Image Analysis and Atlas Construction", in: Fitzpatrick M, Sonka M (ed.), *Handbook on Medical Image Analysis*, SPIE Press 2000.
- [6] Thompson PM, Mega MS, Vidal C, Rapoport JL, Toga AW "Detecting Disease-Specific Patterns of Brain Structure using Cortical Pattern Matching and a Population-Based Probabilistic Brain Atlas" 2001.
- [7] Benoit Da Mota, Vincent Frouin, Edouard Duchesnay, Soizic Laguitton, Gael Varoquaux, Jean-Baptiste Poline, Bertrand Thirion "A fast computational framework for genome-wide association studies with neuroimaging data" *20th International Conference on Computational Statistics*, 2012.
- [8] Fernando Calamante, Jacques-Donald Tournier, Robin M. Heidemann, Alfred Anwander, Graeme D. Jackson, Alan Connelly "Track density imaging (TDI): validation of super-resolution property", *NeuroImage*, Volume 56, Issue 3, 1 June 2011, Pages 1259–1266.
- [9] Christopher Town "Ontological Inference for Image and Video Analysis" *Machine Vision and Applications*, May 2006, Volume 17, Issue 2, pp 94-115 .
- [10] Hai-Guang Li, Gong-Qing Wu, Xue-Gang Hu, Jing Zhang, Lian Li, Xindong Wu "K-Means Clustering with Bagging and MapReduce", *System Sciences (HICSS)*, 2011 44th Hawaii International Conference.
- [11] Weiling Cai, Songcan Chen, Daoqiang Zhang "Fast and Robust Fuzzy C-Means Clustering Algorithms Incorporating Local Information for Image Segmentation" *Pattern Recognition*, Volume 40, Issue 3, March 2007, Pages 825–838.
- [12] Weizhong Zhao, Huifang Ma, Qing He "Parallel K-Means Clustering Based on MapReduce" *Cloud Computing Lecture Notes in Computer Science* Volume 5931, 2009, pp 674-679 .
- [13] Imianvan A.Al. Obi J.C "Diagnostic Evaluation Of Hepatitis Utilizing Fuzzy Clustering Means" *World Journal of Applied Science and Technology*, Vol.3. No.1 (2011). 23-30. 23.
- [14] Chih-Cheng Hung, Sameer Kulkarni, Bor-Chen Kuo, "A New Weighted Fuzzy CMeans Clustering Algorithm for Remotely Sensed Image Classification" *Selected Topics in Signal Processing, IEEE Journal* (Volume:5 , Issue: 3).
- [15] Dzung L. Pham, Jerry. Prince "An Adaptive Fuzzy C Means Algorithm for Image Segmentation in the Presence of Intensity Inhomogeneities", *Pattern Recognition Letters*, 2009.
- [16] Neelum Noreen, Khizar Hayat and Sajjad A. Madani "MRI Segmentation through Wavelets and Fuzzy C-Means" *World Applied Sciences Journal* 13 (Special Issue of Applied Math): 34-39, 2011.
- [17] Leehter Yao, Kuei-Sung Weng "On A Type-2 Fuzzy Clustering Algorithm" 2012.
- [18] Francesco Masulli, Andrea Schenone "A fuzzy clustering based segmentation system as support to diagnosis in medical imaging" *Artificial Intelligence in Medicine* Volume 16, Issue 2, June 1999, Pages 129–147.
- [19] Robert L. Cannon, Jitendra V. Dave, James C. Bezdek "Efficient Implementation Of The Fuzzy C-Means Clustering Algorithms" *Pattern Analysis and Machine Intelligence, IEEE Transactions* (Volume: PAMI-8, Issue: 2).
- [20] Payman Milanfar "Super resolution IMAGING" CRC Press, 2010.
- [21] M. T. Merino "Super-Resolution with Additive-Substitutive Wavelets" *IEEE Signal Processing Magazine* 06/2003.
- [22] Tinku Acharya, Ping-Sing Tsai "Computational Foundations of Image Interpolation Algorithms" *Magazine Ubiquity* archive Volume 2007 Issue October Article No. 4 .
- [23] Dinggang Shen "Image registration by local histogram matching" 2006.
- [24] David Capel, Andrew Zisserman "Super-resolution Enhancement of Text Image Sequences" *Pattern Recognition*, Volume 40, Issue 4, April 2007, Pages 1161–1172.

- [25] Assaf Zomet, Alex Rav-Acha, Shmuel Peleg “Robust Super-Resolution” *Proceedings of the International Conference on Computer Vision and Pattern Recognition (CVPR)*, Hawaii, December 2001.
- [26] Peyman Milanfar, Filip Sroubek, Jan Kamenick “Superfast superresolution” 2011.
- [27] Wilhelm Burger, Mark James Burge “Digital Image Processing An algorithmic introduction using Java” January 19, 2012 ISBN-10: 1846283795.
- [28] D. Huang, E.A. Swanson, C.P. Lin, J.S. Schuman, W.G. Stinson, W. Chang, M.R. Hee, T. Flotte, K. Gregory “Optical coherence tomography” *Science* 22 November 1991:Vol. 254 no. 5035 pp. 1178-1181 .
- [29] Sean Owen, Robert Anil, Ted Dunning, Ellen Friedman “Mahout in Action” Manning Publications (October 14, 2011) .
- [30] Ding Feng “Segmentation of Bone Structures in X-ray Images”, *Advances in Electrical and Computer Engineering*, 2013-02-28, Volume 13, Issue 1, Year 2013, page(s): 87 - 94 2006.
- [31] M. Dirk Robinson, Stephanie J. Chiu, Cynthia A. Toth, Joseph A. Izatt, Joseph Y. Lo, Sina Farsiu “New Applications of Super-resolution in Medical Imaging” *Super-Resolution Imaging*, P. Milanfar, ed.(CRC, 2010), pp. 383–412.
- [32] Tom White “Hadoop: The Definitive Guide” *O'Reilly Media / Yahoo Press*, 2011.
- [33] Sang C. Suh and Kalyani Komatireddy “Clustering of Ontology in Preventive Health Care Through Relational Ontology” KE’11, World comp 2011, Las Vegas, Nevada,USA.
- [34] Thomas Bittner, Louis J. Goldberg and Maureen Donnelly “Ontology and qualitative medical images analysis” 2010.