Deep Learning over Conventional Image Processing for Contrast Enhancement and Auto-Segmentation of Super-Resolved Neuronal Brain Images: A Comparative Study

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Abstract - *Segmentation and analysis of neuronal and fibril structures obtained by electron microscopy to develop 3D maps of connections in the brain is an involved research domain in computer vision and neuroscience. Interactive understanding of neuronal and fibril connections in the brain can enable neuroscientists to draw significant conclusions for applications in artificial intelligence, better understand the disease and possibly arrive at a cure. Conventional methods used for biomedical image enhancement and segmentation often fail to generalize and identify non-convex morphologies and deep connections in the brain. In this paper, deep learning is compared with traditional mathematical image processing to understand its applicability as a promising solution for contrast enhancement and auto-segmentation of super-resolved neuronal brain images. The paper also throws light on existing non deep learning techniques for image enhancement and segmentation to develop a comparative opinion. In addition to this, the open research challenges for ensuring robustness in the field of deep learning-based bio-medical imaging have been discussed.*

***Key Words*: Deep Learning, Image Processing, Contrast Enhancement, Auto-Segmentation, Deep-Tissue Super Resolution, Neuronal Network**

1. INTRODUCTION

Image interpretation and processing is subjective to the complexity of the image, extensive variations across different interpreters, computational cost, availability of data, application-specific requirements and memory. Due to tremendous enhancement in the availability of data and image acquisition devices, manual analysis of neuronal data is prone to human error and is often time-consuming and challenging. Another solution is applying machine learning[1] to automate the contrast enhancement and auto segmentation tasks. However, traditional machine learning techniques like regression, clustering and classification are not sufficient to deal with the complexity of identifying and segmenting neuronal fiber structure in a super-resolved image of the brain. Deep learning models are exceedingly advantageous in extracting complicated information and features from input images with promising accuracy and are observed as a potential method for key implementation of image processing and segmentation tasks such as identification of neuronal fibers in brain image[2]. Recent developments in deep learning methodology have played an important role in medical image processing, image interpretation, image fusion, image segmentation, computer-aided diagnosis and image-guided therapy[3].

The motivation of this paper is to provide a comprehensive analysis, comparison and challenges of deep learning-based approach for the contrast enhancement and auto-segmentation of super-resolved neuronal brain images compared with traditional mathematical image processing techniques.

2. NON DEEP LEARNING IMAGE ENHANCEMENT TECHNIQUES

To establish a potential comparative study between deep learning and non-deep learning-based methods, it is crucial to review promising non-deep learning-based techniques[4] that can be used for contrast enhancement. Intensity transformations such as log transformation and gamma transformation and image quality enhancers such as histogram equalization employed for contrast enhancement generally involve direct manipulation of image pixels as discussed in the following section.

- Log Transformation: Maps the higher range of high-intensity input levels x to narrow range of output levels y and narrow range of low-intensity values x is mapped to wider range of output values y, i.e. it compresses the dynamic range of images with large variation in the pixel value. Mathematically, y = log (1+b*x) represents Log Transformation where b is a constant.

- Gamma Transformation: Fractional values of r (0.2-0.6) maps a narrow range of dark input values x into a wider range of output values y which allows general-purpose contrast manipulation. Mathematically, y = c * (x^r) represents Gamma Transformation where c is a constant.

- Histogram Equalization: This method usually increases the global contrast of images when its usable data is represented by close contrast values. This ensures that the intensity range of the image has been effectively spread out uniformly allowing the areas of lower contrast to gain a higher contrast which ensures noise removal[5].

Pixel-wise manipulation of an image for contrast enhancement may result in an unintended variation in the intensity of background pixels which leads to addition of abrupt noise in the image. Applications such as identification of deep fibril structure in a brain MRI often demand high level of precision and accuracy. Therefore, a better and generalized contrast enhancement technique with finer precision at computational effectiveness is required.

3. NON DEEP LEARNING AUTO SEGMENTATION TECHNIQUES

To understand the assets of deep learning-based auto-segmentation[6] for identification of fibril structure across different layers in a brain image, it is important to consider a comparative study with other existing segmentation algorithms such as edge detection, thresholding, clustering and marker-controlled watershed algorithm[7]. The algorithms used for image segmentation (edge detection, thresholding, clustering and watershed) essentially divide a digital image into subsets of connected pixels and assigns each pixel a unique label, i.e. pixel-wise image segmentation. A better evaluation reveals that edge detection generates preferable results in images with finer border features such as a flower, thresholding works for images with fewer features such as a cricket-ball and clustering yields better results in segmenting images which can be evenly classified into two or more subclasses such as identifying a blockage in the heart blood vessel. Applications such as identification of tumor in brain MRI images can be fundamentally considered as a classification task and hence these algorithms often work well. In general, an image segmentation problem that does not demand sub-pixel accuracy of classification or connecting pixels i.e., problems with more well-defined divisions are likely to be satisfactorily solved using the algorithmic implementation of image segmentation such as separation of bones from tissues, separation of lungs from ribs, etc. On the other hand, when it comes to the identification of fine neuronal structure in a brain MRI, the algorithmic implementation will not prove fruitful. Therefore, robustness in implementation is required for the identification of different fibril-structures in the images, such that subpixel accuracy is attained[8].

