

E4 project : Maximin Affinity Learning of Image Segmentation

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1 Introduction

2 Maximin Affinity learning

2.1 Method's presentation

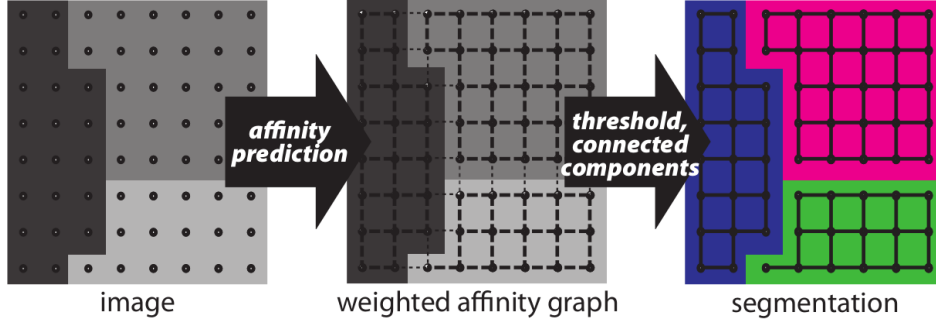


Figure 1: Description of the method, from [1]

The method, as illustrated in figure 1 works in two steps.

The first step is to compute an affinity graph G , with nodes V representing each pixel in the original image and edges E weighted by the affinity between neighbouring pixels. The graph G will be 4-connected and for every pair of pixels $i, j \in V \times V$ there exist an edge $(i, j) \in E$ iff i and j are neighbours. We will note the affinity between neighbouring pixels A_{ij} .

An affinity of 1 between i and j means that they belong to the same object, and an affinity of 0 means that they belong to different objects.

Once we have our affinity graph, with affinities between 0 and 1, we will threshold it and remove edges under a certain affinity to obtain connected components that will be our objects, and this thresholded affinity graph will be our final segmentation.

2.2 Optimizing the Rand Index

There exist various methods of evaluating an image segmentation, one of them being the Rand Index which is defined as follow :

$$1 - RI(\hat{S}, S) = \binom{N}{2}^{-1} \sum_{i < j} |\delta(s_i, s_j) - \delta(\hat{s}_i, \hat{s}_j)|$$

With S our groundtruth segmentation \hat{S} our predicted segmentation and $\delta(s_i, s_j)$ the indicator function taking value 1 if $s_i = s_j$ (if pixels i and j are in the same segment/object) and 0 otherwise.

Intuitively, this can be seen as the fraction of image pixels where both segmentations agree.

This gives us a way to evaluate an image segmentation that penalizes when two objects are merged or split in our final segmentation as we can see in figure 2. On the left, only one edge is misclassified but this merges two objects and will be heavily penalized by the Rand Index (we would see the same results if an object was split). On the contrary if we have misclassified edges inside of objects that do not create any splits, this will not be penalized at all by the loss since our objects are still correctly delimited.

As such the Rand Index seems a good measure of segmentation quality for our problem (edge-based segmentation). We will have to see how exactly can we optimise this metric in our case.

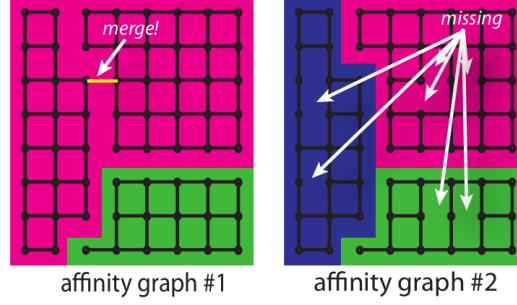


Figure 2: Exemple image segmentations and their affinity graph. On the left we have a merging of two objects due to a misclassified edge and on the right we have edges that should be of value 1 that have been removed. From [1]

2.3 Maximin affinity and the maximin edge

In order to optimize the Rand Index, we must find a way to compute $\delta(\hat{s}_i, \hat{s}_j)$. To do this we will use the concept of maximin affinity, as described in [1].

Let \mathcal{P}_{ij} the set of all paths between i and j in our image. For every path $P \in \mathcal{P}_{ij}$ there is an edge(s) (k, l) with minimal affinity.

This allows us to define the maximin path, which is the path which maximizes the minimal affinity. It is defined as follow :

$$P_{ij}^* = \arg \max_{P \in \mathcal{P}_{ij}} \min_{(k,l) \in P} A_{kl}$$

The edge of minimal affinity in the maximin path will be called the maximin edge and will be written $mm(i, j)$.

It allows to define the maximin affinity which is simply the affinity of the maximin edge.

$$A_{ij}^* = \max_{P \in \mathcal{P}_{ij}} \min_{(k,l) \in P} A_{kl}$$

The most important consequence of this is that a pair of pixels i, j is connected in the thresholded affinity graph iff A_{ij}^* is greater than the threshold value, as shown in [1].

This means that if we can find the maximin affinity efficiently, we will be able to compute the Rand Index efficiently.

In practice the maximin affinities can be computed efficiently using a maximum spanning tree (MST), since any path in the MST is a maximin path.

2.4 Computing an affinity graph

As we can see, once we have our affinity graph, obtaining the segmentation is straightforward, but the issue is : How to obtain an affinity graph?

As stated before, an affinity graph is equivalent to the contours in the image, and as such any method to find the contours in an image can be used to find the affinity graph (with relative success).

The first idea that we could have would be to use a contour detector, such as the Canny filter for example, however this would lead to an obvious over segmentation, which is not desirable here.

