International Journal for Innovative Engineering and Management Research

PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL

www.ijiemr.org

IJIEMR Transactions, online available on 26th Dec 2022. Link

:http://www.ijiemr.org/downloads.php?vol=Volume-11&issue=Issue 12

10.48047/IJIEMR/V11/ISSUE 12/152

TITLE: A STUDY OF IMPROVED CONTEXTUAL HIERARCHICAL MODEL USING CONDITIONAL RANDOM FIELD FOR SEMANTIC IMAGE SEGMENTATION AND EDGE DETECTION

Volume 11, ISSUE 12, Pages: 1134-1139

Paper Authors **NAVEEN KUMAR, DR. AKASH SAXENA**

International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

A STUDY OF IMPROVED CONTEXTUAL HIERARCHICAL MODEL USING CONDITIONAL RANDOM FIELD FOR SEMANTICIMAGE SEGMENTATION AND EDGE DETECTION

CANDIDATE NAME = NAVEEN KUMAR
DESIGNATION= RESEARCH SCHOLAR SHRIDHAR UNIVERSITY PILANI CHIRAWA ROAD, PILANI RAJASTHAN
GUIDE NAME= DR. AKASH SAXENA
DESIGNATION= ASSOCIATE PROFESSOR SHRIDHAR UNIVERSITY PILANI CHIRAWA ROAD, PILANI RAJASTHAN

ABSTRACT
With an emphasis on hierarchical picture and edge detection, this research provides a critical analysis of ontologies within the framework of higher order function support for optimum learning. The formal representation of knowledge known as ontology is crucial in the structuring and organization of data across many fields. Picture edge detection is crucial for many computer vision tasks, including object identification, scene analysis, and picture segmentation. The purpose of this research is to learn how ontologies may be used to improve the efficiency of higher-order functions, with a focus on hierarchical picture and edge recognition methods. Our goal is to improve these algorithms' precision, productivity, and sturdiness by incorporating ontology into their training processes. The potential of ontology to aid in the transfer of information across different learning challenges and domains is also investigated. For these goals, we perform a systematic literature assessment of ontology-driven higher order functions in the context of image and edge detection to discover current techniques.

KEYWORDS: Hierarchical Model, Conditional Random Field, Semantic Image Segmentation, EDGE Detection, optimum learning

INTRODUCTION

The goal of semantic image segmentation is to divide a picture into a set of meaningful, non-overlapping areas. For the purposes of semantic picture segmentation and edge detection, a contextual framework called Contextual Hierarchical Model (CHM) was designed to learn the appropriate data across hierarchical framework. CHM is an effective model that incorporates scene context information across various hierarchy levels. Logistic sigmoid functions were employed to build an adaptive layer in the LDNN, which was then followed by two fixed layers of logistic units used at each hierarchical level. Minimizing the LDNN classifier's quadratic error using gradient descent One post-processing step utilized in CHM-based edge detection was Non-Maximal Suppression (NMS) to pick up on the thinner edges.

CHM based semantic picture segmentation and edge detection, however, performs poorly in terms of class accuracy due to the lack of a global constraint. To address this issue, the research effort introduces a conventional CRF. By applying an energy function to a discrete random field, CRF defines the global limitations. However, the global node of the CRF graph model does not allow for numerous classes to be assigned to a single area. Therefore, an

HCRF model is presented to fix CRF's flaws and specify the world's limitations. The energy function on unary, pairwise and higher order potentials is used to determine the global restrictions in HCRF. Using features that rely on lengthy continuous label sequences, HHCRF aims to be a cost-effective method for an HCRF, so long as the variety of label sequences used in the features is kept to a minimum. As a result, conditional random fields are able to become a powerful learning method. For semantic picture segmentation and edge detection, various resolutions are used to train the pixels with the minimal energy function. Figure 3.1 depicts the overall progression of this research stage.

