International Journal For Advanced Research In Science & Technology
A peer reviewed international journal www.ijarst.in
ISSN: 2457-0362
IJARST

AN ONTOLOGY BASED CONTEXTUAL KNOWLEDGE REPRESENTATION FOR SEMANTIC IMAGE SEGMENTATION

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ABSTRACT

In addition, this study suggests a framework that makes use of ontology-driven higher-order functions and the hierarchical structure of pictures in the edge identification process. To enhance precision and efficiency in edge detection tasks, the framework combines the strengths of ontological representation, semantic reasoning, and machine learning techniques. The effectiveness of the proposed framework is measured against standard benchmarks. The findings show that ontology-driven higher-order functions are useful for improving learning outcomes in hierarchical image and edge recognition tasks. When compared to more conventional approaches, the benefits of using ontology in the classroom become clear. Finally, this research provides a critical analysis of ontology-driven higher order function support in the context of hierarchical picture and edge detection, which is a significant contribution to the fields of computer vision and machine learning. The results demonstrate the promise of ontology in boosting educational achievements, boosting precision, and easing the transfer of information across disciplines.

KEYWORDS: Contextual Knowledge, Semantic Image Segmentation, ontology-driven, higher-order functions, hierarchical structure

INTRODUCTION

In this new phase of the study, ontology-based contextual information representation in CHM is used to further enhance CHM-HHCRF-IOLDNN based semantic picture segmentation. A connection is built using taxonomic connections in the ontology-based contextual knowledge representation. Fuzzification, a new addition to ontology, is used to describe the semantic link between ideas in a way that better accounts for the complexities inherent in dealing with relations between pictures. Fuzzy taxonomy is used to build a relation that is sent into the CHM as supplementary input during semantic image segmentation. The segmentation findings of CHM are modified by the ontological taxonomic knowledge representation according to taxonomic ties. In terms of class accuracy, pixel accuracy, F-measure, and GMean, the experimental findings suggest that the proposed Ontology-based contextual knowledge representation using CHM- Higher order Hierarchical CRF-Improved Optimized LDNN (OCHM-HHCRF-IOLDNN) performs better than the other techniques. Figure 1 depicts the data glut that resulted from this stage of the study.