An other idea (the idea used in [1]) would be to use a neural network to obtain our affinity graph. Neural networks, and particularly convolutional neural networks (CNNs) have proven to be an extremely powerful tool in image processing and especially in image classification and segmentation, which makes

them a good candidate for MALIS.

The architecture used originally is a fully convolutional neural network (FCNN) which is a CNN with only convolutional layers. As such they can work with various input sizes which is always a nice feature.

Now that we have seen how we can compute an affinity graph, let's see how we can train this classifier, and if it even possible to train it with the Rand Index as a loss function.

2.5 Training a classifier

As stated before, the goal of this method is to optimise the Rand Index, defined as:

$$1 - RI(\hat{S}, S) = \binom{N}{2}^{-1} \sum_{i < j} |\delta(s_i, s_j) - \delta(\hat{s}_i, \hat{s}_j)|$$

with S our groundtruth and \hat{S} our predicted segmentation.

We can define $A_{ij}^*(I, \theta)$ the maximin affinity of pixels i and j in the predicted affinity graph of our classifier on I with parameters θ . We can rewrite the previous equation as :

$$1 - RI(I, \theta, S) = \binom{N}{2}^{-1} \sum_{i < j} |\delta(s_i, s_j) - A_{ij}^*(I, \theta)|$$

However this function is not differentiable everywhere so we cannot use it directly for our training. We will replace the absolute value with a smooth loss function l such as the mean squared error. This relaxation will allow us to use gradient descent to train our classifier (refer to [1] for more details on this).

Thus our final loss function will be :

$$L(I, \theta, S) = \binom{N}{2}^{-1} \sum_{i < j} l(\delta(s_i, s_j), A_{ij}^*(I, \theta)) = \binom{N}{2}^{-1} \sum_{i < j} l(\delta(s_i, s_j), A_{mm(i,j)}(I, \theta))$$

We can now look at what the training loop will look like.

Algorithm 1 MALIS training loop, from [1]

- 1: **repeat**
- 2: Predict the affinity graph for an image I
- 3: Pick two random pixels i, j from I
- 4: Find the maximin edge $mm(i, j)$
- 5: Update our parameters θ with gradient

$$\nabla l(\delta(s_i, s_j), A_{mm(i,j)}(I, \theta))$$

- 6: **until** convergence is reached
-

In practice we won't train on the whole image since it would be too long to compute the maximin edge in the whole image. We will instead train on 21x21 patches of the image. We have to choose these patches carefully as most of them will mostly be in an object and not around a border.

Since borders between objects are far less common than the "inside" of an object, we may most of the time train only for pixels inside a same object.

This would result in class imbalance between our "borders" (affinity of value 0) and or "inside" (affinity of value 1). Training with such imbalance would lead to worsened results since borders would not be present most of the time in the chosen image. (one example of such pathological behaviour would be the prediction of affinity 1 everywhere, far from what we desire)

As such when training we need to be careful about what training image we select.

3 Implementation

3.1 Inputs and outputs of the NN

After reading the original paper [1] we realized that there was some missing information on implementation details. One of the most important points, the input and the output of the neural network, was not clear. After some research we were lucky to find Srinivas Turaga's Phd thesis [2]. In it MALIS was presented in more details, especially the neural network used in the experiments.

The network predicts the affinity following each axis. As we can see in figure 3, in the case where the network is fed a 3D image, it outputs three affinity images following the axis X, Y and Z. Then we have to merge these three images in a way to obtain the complete affinity graph.

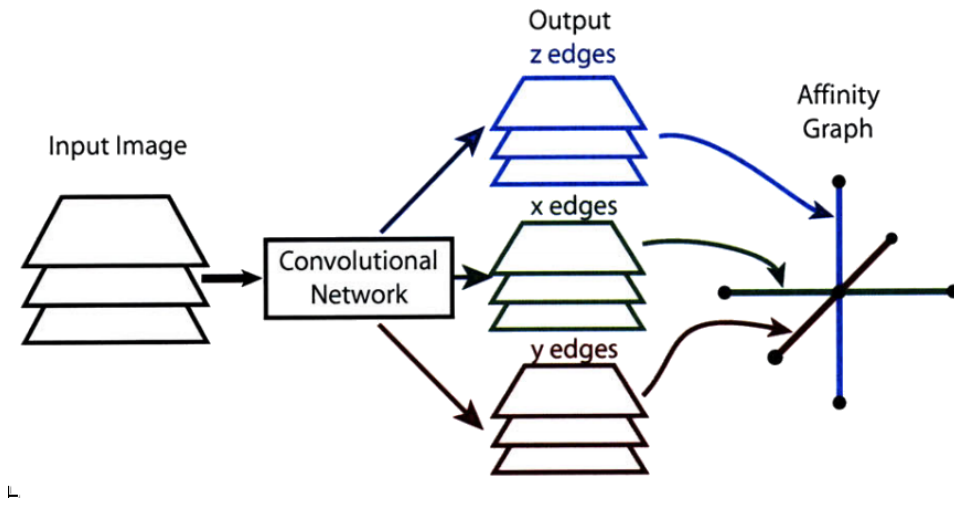


Figure 3: Creating the affinity graph using a convolutional network. The input to the network is the 3d EM image and the desired output is a set of 3d images: one each for the x, y and z directions representing the affinity graph, from [2]

Another problem was to understand the input shape. In the paper, they use a patch size of $21 \times 21 \times 21$. But it is also said that it led to an affinity classifier that use a patch with a shape of $17 \times 17 \times 17$ to classify an affinity edge. In a first time it was kind of blur but we figured out that 17 correspond to the volume taking in account after four convolution layers with a kernel size of 5×5 , reminiscent to the proposed architecture. The patch size is also arbitrary as we are using a FCN that, by definition, don't care about the input shape.