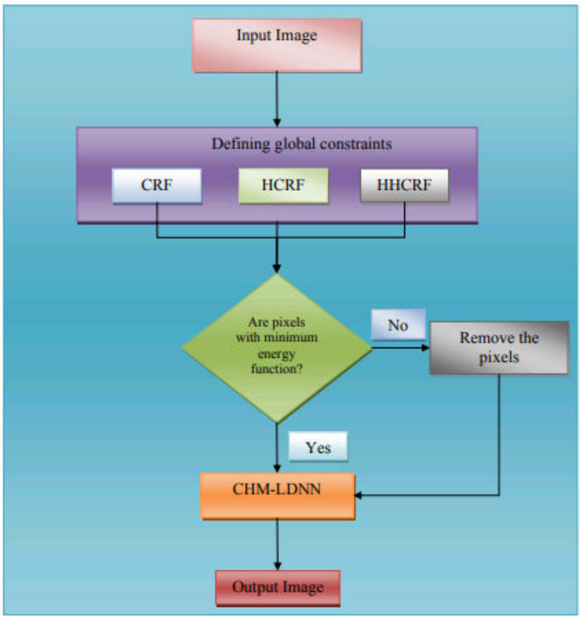

Figure 1 Flow diagram of CHM-LDNN with different CRF models

DIFFERENT CONDITIONAL RANDOM FIELD BASED CONTEXTUAL HIERARCHICAL MODEL FOR SEMANTIC IMAGE SEGMENTATION AND EDGE DETECTION

Down sampling is done successively to the input picture in the Contextual Hierarchical Model (CHM). Which results in a multi-resolution copy of the input picture being returned? Then, depending on the results of the previous classifier in the hierarchy and the resolution of the input picture, a succession of classifiers is trained at completely different resolutions. Each classifier is then used to train a third classifier, which is utilized to draw a conclusion about the results. It is capable of modeling the scene's global context. However, it is possible to endure it accidentally since there are no universal limitations. In this stage of the research process, the energy function of CRF, HCRF, and High-order HCRF are all specified in terms of the global constraint. Last but not least, CHM incorporates the global constraint to boost the precision of semantic picture segmentation and edge detection.

AN EFFICIENT LOGISTICALLY DISJUNCTIVE NORMAL NETWORK CLASSIFIER FOR SEGMENTING IMAGES AND DETECTING THEIR EDGES

For semantic picture segmentation and edge detection, this chapter explains the CHM-HHCRF-Improved Logistic Disjunctive Normal Network (CHM-HHCRF-ILDNN) and the CHM-HHCRF-Improved Optimized LDNN (CHM-HHCRF-IOLDNN). In the bottom-up stage of CHM, we analyze the CRF, HCRF, and HHCRF, and then we use the result to train a Logistic Disjunctive Normal Network (LDNN). Within the top-down phase of CHM, it identifies the edges and semantically segments the pictures. In LDNN, the quadratic error is

International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

minimized via a gradient descent. The performance of LDNN may suffer, however, due to the gradient descent's poor convergence rate. Therefore, CHM-HHCRF-ILDNN and CHM-HHCRF-IOLDNN strategies are suggested in this stage of study work to deal with the aforementioned difficulty and improve the performance of CHM-HHCRF-LDNN. The quadratic error in CHM-HHCRF-ILDNN is minimized using a proximal gradient approach, which has a quick convergence rate. The classification accuracy is enhanced and the time complexity of LDNN is decreased by using Grey Wolf Optimization (GWO) to optimize the weight and bias term of LDNN in CHM-HHCRF-IOLDNN. Next, LDNN employs the improved weight and bias term to perform accurate picture classification. By using the results from lower-level LDNN classifiers, higher-level LDNN classifiers may be trained to take use of the wealth of contextual information available across resolutions.

EFFORTLESS EDGE DETECTION WITH ENHANCED OPTIMISED LOGISTIC DISJUNCTIVE ROUTING A CLASSIFIER BASED ON NORMAL NETWORKS WITH ENHANCED NONMAXIMAL COMPRESSION

CHM-HHCRF-NMS-IOLDNN uses a multiscale approach to calculate edge maps during the edge detection process. To get the elongated edges in photographs, a Non-Maximum Suppression (NMS) is used. However, this is a post-processing step that adds extra time to the overall edge detection procedure. Edge detection is understood as a classification issue at this stage of the research process, with the thinned edges in pictures collected prior to any post-processing. Time savings result from this. NMS incorporates loss and joint processing, two essential aspects for enhancing thin-edge detection. The double-edge detection is punished with the loss. Joint processing, in which two features are used for edge detection instead of just one, and reduces the amount of information lost while doing so. The effectiveness of CHMHHCRF-NMS-IOLDNN based edge detection is enhanced by the use of pair features, Haar, Histogram of Gradient (HOG), and SIFT features as input to LDNN.

