



LEVEL SET METHOD-BASED IMAGE SEGMENTATION AND DEEP LEARNING TECHNIQUES

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Abstract - Image segmentation is the division of an image into a number of segments. This lessens the image's intricacy and produces the desired processed image. In this project, a picture is applied to the FCN algorithm, which removes the thick layers in the image by utilising FCN for the image segmentation and analysis. Noise, irregular boundaries, and lack of a preceding shape are drawbacks of this method. As a result, this study suggests using a level set with deep priors to segment images using the priors that FCNs have learnt. A probability map is created using the output of FCNs, where each pixel represents a separate category. Although being chaotic, the probability map-represented segmentation still has Correcting that segmentation in large part. As a result, using the GAT method, the standard shape mask of the image can be transformed in the best possible way depending on its "probability" shape. In order to accomplish image segmentation, the level set method's input is the image, the probability map.

FCN, DCCN, Probability Map, GAT Method, Level Set Method are some of the keywords.

1. INTRODUCTION

The field of computer vision and digital image processing known as "image segmentation" focuses on categorising similar areas or segments of a picture. Despite the fact that the entire process is digital and uses segments rather than pixels to depict the analogue image, the task of manufacturing segments is to the form of segments rather than pixels, the work of creating segments is to the task of grouping pixels of pixels is accessible. Semantic segmentation, which is used in this research, is the categorization of pixels in a picture into semantic classes. Without considering any further context or data, pixels that belong to a class are just assigned to that class. In this research, region-based segmentation algorithms operate by identifying commonalities among neighboring pixels and classifying them accordingly. The the algorithm operates by identifying the near boundaries of the seed pixels and categorising them as similar or dissimilar. Certain pixels are designated as seed pixels. Segment maps are the outputs that semantic segmentation models produce in response to the inputs they are fed. The model's result The predictions are represented in a two-dimensional one-hot encoded representation in a "n-channel" binary format. An encoder, a bottleneck, and a decoder are part of the standard encoder-decoder structure employed by neural networks for segmentation., and a decoder or upsampling layer that starts at the bottleneck (like in the FCN).

Strictly speaking, Segmentation involves giving labels to individual pixels in an image so that objects, people, or other important details may be distinguished. Image segmentation is frequently used for object detection. The segmentation algorithm's previously created bounding box can then be used by the object detector. Accuracy is improved and inference time is reduced by preventing the detector from processing the entire image. Image segmentation is a vital part of computer vision algorithms and technologies. It is used in many different practical situations, such as face identification and recognition in video surveillance, medical image analysis, computer vision for autonomous vehicles, and satellite image analysis. Image segmentation is a procedure that takes input images and produces an output. In the output, a mask or matrix with multiple elements specifies the object class or instance for each pixel. For picture segmentation, a number of pertinent heuristics, or high-level image attributes, can be helpful. Standard image segmentation algorithms, which include grouping methods like edges and histograms, are built on these attributes.

The heuristic of using colour as an example is common. To provide a uniform colour for the image backdrop, graphic designers may employ a green screen. This allows for automated background detection and replacement during post-processing. Contrast is another example of a helpful heuristic; image segmentation software can quickly tell a dark figure from a light background. The software recognises pixels boundaries set on the basis of sharply divergent values. Even though traditional picture segmentation methods based on these heuristics can be quick and easy, they frequently need a lot of fine-tuning to accommodate particular use cases with manually created heuristics. They are not usually precise enough to be used with

complicated imagery. Deep learning and machine learning are used in more recent segmentation methods to improve flexibility and accuracy. Further more suggested was a better network structure search approach for semantic segmentation [12]. Nevertheless, as the scene gets more intricate, these techniques make the model progressively more complex, which limits its usefulness.

Effectiveness of deep convolutional neural networks find the photos' hidden patterns, and develop realistic image skills Deep learning was utilised to derive priors from a large number of examples, and these priors were then used to initialise the level set's surface as the shape prior during the iterative phase [13, 14]. To enhance accuracy, additional accurate information is needed because the prior knowledge created through deep learning is likewise rough and imprecise. Each type of item in this study has an inherent shape that serves as a means of object differentiation, and prior knowledge is used in the form of a probability map. This work suggests a level set with deep prior approach for the segmentation of images based on the shape prior representing to the intrinsic shape of the target. depending on the priors that FCNs have learned. High-level semantic information in the images can be extracted by FCNs and used as the segmentation prior. The success of the suggested strategy will next be confirmed through a series of experiments using the Portrait data set [15]. The experimental results demonstrate that the suggested method can produce segmentation results that are more accurate than those produced by using conventional FCNs.