3.2 Computing the maximin edge

As said earlier, we have to find the maximin edge in order to compute the loss. As we have to do this operation for each training iteration, it is very important to guarantee a very low computational cost. Our first approach was to use the Breadth First Search algorithm on the Maximum Spanning Tree efficiently created with Hight. Sadly, this method was not good because our implementation was suffering from the slowness of Python and it's $\mathcal{O}(n)$ complexity for each pair of pixel, which scales badly with the number of pairs chosen.

In our last version we are computing a Binary Partition Tree, a binary tree by altitude ordering. This tree is build using Kruskal algorithm. The way to build this tree is straightforward, as illustrated in

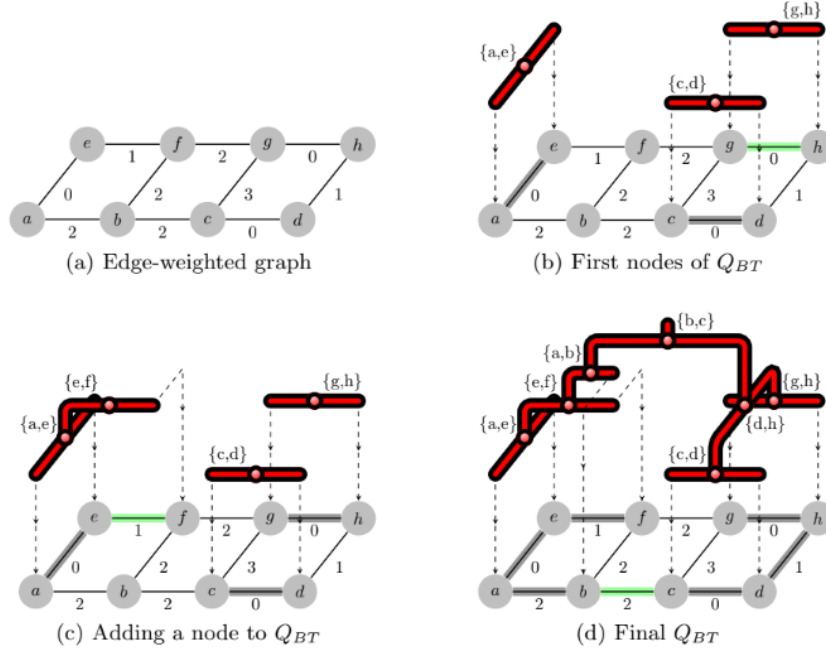


Figure 4: A simple process for obtaining a binary tree providing a strict total order relation on the edges of the MST, from [3]

figure 5. Edges are added to the tree in order of altitude as our MST is built, as described in [3]. This data structure is pretty pertinent as the maximin edge between to pixel i and j is the lowest common ancestor of these two pixels in the BPT. Higura also allow us to compute the loss with a larger number of pairs without an explosion of computing time because picking the lowest common ancestor is achieved in constant time, with a preprocessing in $\mathcal{O}(n \log(n))$.

3.3 Interaction between Higura and PyTorch

We had some trouble with the interaction between Higura and PyTorch. In order to compute the loss, we have to compute a BPT on a graph build from the NN output to find the maximin edge used in the loss computation. As you can see in figure 5, the gradient history is lost by turning the affinities images in graph using Higura.

We were unable to keep tracking the gradient history by working on graphs, even after a thorough examination of each step of the process. Therefore it was impossible to train our model. But without Higura the training would be much longer. And even the previous technique using the Breadth First Search would not work as we are using Higura to compute the MST. We found the solution in a code proposed by Giovanni Chierchia and Benjamin Perret in [4] for computing the subdominant ultrametric, which is analogous to our problem. Higura has a function that allow us to make the correspondence between an edge in the graph and the output affinity image. Consequently, we are able to localise the maximin edge in the output image. Due to the fact that picking an edge does not cause gradient history loss we are done.

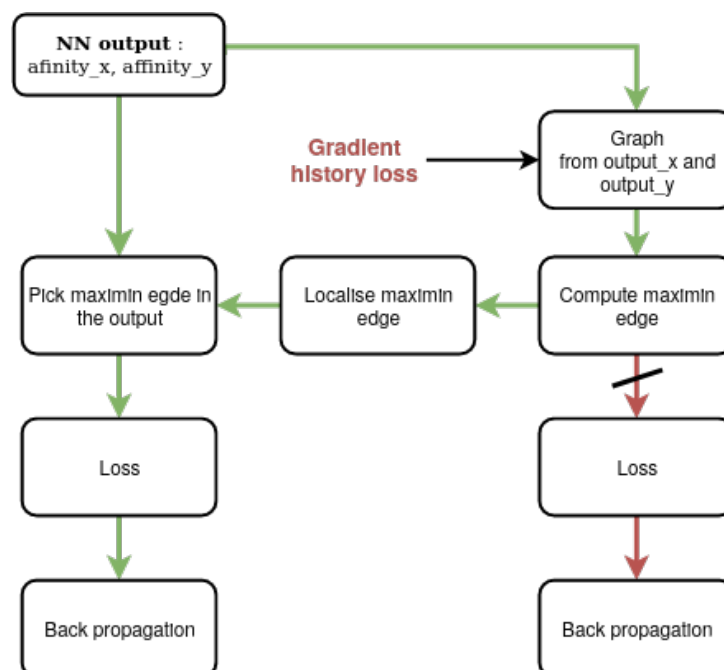


Figure 5: Process to compute the loss from our neural network. The red path was our first idea but proved unsuccessful. The green path represents the process we are using currently.