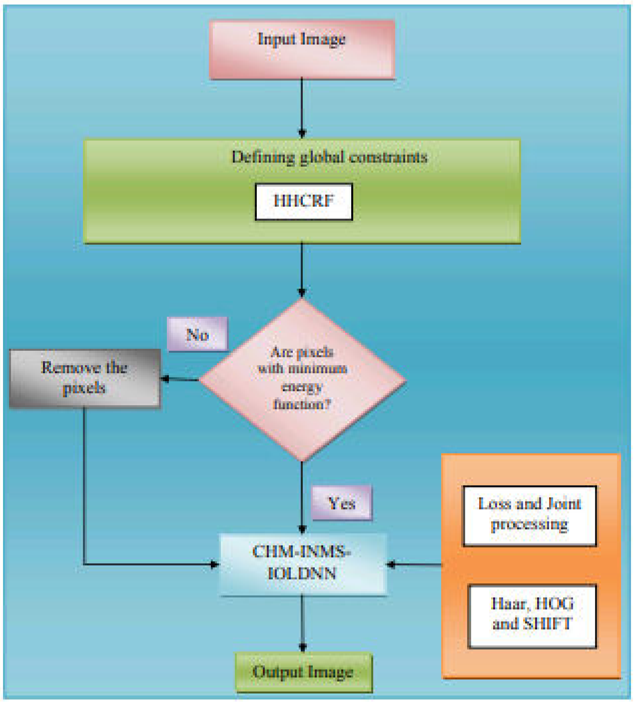

Figure 2 Flow diagram of CHM-INMS-IOLDNN

EDGE DETECTION

NMS for Edge Detection

The thinning edges in CHM are identified using NMS as a post-processing step. Because of the additional time required for post-processing, detecting the smoothed edges is a more laborious operation. Therefore, loss and joint processing are included into NMS to enhance the

International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

performance of edge detection, and a CHM is developed using NMS without post-processing. The key to Non-Maximum Suppression's success is locating the edge's maximum-value pixel. With NMS, only the local maxima of the gradient picture are kept, while the rest are discarded to create razor-sharp edges.

- Take pixel (x, y) as an example, where (x, y) represents the intensity of that pixel.
- Determine the amount and direction of the intensity gradient in the picture in (x, y).
- Calculate rough estimates of the gradient's size and direction along a neighborhood gradient centered on the coordinates (x, y).
- An edge point is not located at (x, y) unless there is a local maximum of the magnitude of the gradient along the direction of the gradient.

NMS without Post-Processing

Window, edge class labels linked with the window, and the network response score all go into the typical NMS. The windows that are not the highest-scoring locally are then removed, leaving the final set of edge detections. A post-processing step in CHM is used to provide the edge-thinning effect. Identifying the borders requires more processing time. Learn the NMS into the classifier to speed up the process. It calculates the chances that a certain edge class is present in an image given a certain detection. Score detectors, as a result, evolve a window for detection space exploration. Class probabilities are computed separately for each edge detection. Because they are essentially looking at the same thing, two substantially overlapping edges in a picture will both get a high score. Depending on the size and shape of the detection windows, different amounts of confidence in the edge detections are generated for each image's content.

NMS generates high confidence edge detections by assuming that adjacent edge detections originate from the same pixel in the picture. The IOLDNN classifier can tell the difference between edge-containing and non-edge-containing picture data. Some degree of overlap between windows and edges characterizes the positive and negative samples used to train the IOLDNN for edge detection. A modest shift in edge location is regarded as a positive sample if it occurs inside a comparable frame that produces a similar level of confidence. The IOLDNN classifier training, on the other hand, actively promotes numerous high-scoring edge detections rather than a single one. There are two main factors to think about while making a single edge detection. The detector must be taught that exactly one edge detection is needed for each pixel in the picture, and one of the elements is a loss that penalizes multiple detections. To further specify whether an edge is detected many times, the detector requires the cooperative processing of nearby detections.