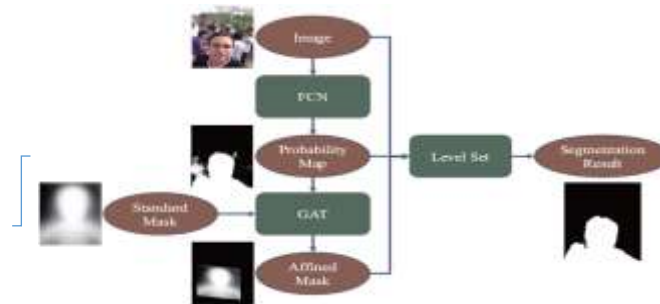


Fig.1. Block Diagram

2. PROPOSED METHODS

2.1 FULLY CONVOLUTION NETWORK

A fully convolutional network (FCN) converts the picture pixels to the pixel classes using a convolutional neural network. A fully convolutional network, in contrast to CNNs that we previously encountered turn the height and width of intermediate feature maps back to those of the input image for object or image recognition. The FCN structure is depicted in fig (2). The transposed convolutional layer shown in the picture allows for this. As a result, the categorization output and the input image are connected at the pixel level. For any output pixel, the channel dimension stores the categorization results for the input pixel at the same spatial position. Fully Convolutional Networks, or FCNs, are a type of architecture that are most frequently utilised. for a segmentation of semantics. The only locally linked layers they may employ are convolution, pooling, and up sampling. There are fewer parameters because dense layers aren't employed.





Fig(3): FCN RESULT

2.2 PROBABILITY MAP WITH DEEP LEARNING:

The deep contextual network's probability map output is highly attractive aesthetically, and we can see that the membrane of unclear zones can occasionally be interrupted. This is mostly due to the probability maps' averaging effect, which is produced by the several trained models. As a result, we used a watershed method that was already available to refine the contour. Figure 1 shows the contour evaluation method (4). Combining a linear combination with a binary contour and the original probability map created the final fusion result. The parameter that was chosen for our tests based on training data to produce the best Rand error outcome. The Rand error can be significantly decreased after combining the data from the watershed approach (CUMedVision-4 (with fusion)), but the warping error has sadly increased. This is the logical since these two mistakes take into account several segmentation evaluation metrics. The latter ignores nontopological mistakes while the former may punish even slightly off-center bounds. The SCI team applied a sophisticated postprocessing method to probability maps produced by the teams DIVE and IDSIA, in contrast to our straightforward postprocessing phase.

Layer ReLU: A no-linear activation function, $f(x) = \max(0, x)$, is all that the ReLU is (0, x). You can think of the activation function as a threshold function. To provide a sparse output, unnecessary nodes' output is muted.

softmax layer: Using the softmax function, the softmax layer transforms the output of the FCN into a kind of probability, as seen below.

$$p_{x,y}(c = i) = \frac{\exp(h_i(x,y))}{\sum_j \exp(h_j(x,y))} \quad (1)$$

where $h_i(x, y)$ represents the value of the i th feature map of the final output of FCN at the position (x, y) and $p_{x,y}(c = i)$ represents the probability of the pixel at (x, y) belonging to the category $c = i$. In this paper, the output of the softmax layer is treated as a probability map to represent the probability of each pixel. Hence, to reduce the amount of uncertainty, the minimising cross entropy approach CNN's network architecture[16].

Convolution kernels in CNNs can be learned and iteratively adjusted using the back propagation approach depending on training set, in contrast to conventional convolution kernels, which are pre-designed.

In the subsection that follows, the technique for obtaining an ideal affine transformation of a standard shape using the GAT is described.

2.3 Corrected global affine transformation for shape

The Portrait data collection contains a single mean mask for portraits[15]. The standard shape of the prior is translated to the best location of the picture in this paragraph using the probability map that was obtained in the previous subsection. Translation, scale, rotation, and flip are the only components of the transformation, which is believed to be an affine transformation. The assumed transformation is the affine transformation, It only includes translation, scaling, rotation, flip, and shear while preserving the basic geometry of the original object. The ideal situation is when the probability map mimics the real shape. An affine transformation of the common shape prior can be created based on the probability map. A transformation matrix M and its inverse M^{-1} are commonly used to apply affine transformations. The following equation results from applying an affine transformation to the three-dimensional point P to make point Q .

$$Q = MP \quad (2)$$

The may be given in its expanded form as follows, keeping in mind that the coordinates of Q are a linear combination of the points P.