4 Results

4.1 Evaluation method

We evaluated our method with two different datasets : CREMI and ISBI 2012 datasets. Both are composed of Drosophila adult brain images.

A very simple architecture is used for the training. It's composed of 6 layers of convolution. In [1], the original architecture had 4 convolutional layers with 5 features in each. We decided to add more layers and features as it gave us better results. Batch normalisation was also added as it has also given us better results in our experiments.

The architecture is described in detail in table 1. As we can see, our network takes a 2D image as input whereas both datasets (as we will detail afterwards) are 3D images. We decided to use 2D images as it was a simplification of the problem and reduced training time drastically, allowing us to test our method more effectively.

In all of our test, a 3D image of size $X \times Y \times Z$ is considered as Z images of size $X \times Y$ which were stacked together to get back a 3D image.

Layer	Kernel	Strides	Features	BN	Activation	Output shape
Input						(21, 21, 1)
Convolution	(5, 5)	(1, 1)	8	Y	ReLU	(21, 21, 8)
Convolution	(5, 5)	(1, 1)	32	Y	ReLU	(21, 21, 32)
Convolution	(5, 5)	(1, 1)	32	Y	ReLU	(21, 21, 32)
Convolution	(5, 5)	(1, 1)	32	Y	ReLU	(21, 21, 32)
Convolution	(5, 5)	(1, 1)	8	Y	ReLU	(21, 21, 8)
Convolution	(5, 5)	(1, 1)	2	N	sigmoid	(21, 21, 2)

Table 1: Architecture used in all of our experiments

4.2 CREMI

The CREMI (Circuit Reconstruction from Electron Microscopy Images) dataset has three volumes but we decided to use only one (volume A) for our training. This allows us to use the remaining two for validation and testing.

This 3D image has a size of 1250x1250x125. Its corresponding groundtruth was also provided in the dataset. The segmentation constitutes of labeled connected components with really thin edges, we can see an example in figure 6.

Having labeled connected components instead of borders was really helpful for our training since we need to know if two pixels belong to the same object, which was pretty straightforward with this format.

For the evaluation, we used the CREMI library that was given with the dataset in Python 2. We, then, adapted it in Python 3 as to use it more efficiently with our existing codebase.

Once our model is trained a question arises : how to get an image segmentation from the affinity graph ?

The affinities were averaged/weighted in [1] but other methods could also work.

We used two different methods to answer this problem.

First of all, a BPT (Binary Partition Tree) of our affinity graph and then a graph cut could be a first idea, which is a bit more complex than just averaging the affinities.

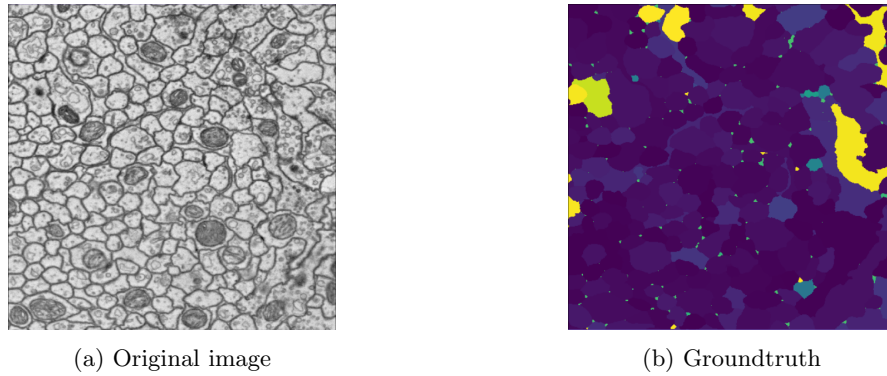


Figure 6: CREMI dataset (volume A)

However, even with a strong threshold for our cut (around 0.99), isthmus appeared and fused two different objects together. This is heavily penalized by the Rand Index and not a desirable outcome.

An other method, that got rid of isthmus, was to average the affinities and then threshold the result, which we used in all of our testing as it was the best solution (relative to the BPT + graph cut).

An illustration of the isthmus issue can be seen in figure 7 .

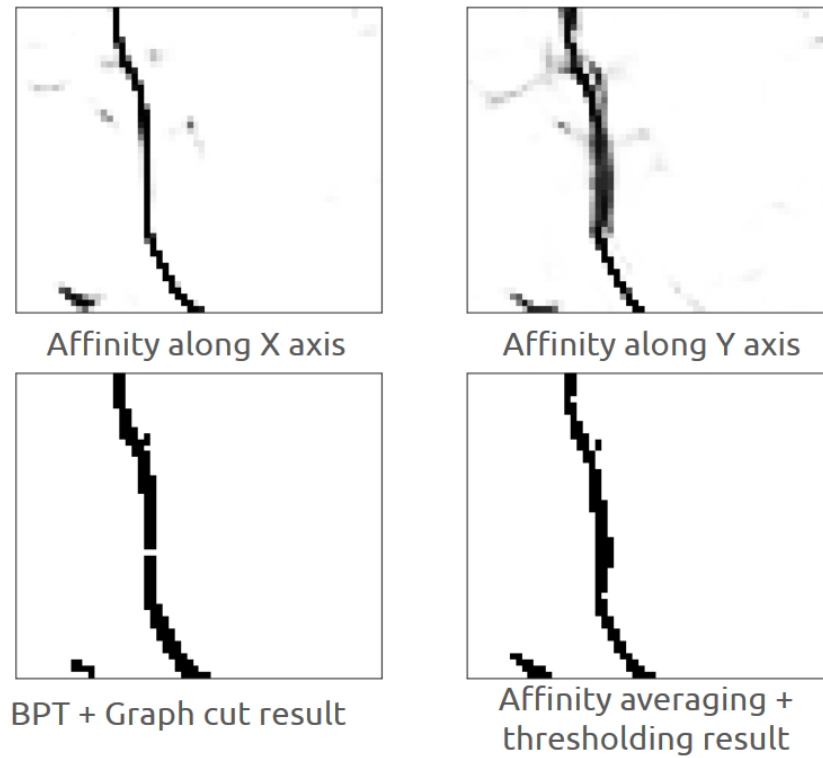


Figure 7: Illustration of the isthmus issue in our segmentation

Our results are promising as the different objects are well segmented, as illustrated in figure 8. However we can see that the nuclei are not well segmented as they should be part of the cell. This is a logical issue since on a local scale, it is hard to differentiate between the border of a nucleus and the border of a cell.