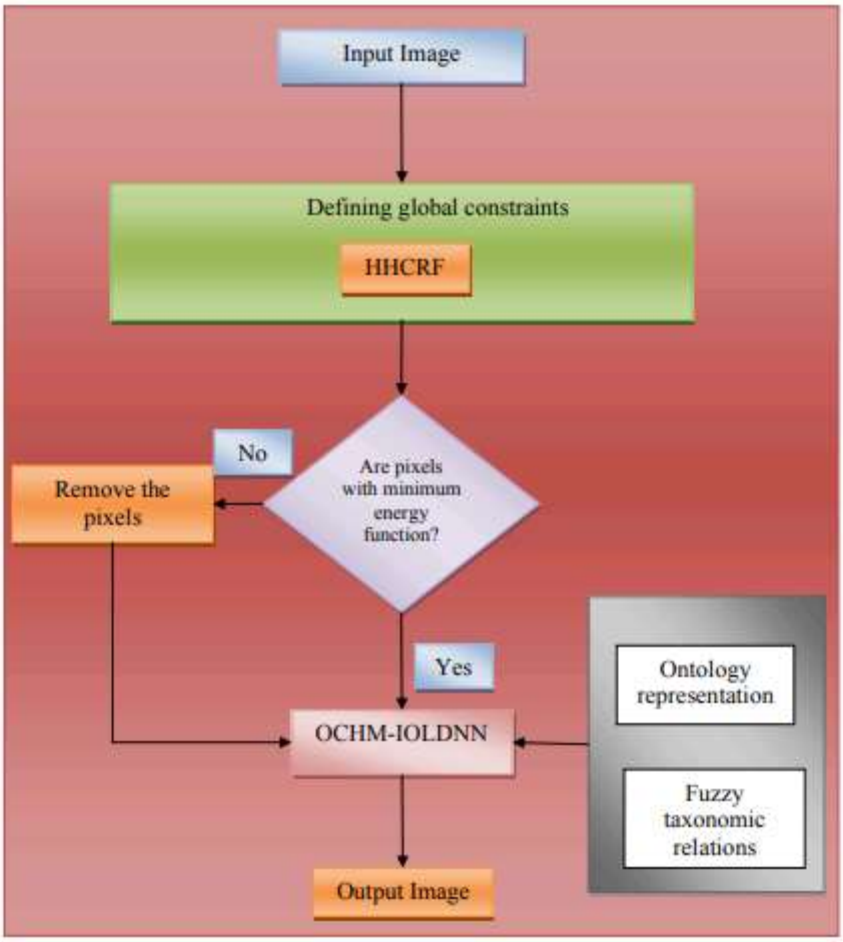

Figure 1 Flow diagram of OCHM-IOLDNN

ONTOLOGY-BASED CONTEXTUAL KNOWLEDGE REPRESENTATION

The depiction of ontological taxonomy information determines the meaning of the connections between ideas shown in a picture. There has to be a significant number of unique and varied connections between ideas in a knowledge model. Ontology introduces the notion of fuzzification to describe more nuanced kinds of semantic interactions. The fuzzy taxonomic connections are then used to build a relation. CHM-HHCRF-IOLDNN is able to segment pictures while taking semantic connection into account, thanks to the extra input provided by the created semantic relations.

Images may be analyzed either manually or automatically, and the semantics of their content can be expressed in ontologies. The ontologies may be stated formally as:

$$O = \left\{C, \left\{R_{xy}\right\}\right\}, where\ R_{xy}: C \times C \rightarrow \{0,1\} \quad (1)$$

In (4.1), O is an ontology, C is the set of image ideas defined by the ontology, x and y are two concepts x, y C, and Rxy is the semantic connection between these four terms. MPEG-7 MDS [TRO07], which incorporates all kinds of semantic relations, is mined for their concept-to-concept meaning. The CHM-HHCRF-IOLDNN is used for semantic image segmentation, and it is fed an ontology-based contextual knowledge representation model consisting of a collection of concepts and relations between them. In this study, we use three distinct kinds of semantic relations: those pertaining to specialization, to parts of objects, and to properties.

In the ontology, the connection between any two ideas is defined by their semantic relation. A pair of ideas x and y may be related to one another or disrelated via the semantic relation Rxy. Knowledge representation is built using a taxonomic relation, which allows for the inclusion of any kind of connection in the ontology. The crisp semantic connection may be expressed as fuzzy ordering relations to enhance the ontology-based contextual knowledge representation. Fuzzy taxonomy may be generated by combining the fuzzy ordering relations. The ontologies may be re-formalized based on the fuzzy ordering relation as:

$$O_F = \left\{C, \{r_{xy}\}\right\}, where\ r_{xy} = F(R_{xy}): C \times C \rightarrow [0,1] \quad (2)$$

In (4.2), OF is a fuzzy ontology, where rxy represents the fuzzy connection between xy and C. A fuzzy semantic connection is a relation between two ideas x and y that has a degree of membership z. A value of 0 or 1 may be assigned to the fuzzy semantic relation rxy. The membership function of a fuzzy set F on C is a triangle, denoted by F: C [0,1]. The definition of the fuzzy set F on C is as follows:

$$F = \sum_{i=1}^{n} \frac{c_i}{w_i} = \left\{\frac{c_1}{w_1}, \frac{c_2}{w_2}, \dots \frac{c_n}{w_n}\right\} \quad (3)$$

