An Efficient Evaluation Of Accuracy In Image Processing Analysis Using Local Contrast Hole-Filling, Image Processing Chain Optimization, And Multiple Image Processing Chain Optimisation Algorithms

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Abstract— An algorithm is a step-by-step procedure or set of rules designed to perform a specific task or solve a problem. In the context of this study, it refers to a sequence of computational steps used to enhance image processing. The study on designing an algorithm for image processing is delimited to focusing on the development and evaluation of a novel algorithm that integrates advanced techniques for both fields. The research will be constrained to the analysis of image processing algorithms that are applicable to real-time systems and high-resolution images. The study will also exclude comparative analysis with all possible algorithms, focusing instead on a select range of contemporary techniques to ensure depth and relevance. Furthermore, the evaluation will be limited to performance metrics such as processing speed, accuracy, and robustness, without delving into specific application scenarios beyond those identified during the algorithm's design phase. Genetic algorithms, Differential evolution, and rank-based uniform crossover are the core components of the two algorithms that have been suggested for optimizing image processing chains: LCHF, IPCO and MIPCO.

***Index Terms*— Local Contrast Hole-Filling (LCHF), Picture Processing Chain Optimization (IPCO), Multiple Image Handling Chain Optimization (MIPCO) network etc.,**

I. INTRODUCTION

LCHF Algorithm

One such technique is LCHF, which stands for Local Contrast Hole-Filling based Membrane Detection. It can identify cell membranes but not organelles. Choosing the optimal tuning of a previously defined processing pipeline was the current objective. Since certain parameters are crucial to the component techniques, this step also determines the parameter ranges that the processing pipeline can employ to detect cell membranes that can ignore organelles. In its most basic form, LCHF is a series of operations that begin with preprocessing (denoising and contrast enhancement), continue with classification (threading and holefilling), and conclude with postprocessing (morphological operator smoothing). It is necessary to fine-tune the parameters of each processing step depending on the data.

IPCO and MIPCO Algorithms

Image Processing Chain Optimization (IPCO) is the second algorithm main outcomes of IPCO tests and the part played in developing the algorithms, according to the procedures outlined in the methodology section, are also covered. This method is brand new; it builds on top of the IPCO algorithm, which employs existing image processing capabilities. The algorithm's novel "combiner" function is the main innovation. To promote "image blending" (the merging of two outputs), this function is structured in a way that allows it to take input from earlier functions in the processing chain. Multiple Image Processing Chain Optimisation Network (MIPCO), the third algorithm, is covered in this chapter. Based on the methodologies mentioned in the Methodology chapter, the study contributed to the design of the algorithm and the important findings of tests were presented using the MIPCO parallel network. Also analyzed and understood are the outputs and outcomes acquired throughout the experiments.

II. RESEARCH METHODOLOGY

The accuracy of the three methods that were suggested—IPCO, MIPCO, and Local Contrast HoleFilling (LCHF)—was evaluated by calculating their precision, recall, and F1 score, where tp represents the number of true positives, fp represents the number of false positives, and tn represents the number of true negatives. A confusion matrix and the associated precision, recall, and F1 scores were calculated for every slice. From the output results for each of the 30 slices, the final performance numbers were calculated as an average. Instead of only using the arithmetic mean, the F1 score metrics combine Precision and Recall to get a harmonic mean. To illustrate the point, if the precision is 0 and the recall is 1, then the arithmetic mean would return 0.5 (the poorest possible output) and be 50% accurate, but the harmonic mean would return zero (F1

measurements). That is to say, although the denominators of recall and accuracy are different, the numerators both contain true positives. Since averaging their reciprocals is the only reasonable way to do it, harmonic mean is the method of choice. Therefore, excellent recall and precision are necessary for a high F1 score.
As stated above, the performance of the algorithm was measured in terms of Precision, Recall, and F1 score:

$$\text{Precision} = tp/(tp + fp) \quad (1)$$

Where tp is true positives (i.e., the number of pixels correctly labelled as belonging to the positive class) and fp is false positives (i.e., number of pixels incorrectly labelled as belonging to the membrane class).

$$\text{Recall} = tp/(tp + fn) \quad (2)$$

Where tp is true positives and fn is false negatives (i.e., number of pixels which were not labelled as belonging to the positive class, but should have been). Pixels that are falsely identified as a boundary in the output, but are classed as the cell interior pixels in the ground-truth image are referred to as false positives. Conversely, pixels that are identified as interior in the output, but are classed as a boundary in the ground-truth image are referred to as false negatives.

$$F1 = 2((\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall})) \quad (3)$$

Where F1 is the accuracy measure for the test. With a maximum value of one and a minimum value of zero, the F1 score can be seen as a weighted average of the recall and precision. The precision, recall, and F1 scores for each slice were obtained after a confusion matrix (3). Results for each of the 30 slices were averaged to get the final performance values.