The second volume (volume B) was used as the test set. The image was similar to the one in the first

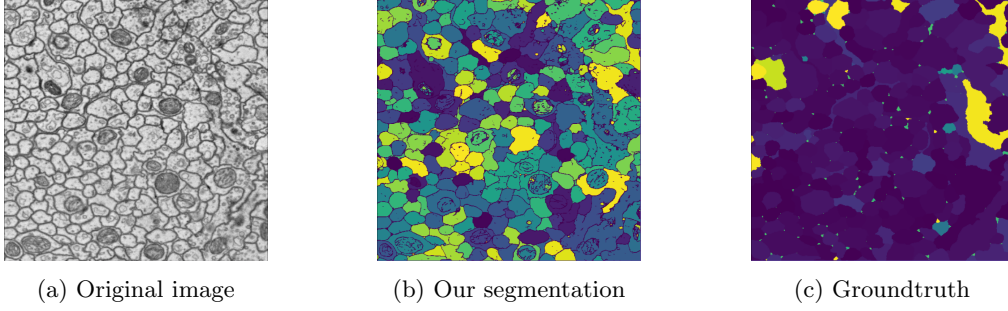


Figure 8: Results on the CREMI dataset volume A (Training set)

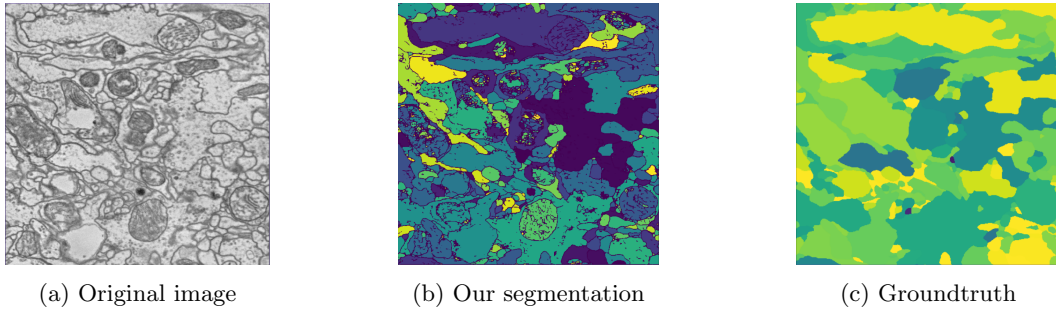


Figure 9: Results on the CREMI dataset volume B (Test set)

volume but the objects are more "stretched out."

As we can see in figure 9 the objects are well segmented but we had the same issues as on our training set.

The segmentation is obviously a bit worse since we didn't train on this image, but they are still encouraging.

To get a better understanding of our results, we can evaluate the segmentation, according to the Rand index and the VOI (variation of information) merge and split.

The Rand index should be the highest as possible, closer to 1 and VOI should be lower to be better.

In this example, we evaluated on all slices of our 3D images and averaged the final result.

	Rand index	VOI merge (lower is better)	VOI split (lower is better)
MALIS : Training set (original architecture)	0.53	2.08	1.32
MALIS : Training set	0.61	1.25	1.03
MALIS : Test set	0.53	1.57	1.38

Table 2: Results on the CREMI dataset

As we can see in table 2, in the original architecture of 4 layers, the Rand index is 0.53 while we got 0.61 with our training set and 0.53 with our test set. We achieved better results than the original architecture with our small improvements, but it will be hard to improve them much more with the current method.

Thus, our results are hopeful knowing the architecture used was really simple.

Our results are still far from the state of the art but it could get even better by improving various parts

of the methos, as we will detail later.

4.3 ISBI 2012

We also evaluated our method on the ISBI 2012 Challenge dataset which is composed of a single $512 \times 512 \times 30$ image of drosophila brain image.

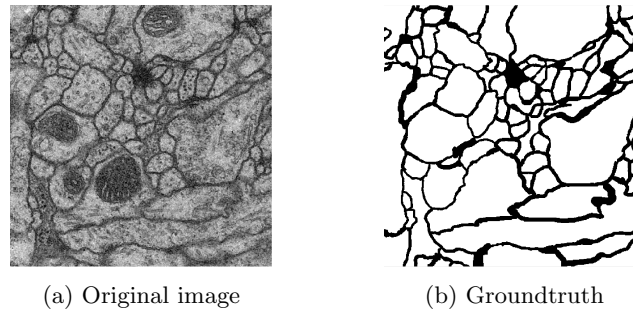


Figure 10: ISBI dataset example

The groundtruth provided with the dataset is composed of borders in black and cells in white, which we then computed the labeled connected components of as pre processing for our trainig. The test set was given with no groundtruth (as it is a challenge) and we had to submit our output to the challenge's leaderboard to get our scores. We evaluated using FIJI (Fiji Is Just Imagej) on the training set as an evaluation script was given for it in the challenge.