The cardinality of the set C and the notion ci C is denoted by n = |C| in (4.3). The triangle membership function F () is defined by the membership degree wi, as wi = F (ci). If we define a fuzzy relation on C as the function rxy: C C [0,1], then we can write its inverse as rxy 1 = rxy. For semantic picture segmentation, we employ the aforementioned collection of fuzzy taxonomic relations Sx, X, and Xr to build the following relation T:

$$T = Tr^t(S_x \cup X^{-1} \cup Xr^{-1}) \quad (4)$$

In (4.4), when an image is semantically connected to y, then it is most likely related to x as well, as large values of Sx (x, y) suggest that the meaning of q approaches the meaning of x. However, if Sx (x, y) diminishes, the meaning of y becomes narrower than the meaning of x, and the relationship between an image and y will not indicate a relationship between the two to the same degree. Similar interpretations hold true for the other two relations' degrees, which may be thought of as implied probabilities. MPEG-7 MDS includes both the positive and negative forms of all possible semantic connections. It's not always the semantic connections that carry the most weight, but rather the inverses. If and only if y is a component of x, then we may say that the two entities share the relation part (x, y). For the property relation Xr, the opposite is chosen. For an alternative interpretation, one may say that x is a specialization of y if and only if y is a specialization meaning of x, as defined by the specialization relation Sx (x, y). A relation T is built up based on the functions and meanings assigned to Sx, X, and Xr. For a relation T to be taxonomic, it must have a transitive closure Tr t, as the union of transitive relations is not always transitive. The segmentation results are fine-tuned based on the semantic link between taxonomic categories using the produced T as an extra input to the CHM-HHCRF-IOLDNN.

IMAGE PROCESSING

The field of software engineering devoted to image processing [CHI14; ACH05] is expanding quickly. Innovations in digital imagery, computer processors, and mass storage devices have fueled its growth. Many industries that formerly relied on analog imaging are making the switch to digital due to the lower cost and greater versatility of digital technologies. Information extraction is the primary focus of digital image processing [ANN07; SRI16]. In an ideal world, computers would handle digital image processing [JAY17; RAF10] entirely by themselves. There are three tiers at which image processing may be placed. At the most fundamental level of image processing, algorithms such as de-noising and edge detection work directly with the raw, potentially noisy pixel values Algorithms at the intermediate level of image processing use low-level findings for additional purposes, such as segmentation and edge linkage. Semantic meaning is extracted from the data supplied by lower levels of image processing by procedures at the highest level.

IMPORTANCE OF IMAGE PROCESSING

Image processing [KUM15] is essential because it enhances visual data for human comprehension. Satellite imagery has several applications in the fields of geography, earth science, and crop forecasting. Object identification and analysis are two of many uses for photos. These days, it's common practice to use image processing methods for such ends. While these two issues are independent, the difficulty in extracting objects from photos necessitates the development of techniques that may improve data for human interpretation and analysis. The process of identifying and removing items from photographs relies heavily on image processing.

1.1 IMAGE SEGMENTATION

Segmentation [SIN15; ZAI15] is the process of dividing a picture into distinct, linked parts that have a common feature, such texture or intensity, but do not overlap. The image domain is denoted by I. Finding the collection of linked subsets of areas is the goal of the segmentation issue. $\{R_1, R_2, \ldots R_K\}$, where $R_K \subset I$ such that

$$\bigcup_{k=1}^{K} R_K = I \text{ with } R_i \cap R_j = \emptyset, \forall i \neq j \quad (1)$$

Pixel categorization refers to the division if disconnection between regions Ri is permitted. In many real-world contexts, pixel categorization is sufficient. The primary goal of picture segmentation is to identify the biggest homogeneous areas, Ri, feasible. Let's use (.) as our homogeneity criterion. For all regions, (RK) must evaluate to true, and any pair of neighboring regions, Ri and Rj, must have (Ri U Rj) evaluate to false.

Finding an appropriate area RK and defining an appropriate homogeneity criteria P that achieves the required segmentation of pictures for a given application is the primary difficulty in image segmentation [BHA12]. Thresholding is the quickest and least complicated approach to segmentation. It takes an input picture and converts it into a binary mask, where pixels whose intensities are below a certain threshold are set to zero and those above are set to one. Each segment of RK is represented by a linked set of 0s and 1s. In thresholding segmentation [BHAR14], the predicate Pt is expressed as,

BOTTOM-UP APPROACHES FOR IMAGE SEGMENTATION

<u>Patches</u>

Patch-based segmentation is a straightforward approach for image analysis [WOL06]. There is more than one method for generating irregular or periodic patches. Patches are randomly generated using a sampling method. The density of samples might be consistent throughout a

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ISSN: 2457-0362

picture, or it can be increased in key areas. Merging adjacent patches with the same categorization yields the final segmentation.