Just premultiply both sides of an earlier equation by the inverse of transformation matrix M-1 to obtain the following in order to turn point Q back into point P.

$$P=M^{-1} Q \quad (3)$$

It's crucial to understand the distinction between a point and a directed vector before getting into global affine transformation. A directional vector represents a direction with respect to a particular point and is commonly represented as a point and a unit sphere centred on the origin while a point is fixed in three dimensions and fully characterises a position. While discussing the affine transformation, points are denoted by $P = (P_x, P_y, P_z, 1)$ and vectors by $v = (v_x, v_y, v_z, 0)$. Why this is the case .When thinking about implementing a translation transformation, this will be obvious.



Fig.4. Process of contour evolution



Fig.5. Process of contour evolution

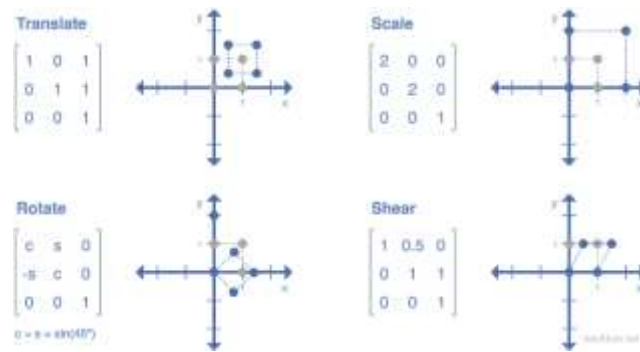


Fig.6. Global Affline transformation method

3. IMAGE SEGMENTATION TECHINQUES

3.1 Image segmentation using the level set method:

Using the level set method and the level set with deep prior approach, complicated sense can be objectively segmented completely and FCN performance is improved. The output of the FCNs is utilised to produce a probability map, where each pixel stands for a distinct category. even when a probability map's segmentation form is noisy, a significant portion of the proper segmentation is still present. Consequently, using the GAT approach and the "probability" shape, it is possible to derive an optimal affine transformation of the conventional shape mask of the image. The level set method's preliminary results are shown in Fig. (7), and the complete results are shown in Fig. (8). In order to accomplish image segmentation, the level set method's inputs of the picture, probability map, and affine mask are used. The level set method is a region-based approach to image segmentation.

The level set method for image segmentation uses the region-based active contour model, a variational approach based on energy reduction to evolve the level set [19]. The target zone is thought to represent the area around the number 0. The zero level = 0 is regarded as the contour of a target, and the level set is denoted by. One can consider the level set as a potential function is represented by how strongly each point is connected to the image. Level set can be thought of as a type of probability density that indicates the likelihood that a given point will be met. The level set method's energy objective function can also be used with a variety of energy-based probability models to increase its versatility [18]. The CV model put forward by Chan and Vese is the most traditional level set methodology, and the equation below yields the energy function of the contour.

$$f(C, c1, c2) = \lambda_1 \int_{outside(C)} |i(x) - c1| dx + \lambda_2 \int_{insideside(C)} |i(x) - c2| dx + v|c| \quad (4)$$

|where outside(C) and inside(C) are, respectively, outside and inside regions in the contour C. X is the two-dimensional vector that the image uses to represent it. The contour's length C is denoted by C. The statistics of the pixels outside and inside the

contour are given by c_1 and c_2 , respectively. The level set function, as indicated below, can be used to rewrite the energy function.

where $H(z)$ is the Heaviside function, which identifies the exterior and interior regions that the level set function represents. to present energy-based variational techniques. The probability map, the corrected shape prior information, and the original image can all be combined into one energy function thanks to the level set method's relatively flexible specification of the energy function. The following is a definition of the energy function:

$$\mathcal{A}(\phi) = \mathcal{E}_{img} + \mathcal{E}_{shape} + \mathcal{E}_{edge} + \mathcal{E}_{reg} \quad (5)$$

The function is iteratively calculated.

$$\phi_t = \phi_{t-1} + \Delta t \cdot \partial \phi / \partial t \quad (6)$$

The Level Set Technique is discussed in the equation above.



Fig.7. Level Set method partial results.



Fig.8. Leve Set method results.

3.2 IMAGE SEGMENTATION USING DEEP LEARNING

One of the most important steps in computer vision is segmentation. The technique of grouping together areas of an image that match to the same item class is known as image segmentation. Also called "pixel-level classification," this technique. In other words, it requires breaking the image up into several parts or items. Picture segmentation algorithms come in a variety of forms. Examples of older techniques include thresholding, histogram-based bundling, region expanding, k-means clustering, or watersheds. More complex algorithms are built on top of active contours, graph cuts, conditional and Markov random fields, and sparsity-based methods. Deep Learning models have recently produced a new class of image segmentation algorithms with appreciable performance improvements. Deep learning-based picture segmentation frequently achieves the highest accuracy



rates models. On the widely used benchmarks, causing an industry-wide paradigm shift. One of the high-performance approaches to understanding images that has arisen as a result of recent advancements in deep-learning technologies based on neural networks is object recognition via picture segmentation.