The same architecture that we used for the CREMI dataset was used for the ISBI dataset.

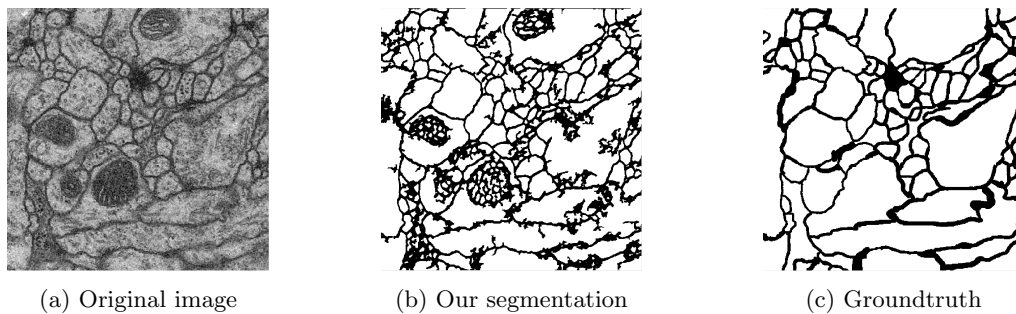


Figure 11: Results on the ISBI dataset (Training set)

As we can see in figure 11 we are able to get a good segmentation, with the same issue as before with the darker nuclei. We can also see some "cracks" in our objects which was not an issue with the CREMI dataset.

However the results are not always this good. As we can see in figure 12, we obtain a poor segmentation, where every object is oversegmented and few borders are visible. This was the worst result that we got. This image is also the least contrasted, that's why we can hypotesize that the oversegmentation issue comed from the lack of contrast of the image.

We evaluate through the same metrics as for the CREMI dataset, that is to say the Rand index and the VOI. This time the VOI should be higher to be better.

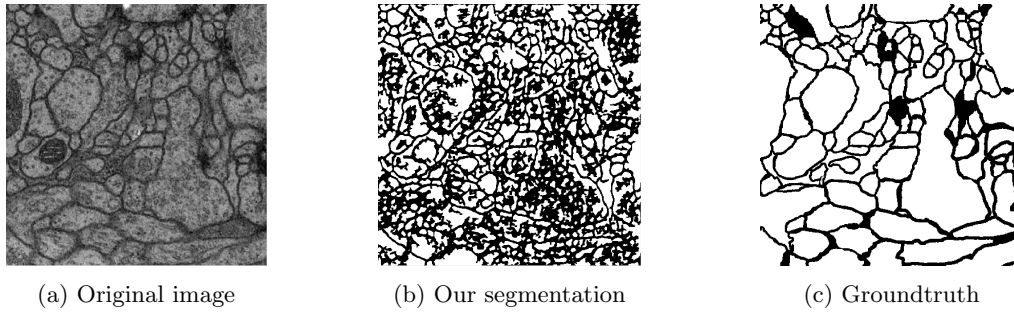


Figure 12: Results on a less contrasted image of the ISBI dataset (Training set)

We were not able to find exactly how the VOI was computed in both cases and where the difference lies as to which values are obtained. More works need to be put on understanding the computations of those metrics as to be able to analyze them better.

	Rand index	VOI
MALIS : Training set	0.76	0.89
MALIS : Test set	0.73	0.87
Thresholding : Test set	0.752	0.82

Table 3: Results on the ISBI dataset

As we can see in table 3 the Rand index on our training set was 0.76 and 0.73 for the test test, which is similar but still higher than a thresholding which gets a Rand index of 0.72. Our VOI is also a bit higher than the threshold.

Those are better results than CREMI's probably due to the small size of the image and the thick borders in the output segmentation.

The results are also encouraging, as was to be expected since both datasets are very similar.

5 Going forward

5.1 Improvement on MALIS

As we have seen before, MALIS performs really well, but can still be improved.

It was most notably improved in [5] where they were able to improve the affinity prediction using more recent architectures, by improving the training and taking full advantage of the MST and by applying a post-processing on the affinity graph instead of a simple thresholding.

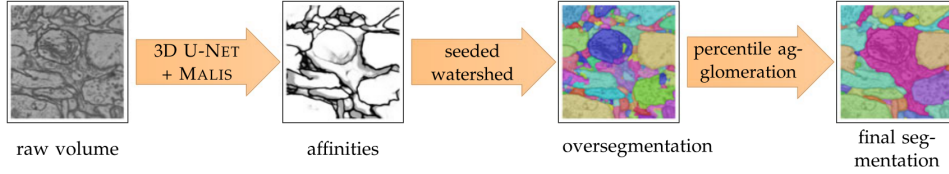


Figure 13: Improves MALIS as described in [5]

As we can see in figure 13 the CNN was replaced by a U-Net, which we will describe afterwards. Then the segmentation is obtained using a seeded-watershed, which is then improved using a percentile agglomeration of small objects.

5.1.1 Using a more potent architecture

Indeed, one of the limits of the previous method was the use of a relatively simple neural network to predict the affinity. This is mostly due to the fact that neural networks have greatly improved since the original paper [1] in 2009.