4. WHY DEEP LEARNING OVER TRADITIONAL IMAGE ENHANCEMENT TECHNIQUES ?

Image enhancement involves sharpening, noise removal and contrast enhancement. A satisfactory image enhancement method is often influenced by human perception which leads to disparity and discrepancy. Moreover, traditional mathematical image processing methods for contrast enhancement perform well only in a fixed circumstance at the cost of decay in other image attributes leading to unintended adverse effects like over-enhancement and halo effect. Methods like histogram equalization and cumulative histogram equalization for image enhancement are highly indiscriminate which may increase the contrast of background noise while decreasing the usable signal. Supervised CNNs[9] allow feature tracking between a training low resolution and high-resolution image pair ensuring contrast enhancement does not occur at the expense of other image attributes like image sharpness and noise content. In addition, unlike pixel-wise traditional image enhancement techniques which may fail to achieve contrast enhancement for super-resolved neuronal images due to involvement of sub-pixel accuracy, CNNs[10] can be trained in accordance with the application requirements by adding more details to the training set i.e. feeding the deep learning model with more high-resolution images. Developments in the availability of memory devices, training data, transfer learning and high-speed processors have further revolutionized the preferability of deep learning over traditional image enhancement techniques[11].

5. WHY AUTO SEGMENTATION WITH DEEP LEARNING OVER MANUAL SEGMENTATION ?

Image segmentation can be defined as the classification of the pixels in an image into different clusters that exhibit similar features. Image segmentation can be broadly classified as manual, semi-automatic and auto-segmentation. Recent advancements in technological modalities and time constraints for manipulation of wide-ranging data especially in the field of biomedical imaging have established auto-segmentation as a much better, quicker and handy alternative as compared to manual and semi-automatic segmentation methods[12]. Manual segmentation methods such as regional growth from seeds is a highly biased and discriminative approach resulting in heterogeneity in segmented output. Deep learning-based auto-segmentation[2] can be quicker, reproducible and more reliable approach than manual segmentation if sufficient training data is available for learning the hypothesized parameters of the model. The usability of manual, semi, or auto-segmentation is highly dependent on the complexity of the application, computational effectiveness and the availability of annotated segmented data.

6. OPEN RESEARCH CHALLENGES

1. Availability of scalable data: Supervised learning in deep convolutional neural networks for image processing applications such as super-resolution and auto-segmentation requires data for training, cross-validation and testing of the proposed model. Obtaining scalable annotated data for mapping from input variables to an

output variable in a deep convolutional neural network is challenging for contrast enhancement and auto-segmentation of neuronal fibers due to the involvement of sub-pixel accuracy.

2. Generalization capabilities: A major drawback of deep learning-based auto-segmentation is that unlike contrast enhancement, deep learning-based auto-segmentation lacks generalization capabilities. In other words, deep learning models tend to be biased by their respective training datasets leaving limited scope for transfer learning[13], unlike contrast enhancement which supports generalization. This shows a need for an adequate manually segmented training data for auto-segmentation.

3. Memory and Computational Cost: Deep learning and artificial intelligence systems rely on massive data for the training of hypothesized parameters. Memory requirements for storage and computational effectiveness of the algorithm are two key factors for real-world bio-medical imaging applications and an active research domain in the semiconductor design industry.

4. Overfitting: It is crucial to avoid overfitting or high-variance in the proposed model to ensure promising results on the testing dataset. Overfitting in a deep learning model may lead to a significant error in pixel-wise super-resolution and auto-segmentation of neuronal structures if there is a vast difference between the training and testing datasets.

5. Image Quality Assessment: Selection of an adequate image quality assessment[14] is crucial for establishing a quantitative and robust base for comparison of results obtained after processing with deep learning with the available ground truth data as it impacts the consistency, completeness and predictive capability of the model. The choice between reference and reference-less image quality metrics depends on the computational complexity and the agreement with the human perception of image quality[15].

7. CONCLUSION

This comparative study throws light on the application of Deep Learning (DL) techniques for contrast enhancement and auto-segmentation to identify neuronal connections across different layers in the brain. Non-DL based image quality enhancement methods including Log and Gamma Transformations and Histogram Equalization are analyzed and compared against DL based contrast enhancement using CNNs to check the preferability of deep learning over traditional mathematical image processing methods. Non-DL based auto-segmentation methods such as edge detection, thresholding, clustering and watershed algorithms are reviewed to establish a comparative opinion. Deep learning is indeed an involved research domain in image processing and computer vision. Future works and researches will facilitate the key implementation of a specific application at cost and computational effectiveness using deep learning methods. This paper explores deep learning as a feasible option for image analysis of neuronal structure in a drosophila brain.

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