Only one high-scoring edge detection should be returned by an IOLDNN-based edge detector. To prevent false positives, the detector's loss should prevent repeated edge detections of the same picture pixel from being made, regardless of how close together they are. The accuracy of NMS-based multiple edge detections is guaranteed by using a matching approach.

A benchmark's assessment criterion defines a matching approach to determine whether edge detections are valid or incorrect; this strategy is used to evaluate the IOLDNN detector. This method is implemented while learning how to recognize edges. Benchmarks rank edge detection in decreasing order of confidence in detection. Next, compare the detected edges to the image's pixels in descending order. To reduce the number of false positives in IOLDNN-based edge detection, this method prevents further matching of pixels in an image that have previously been matched.

CONCLUSION

Image segmentation algorithms have been more popular in recent years within the area of computer vision. Foreground/background separation, object detection/tracking, intelligent monitoring, and other real-world applications all benefit from semantic picture segmentation. Objects in a picture may be identified and located with the help of semantic image segmentation. It's a method for classifying a picture pixel by pixel. In image segmentation, edge detection is used to identify and locate distinct edges within an image. Several methods have been put up for semantic picture segmentation so far. In this respect, the Contextual Hierarchical Model (CHM) is one approach. In this study, many methods were developed to enhance semantic picture segmentation and edge detection using CHM. In conclusion, the study of ontology as a vital tool for supporting higher-order functions in the optimization of learning situations involving hierarchical picture and edge detection has made significant contributions to the fields of computer vision and machine learning. The study's extensive literature research revealed the difficulties and drawbacks of conventional methods for image and edge detection. Accuracy, efficiency, and cross-domain knowledge transfer are just a few of the difficulties we face today. The research attempted to address these issues and boost the efficiency of higher-order functions by introducing ontology into the learning process.

REFERENCES

1. [ACH05] Acharya, T., & Ray, A. K., "Image processing: principles and applications", John Wiley & Sons, 2005.
2. [AKI17] Akinlar, C., & Topal, C, "ColorED: Color edge and segment detection by Edge Drawing (ED)", Journal of Visual Communication and Image Representation, Vol. 44, pp. 82-94, 2017.
3. [AMR16] Amrogowicz, S., Zhao, Y., & Zhao, Y., "An edge detection method using outer totalistic cellular Automata", Neurocomputing, Vol. 214, pp. 643-653, 2014.
4. [ANN07] Annadurai, S., Shanmugalakshmi, R., "Fundamentals of Digital Image Processing", 1st Edition, Pearson Publication, 2007
5. [ARB11] Arbelaez, P., Maire, M., Fowlkes, C., & Malik, J., "Contour detection and hierarchical image segmentation", IEEE transactions on pattern analysis and machine intelligence, Vol. 33(5), pp. 898- 916, 2011.
6. [ATE19] Ates, H. F., & Sunetci, S., "Multi-hypothesis contextual modeling for semantic segmentation", Pattern

Recognition Letters, Vol. 117, pp. 104-110, 2019.

7. [BAS15] Basheer, N. M., Aref, A. M., & Ayyed, D. J., "Digital image sobel edge detection using FPGA", International Journal of Advanced Research in Computer Science and Software Engineering, Vol. 5(7), pp.183-190, 2015.
8. [BHA12] Bhanu, B., & Lee, S., "Genetic learning for adaptive image segmentation", Springer Science & Business Media, Vol. 287, 2012.
9. [BHA14] Bhargavi, K., & Jyothi, S., "A survey on threshold-based segmentation technique in image processing", International Journal of Innovative Research and Development, Vol. 3(12), pp. 234-239, 2014.
10. [BIS18] Biswas, S., & Hazra, R., "Robust edge detection based on Modified Moore-Neighbor" Optik, Vol. 168, pp. 931-943, 2018.
11. [BUL17] Bulo, S. R., Neuhold, G., & Kontschieder, P., "Loss max-pooling for semantic image segmentation", IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 7082-7091, July 2017.
12. [CHE14] Chen, L. C., Papandreou, G., Kokkinos, I., Murphy, K., & Yuille, L., "Semantic image segmentation with deep convolutional nets and fully connected" crfs. arXiv preprint arXiv:1412.7062, 2014.