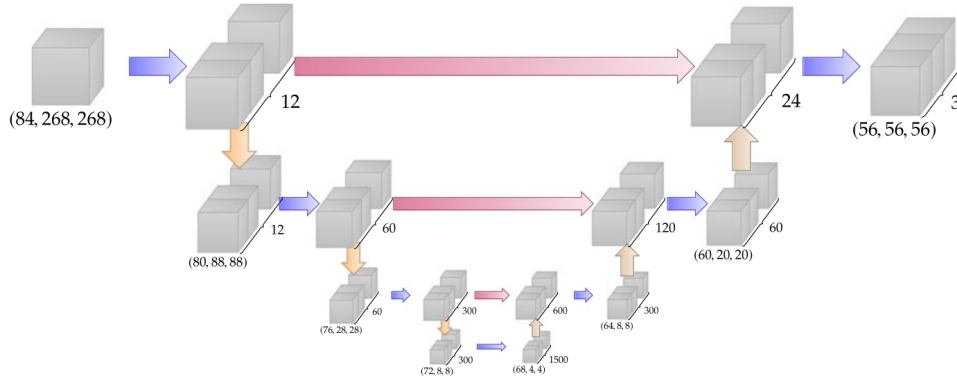


Figure 14: U-Net architecture used on the CREMI dataset from [5]

U-nets especially have been widely used for image segmentation and are thus a natural choice in our case. The architecture used in [5] is shown in figure 14. As we can see, the training will obviously be much longer than previously, but the results should be significantly better.

A question that can arise is why not simply use just a U-Net without the MALIS loss, and as we will see later, the MALIS loss gives us better results on different measures of segmentation quality.

5.1.2 Constrained MALIS loss

Previously, we only computed the maximin edge for a pair of pixels (or a finite amount of pairs), which means that some information from the MST was not used.

However, we would like to compute the maximin edge for all pairs of pixels in the image. This was not

done in the previous paper for time efficiency reasons.

However they describe a way to compute the loss with in quasilinear time instead of in polynomial time.

The main idea is that all maximin edges are in the MST, and there are $n - 1$ edges if we have n pixels in our image. We could then simply compute the loss over all those edges but this would mean that they are all as important as the others. However since we have n^2 pairs of points and $n - 1$ edges in our MST, they will be the maximin edge for a different number of pixel-pairs. So we must find a way to see how often an edge from the MST is a maximin edge.

We won't go into much details here on how exactly this is done, but they are able to find for how many pairs of pixels an edge is a maximin edge when constructing the MST.

When we add an edge using Kruskal's algorithm, we can look at the "size" of the trees it merges and deduce the number of pairs for which the current edge is the minimax edge.

From this, we can define the positive weight of an edge e as the number of pairs from the same object/segment merged by adding e to the MST. More formally we have :

$$w_p(e) = |\{(u, v) \in F^2 \mid \delta(u, v) = 1, e = mm(u, v)\}|$$

Similarly we can define the negative weight of an edge as :

$$w_n(e) = |\{(u, v) \in F^2 \mid \delta(u, v) = 0, e = mm(u, v)\}|$$

These formulations allow us to rewrite our loss function as :

$$L(I, \theta, S) = \sum_{e \in MST(G)} w_p(e)l(1, A_e(I, \theta)) + w_n(e)l(0, A_e(I, \theta))$$

With A_e the affinity of an edge e .

With this loss function being able to be computed in quasilinear time, this will allow us to use the whole image for the loss computation instead of a few pairs of pixels, which should improve the results. This loss function is the same as before, it still is related to the Rand Index, but it should now approximate it much better.

However this doesn't really solve the issue of class imbalance that we noted before. They suggest a way to resolve this by first computing the positive part of the loss first (with w_p) and then the negative part (with w_n). In both case, we set the other edges (the edges between objects for the positive pass) to their groundtruth value so that we only take into account a category of edges.

This means that we will compute the loss for edges between objects and edges inside objects separately, which allows use to combine them afterwards with the appropriate weights so which should resolve the class imbalance issue.

5.1.3 Seeded watershed as post processing

Remember that before, we computed the segmentation by thresholding our affinity graph. However this doesn't give optimal results, as for example locally another threshold would perform better.

An issue that was also encountered was small objects that were inside bigger ones. These objects lead to an oversegmentation and we would like a way to automatically remove those inaccuracies, or at least part of them.

This is where the framework described in [5] comes in play. As we can see in figure 15, the first step of the process is to average the affinities, as we did before. Afterwards the averaged affinities are thresholded at 0.5 (here this threshold is not a parameter). Then a distance transform (or a distance map) is computed from the objects to the borders. In this distance transform, the furthest points from the borders will

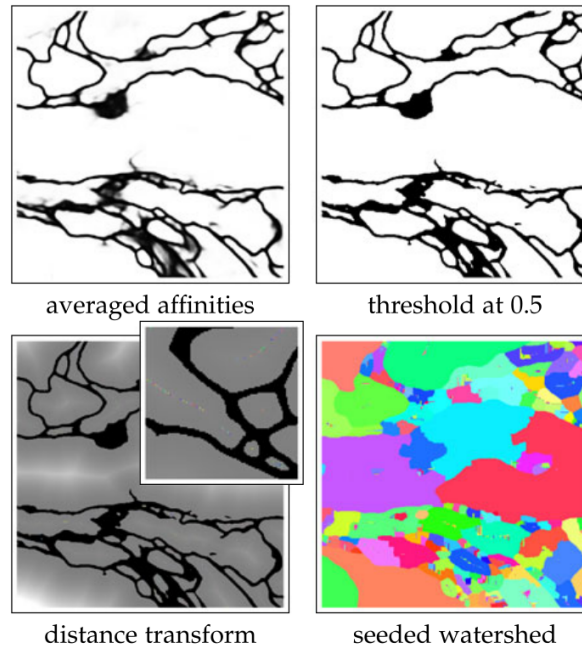


Figure 15: Seeded watershed on an affinity graph, as described in [5]

have the higher values. Then, all the local maxima are taken as seeds for a seeded watershed, which gives a first segmentation.