Rather of using the Rand index, which penalizes even marginally misplaced borders (as per the ISBI challenge), F1 measurements were employed in this study. Rand error computation treats false positives and false negatives equally, taking into account the frequency of pixels corresponding to which objects. Similarly, this study did not use the Warping error measurement since it gives no weight to data pertaining to errors that are not topological. There will be no noticeable changes to the final product's quality due to the pixel error metric's simplicity.

III. PERFORMANCE ANALYSIS OF ALGORITHM

LCHF Algorithm Outcome

LCHF Algorithm presented a straightforward, effective, and non-learning method that relies on LCHF and other fundamental processing processes. The TEM Drosophila dataset, which can be acquired from the IEEE International Symposium on Biomedical Imaging, shows that LCHF can identify membranes effectively; it takes an average of 21 seconds to analyze 30 slices and has an average F1 score of 71%. LCHF performs its output independently of ground truth, making it a non-learning technique. So far, the ground truth data has only been used in this study as an error measuring metric, for the purpose of comparing and gauging the output with the ground truth.

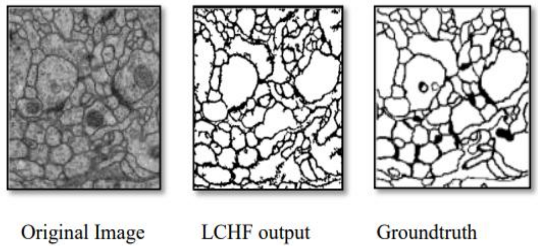

Figure 1: LCHF Output

IPCO Algorithm Outcome

IPCO Algorithm Using an ensemble of classifiers is a straightforward method to boost any classification approach's generalizability. This study also improved F1 scores by combining many IPCO chains in ensembles (by manual selection). The optimal IPCO chain ensemble achieved an average F1 score of 92.11% as of this below figure.

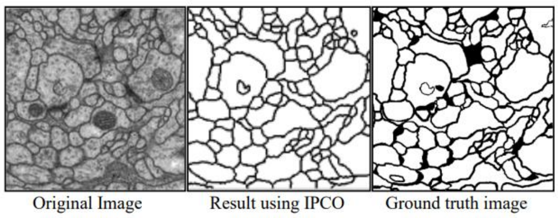

Figure 2: IPCO Output

MIPCO Chain Algorithm Outcome

MIPCO Chain Algorithm are different chain sizes and quantities were tested in many tests. As a result, it was shown that MIPCO could still get consistently high F1 scores (over 91%) with just three chains, which is a rather modest amount. Below figure are the smallest MIPCO examples achieving F1 scores over 91%.

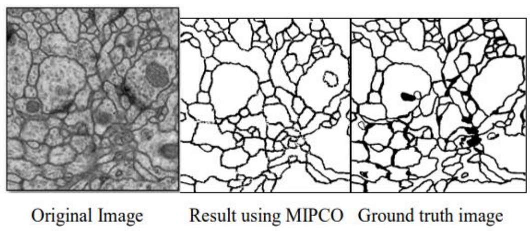

Figure 3: MIPCO Output

Table 1 displays the individual scores; a mean Recall score of 94.50% indicates that the classifier was successful in detecting the membrane voxels. With just 89.28%, Precision did not get a very good result.

Image	Precision	Recall	F1 Score
Slice 1	0.897774	0.952891	0.924512
Slice 2	0.9011562	0.937588	0.919011
Slice 3	0.8847477	0.954205	0.918165

Table 1: Performance score for each slice of the dataset for the score of 91.80%.

IV. CONCLUSION

In terms of successfully differentiating between membranes and organelles, LCHF was up to the task. But the most accurate result ever reported was 71% (Average F1 Score). With average F1 scores of 91.67% and 91.80%, respectively, the second algorithm created in this study, IPCO, and the third algorithm, MIPCO, both did a good job. When compared to the separate IPCO algorithms, MIPCO produced better rates (accuracy). The time required for IPCO optimization is much shorter than that of MIPCO as, on average; IPCO solutions involve fewer functions due to IPCO's optimization of a single chain. Despite IPCO's speed advantage, MIPCO still optimizes the network in 'seconds' each picture and 'minutes' overall.

Therefore, processing steps—including local contrast enhancement, thresholding, denoising, holefilling, watershed segmentation, morphological operators, and integration with combination functions MIPCO is the better choice for users who value accuracy over speed, whereas IPCO is the better choice for users who require an algorithm that can perform well and is also fast. Although it accurately recognizes the whole membrane lines, even a comparable output cannot guarantee a 100% score due to variances in the presented membrane's thickness.

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