Deep learning-based image segmentation has been successfully employed in the field of remote sensing to separate satellite images, including techniques for precision agriculture and urban planning. Deep learning has also been used to categorise drone photo images (UAVs). For segmenting photos, deep learning is an excellent method. Using the hidden features that deep learning algorithms automatically extract from the data, data can be segmented. Deep learning algorithms can learn complex properties that are difficult to manually express. Convolutional neural networks (CNNs), fully connected networks (FCNs), and Recurrent neural networks are one deep learning model that can be applied to image segmentation (RNNs). Each architecture has its own set of benefits and drawbacks. Since convolutional neural networks can directly learn characteristics from the images, they are an excellent option for image segmentation challenges. Several convolutional layers, one or more fully linked layers, and the final layer make up a CNN. Via fully connected layers, every neuron in a layer is linked to every other neuron in the layer underneath it. The network may then identify complex non-linear correlations between image pixels.

4 Results and Discussions:

The level set approach can generate precise segmentation results when there is enough data, according to the experimental results. Several pattern recognition approaches are proposed to provide more information about the target. The target areas, for instance, and how likely it is that each pixel belongs to that target category. In this process of the contour evolution, the level set technique relies on statistics of the pixels inside and outside of the contour that are now fixed, such as mean, weighted mean, and probability model about areas. The level set methodology is more analogous to an information integration method because it uses the energy functional minimization notion to generate potential functions. The Image A portrait will be divided into two parts in the data set to be used for image stylization into a selfie with the intention of changing styles. The easy problem of segmenting a single target in a portrait can be utilised to segment complex scenes. Some images and ground truth from the Portrait data set are shown in Fig. 9. There are 1800 portrait photos in all, and since they are all automatically scaled and cropped to 600 800, they are all standard portraits. The 1800 labelled picture data set was split up by Shen et al. [15] into a 1500 image training data set and a 300 image testing data set. Since the photographs in the Portrait data set were tagged using Photoshop's quick selection tool, there is some noise in the data. the truth seen in Fig. 10.



Fig.9. The Portrait data set's ground truth and some photos.



Fig.10. The Portrait data set contains some noise.

Quantitative Analysis:

Table:1 Quantitative analysis Of Proposed And Existing Methods

Model	Cls. Accuracy.	Segmnted. Acc.	Precision	Recall	F1-Score
LSM-baseline	-	0.6568	0.4127	0.8359	0.4880
B Box-baseline	0.6695	0.6577	0.4129	0.6425	0.4047
DCLSM	0.6695	0.7598	0.5444	0.5085	0.4242

Both the LSM-baseline and the B Box-baseline baseline segmentation accuracy for the baseline approaches was about 0.66. In contrast, a suggested method that integrates the CNN prior into the Level Set Method produced a segmentation accuracy of 0.7598. This outcome shows a 15.74% relative improvement over accuracy at the baseline. While DCLSM scored the greatest in accuracy measures, it did so at the expense of LSM-baseline in segmentation recall. LSM-baseline produced a recall of 0.8359, significantly greater than any other approach, by initialising using an uninformative prior, i.e., always initialising from the image's borders. The Level Set Technique would segment an image almost universally by initialising at the image's edges. It makes intuitive sense that by beginning the curve's growth from an image's edges, Level Set Method. In this situation, the recall score would be ideal because it is the simplest way to obtain a full recall score. While DCLSM is more accurate at locating the object, it is the reason why it had a lower recall score. Eventually, DCLSM outperformed both the LSM-baseline and the B Box-baseline in terms of precision. DCLSM produced results of 0.5444 for precision and 0.5085 for recall. In other words, while only trading down 13.11% from the F1 score, the precision score increased by 32% in comparison to the LSM baseline. Overall, the proposed technique produced the greatest balanced precision and recall outcomes.

5 CONCLUSION



The level set segmentation technique used in this project was based on priors that the FCNs had learned. A probability map is used to depict the target pattern's likelihood using an FCN's output. Based on the pattern prior that the FCNs have acquired from the training set, the intrinsic prior shape is changed for a specific image. The suggested level set with a deep prior and the probability map approach, and the corrected prior shape for an image segmentation can all be integrated. Ultimately, the usefulness of the suggested strategy is confirmed through some experiments using the Portrait data set. The experimental findings show that the suggested approach can produce more accurate outcomes. when compared to the conventional FCNs results. In order to make GAT and level set technique a part of the network, we will the proposed method may handle more complex circumstances by developing a multi-objective matching strategy.