This is still an oversegmentation, but a fragment agglomeration algorithm is then used to fuse regions together. multiple criteria can be used to determine which regions to merge together and they are described in [5].

When all of those steps are done, we obtain the final segmentation.

As we can see the process is greatly improved from the first version of MALIS, with the loss function, the neural network architecture and the post processign used being much more powerful than their previous counterparts.

5.2 Goals for the second semester

The main goal for this next semester will be to implement this improved MALIS. The mains components to implement are as follow:

- Implement the U-Net
- Implement the constrained MALIS loss, with it's optimizations
- Implement the seeded watershed and fragment agglomeration
- Try other methods of post processing

Although this is a very important step and a large amount of work, the good thing with theses improvements is that we can still use parts of the older method while implementing new ones. For example we can try the U-Net with the first MALIS loss and no post processing, and the same is true for every new component that we will implement.

Once we have a working implementation the goal will be to try the method on various datasets. The CREMI dataset will provide us a baseline to compare our results with those obtained in [5]. We will also try the method on other dataset such as the BSDS500 dataset, which is composed of more varied types of images and not just connectomes.

These are our main goals for the second semester, but if we are able to finish all of this early, there are a lot of interesting experiments where we could further test the limits of this method.

6 Teamwork

6.1 Team organization

In order to have an overview of the tasks, we are using the software Trello. With this, we can write all tasks that we need to do, who is responsible of the task and the progression of the project: we can see what is already done and what the other members are currently working on. We communicate with each other using Slack in which we put information and additional contents related to the project.

Using Trello was really helpful as it always gave us the feeling that we were progressing, even when we didn't get substantial improvements, we knew that we had worked and that we were closer to our goal. This helped us stay motivated at all times.

After knowing what tasks we had to do, we split the work based on preferences of everyone. Quentin was chosen team leader, he worked on a lot of things in the project and supervised the other team members. Annie worked on the datasets, both by exploring them and preparing them. Josselin worked on the computation of the loss and the maximum spanning tree. Tiphany worked on the evaluation and the image generation from the output of our neural network. We kept everybody informed at all time of what other people did so that everybody could understand every part of the work.

Every week, we had a meeting with our supervisor in which we discussed about what we did during the week, our issues and solutions if we had some and what we will do afterwards. During each meeting, a different person lead the discussion. This helped us improve our communication skills as we had to present both our work and the works others did, and made sure that everybody spoke for the same amount of time overall. We implemented this since discussions were almost one-sided before which was not the best solution.

We also wrote a report every week in which we wrote what we did in the week to prepare for the meeting and to show results, or more graphical elements. We wrote all the codes in documented jupyter notebooks that we will clean and put on GitHub.

6.2 Task distribution

As we can see in table 4 we tried to distribute the work based on affinity, and even though the table is unbalanced, everybody put their fair share of work into the project.

One aspect that is absent from this table is all that we learned. As we will detail in the next section, everybody didn't have the same knowledge at the beginning of the project and it took everybody a different amount of time to learn the necessary information.

Annie	Josselin	Quentin	Tiphanie
Find dataset	Computation of MST	Finalize the saliency notebook	Affinity graph thresholding
Exploration of dataset	Computation and optimisation of the path between i and j	Add features in the saliency notebook	Computation of connected components
Analyze what is the input and output of the neural network and their size	Computation of the maximum path in the MST	Graph generation from output of neural network	Image generation
Understand how to use hdf files	Computation of the loss	Preparation of the dataset	Finishing inference by creating segmentation
Create architecture of convolutional neural network	Find interesting patches in dataset	Get vertices pairs in same and different object	Learn PyTorch
Load ISBI-2012 data	Train and evaluate on ISBI in 2D	Train the network on maximin affinity	
Learn PyTorch	Learn PyTorch	Image reconstruction with inference	
		Fiji for evaluation on ISBI	
		Load ISBI-2012 data	
		Train and evaluate on ISBI in 2D	
		Learn PyTorch	

Table 4: List of the main tasks and their repartition (from our Trello board)

6.3 Obstacles and overcoming them

The subject of this project was quite difficult at first because we did not have any knowledge on image segmentation or morphology. Moreover, it was also hard to read and understand the scientific papers at first because they were written in English and the we didn't have the knowledge to understand them clearly at first. To overcome this difficulty, we planned several hours to go through the important things that we needed to retain, and over time we were able to grasp more detail from the papers since our knowledge improved throughout the project.

After knowing what we had to do, the next step was to figure out how to implement these ideas. We took some time to know exactly what we needed to do and how to do it in detail for the implementation. Once we knew, we just needed to find the right functions in Higgs. It took us some time to understand how the functions work, as we never used it before. Documentation is available online and we spent a lot of time learning how to use the functions. Afterwards, we choose to use the PyTorch library for the deep learning component of the project, which nobody was familiar with in the group. This lack of experience with it meant that we had to spend more time learning it. However there is a nice tutorial on PyTorch's website that allowed us to be able to use it fairly quickly. Their documentation on Autograd was also really helpful when debugging the gradient history loss. Overall the PyTorch API was really helpful and allowed us to use PyTorch with a relative ease.

During this project, we also received a lot of help from Quentin. This project would have been really hard to do if he was not there, having no great knowledge in image segmentation and machine learning. Thanks to him, we were able to have a better understanding of the papers by having him explain them to us. It would have taken us a lot longer to understand the papers and how to implement them without him.

Overall, being aware of the work done by others helped us immensely when facing issues as we could all think together and challenge each other's understanding of different topics. This allowed us to overcome all those difficulties more easily and in a more enjoyable way.

7 Conclusion

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