Contour Detection

Even though contour detection isn't technically a segmentation technique, it is often used in that capacity. Segmentation's contour detection process is twofold. When processing segmentation, it is always possible to produce closed contours based on the segment borders. Unfortunately, contours don't have to be closed, making it more difficult to generate regions from contours via the inverse technique. A common job in computer vision, contour detection is analogous to edge detection. The goal of this feature is to identify the edges of objects in a picture. Contrast this with edges, which represent changes in intensity levels, and contours, which should represent prominent features.

Region Growing

The region growth method is another technique for achieving bottom-up segmentation based on regions. Homogeneity criteria (.) for nearby areas are evaluated by starting with tiny beginning regions. If the criterion shows that the homogeneity is maintained after combining adjacent areas, the regions are combined.

Separate and Combine

The region-growing approach is the inverse of the split-and-merge method [RAV11]. The procedure of dividing and reassembling an image applies to the whole picture. It's a top-down method that starts with the whole picture and slices it up in such a way that the individual parts seem more like each other than the whole. Single-splitting isn't enough for reasonable segmentation since it drastically restricts the possible segment forms. Therefore, an approach that involves separating an area into smaller ones and then merging them back together again is preferable. An image's regions are subdivided into smaller regions, and the right parts of several pictures are pieced together to form a larger area. Instead of picking kernel points, users may divide a picture into a collection of randomly disconnected sections. After that, we try to merge the sections such that they conform to the reasonable picture segmentation forms. Regions are divided and combined using information from quad trees.

$$P_t(R_i) = \begin{cases} true, & iff \max\big(Im(R_i)\big) < t \; or \min\big(Im(R_i)\big) \geq t \\ false, & otherwise \end{cases} \quad (2)$$

Processing direction is often used to classify picture segmentation algorithms. Algorithms may be broken down into two primary categories: top-down and bottom-up. The pixels of a picture are the building blocks upon which a bottom-up method rests. The picture data alone is used to generate the segments. Top-down methods, on the other hand, presuppose an existing model of the items that should be present in the picture. To create the segments, a top-down algorithm first attempts to fit the model to the available picture data. Over-segmentation occurs when the item of interest is broken up into too many pieces by the segmentation algorithm. The picture may be simplified for subsequent processing by over segmenting it into a bunch of little homogeneous sections. Super-pixels is a common term for such localized areas.

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IJARST
ISSN: 2457-0362

CONCLUSION

The research suggested a framework that makes use of both the hierarchical nature of pictures and the edge detection process, while also including higher order functions that are driven by ontologies. This framework integrated ontological modeling, semantic reasoning, and machine learning techniques to improve edge detection performance. Exploring the combination of ontology-driven approaches with other cutting-edge methods like deep learning and neural networks might provide even better results in terms of optimal learning. We can open up new avenues in computer vision and move the field forward in the direction of more efficient and accurate solutions if we keep pushing the limits of knowledge representation and reasoning. To improve CHM's performance in terms of class accuracy, many Conditional Random Field (CRF) approaches are suggested in the initial stage of the study. Global restrictions are imposed in the form of energy functions on a discrete random field, ushering in a conventional CRF approach. However, CRF does not permit many categories to be applied to a single area. The energy function on unary, pairwise and higher order potentials is described to create global restrictions in Hierarchical CRF (HCRF). When a limited number of different label sequences are utilized in the features, the HCRF is further enhanced by the introduction of HCRF with higher order features, where an efficient method for an HCRF is constructed utilizing such features. In CHM, a semantic picture is created using the pixels that have the lowest energy functions. Improved classification accuracy is a direct result of the global constraints imposed by the energy functions of CRF, HCRF, and HHCRF.

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