REFERENCES:

- [1] Pal, N.R., Pal, S.K.: 'A review on image segmentation techniques', *Pattern Recognit.*, 1993, vol. 26,no. (9), pp. 1277–1294
- [2] LeCun, Y., Bengio, Y., Hinton, G.: 'Deep learning', *Nature*, 2015, 521,(7553), p. 436
- [3] Sezgin, M., Sankur, B.: 'Survey over image thresholding techniques and quantitative performance evaluation', *J. Electron. Imaging*, 2004, vol.13, no.(1), pp.146–166.
- [4] Senthilkumar, N., Rajesh, R.: 'Edge detection techniques for imagesegmentation—a survey of soft computing approaches', *Int. J. Recent TrendsEng.*, 2009,vol. 1,no. (2), pp. 250–254
- [5] N. Dhanachandra, K. Manglem, and Y. J. Chanu, "Image segmentation using k-means clustering algorithm and subtractive clustering algorithm," *Procedia Computer Science*, vol. 54, pp. 764–771, 2015.
- [6] Achanta, R., Shaji, A., Smith, K., et al.: 'SLIC superpixels compared to state_x0002_of-the-art superpixel methods', *IEEE Trans. Pattern Anal. Mach. Intell.*, 2012,vol.34,no. (11), pp. 2274–2282
- [7] Felzenszwalb, P.F., Huttenlocher, D.P.: 'Efficient graph-based image segmentation', *Int. J. Comput. Vis.*, 2004, vol.59,no. (2), pp. 167–181
- [8] J.-L. Starck, M. Elad, and D. L. Donoho, "Image decomposition via the combination of sparse representations and a variational approach," *IEEE transactions on image processing*, vol. 14, no. 10, pp. 1570–1582, 2005.
- [9] Wu, Z., Shen, C., Van Den Hengel, A.: 'Wider or deeper: revisiting the ResNet model for visual recognition', *Pattern Recognit.*, 2019, 90, pp. 119– 133.
- [10] Chen, L.C., Zhu, Y., Papandreou, G., et al.: 'Encoder–decoder with atrous separable convolution for semantic image segmentation', *arXiv preprint arXiv:180202611*, 2018
- [11] Li, H., Xiong, P., Fan, H., et al.: 'DFANet: deep feature aggregation for realtime semantic segmentation', *arXiv preprint arXiv:190402216*, 2019.
- [12] Liu, C., Chen, L.C., Schroff, F., et al.: 'Auto-DeepLab: hierarchical neural architecture search for semantic image segmentation', *arXiv preprint arXiv:190102985*, 2019.
- [13] Hu, P., Shuai, B., Liu, J., et al.: 'Deep level sets for salient object detection'. *IEEE Conf. on Computer Vision and Pattern Recognition (CVPR)*, Hawaii, USA, 2017
- [14] Tang, M., Valipour, S., Zhang, Z., et al.: 'A deep level set method for image segmentation'. *Deep Learning in Medical Image Analysis and Multimodal Learning for Clinical Decision Support*, Québec City, Canada, 2017, pp. 126– 134
- [15] Shen, X., Hertzmann, A., Jia, J., et al.: 'Automatic portrait segmentation for image stylization'. *Computer Graphics Forum*, 2016, vol. 35, pp. 93–102
- [16] Zhou, B., Khosla, A., Lapedriza, A., et al.: 'Learning deep features for discriminative localization'. *2016 IEEE Conf. on Computer Vision and Pattern Recognition (CVPR)*, Las Vegas, USA, 2016, pp. 2921–2929
- [17] Kingma, D.P., Welling, M.: 'Auto-encoding variational Bayes', *arXiv preprint arXiv:13126114*, 2013
- [18] Chen, F., Yu, H., Hu, R., et al.: 'Deep learning shape priors for object segmentation'. *2013 IEEE Conf. Computer Vision and Pattern Recognition (CVPR)*, Portland, USA, 2013, pp. 1870–1877
- [19] Malladi, R., Sethian, J.A., Vemuri, B.C.: 'Shape modeling with front propagation: a level set approach', *IEEE Trans. Pattern Anal. Mach. Intell.*, 1995,vol. 17,no. (2), pp. 158–175
- [20] G. Eason, B. Noble, and I. N. Sneddon, "On certain integrals of Lipschitz-Hankel type involving products of Bes(references) [21] Liu, C., Chen, L.C.,DeepLab: hierarchical neural architecture search for semantic image segmentation", *arXiv*