Fast Laminart Algorithm

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1 Introduction

The fast Laminart algorithm has been developed in order to study how the human visual cortical cortex may help computer vision. The human brain uses a segmentation process to recognize an object with an almost infinite number of scenes, even if we have never previously seen the object in that scene. The visual system of a human certainly help humans and other animals to understand and interact with our world. But despite the amazing evolution of our visual system, our vision can be tricked and one may perceived illusions. Many vision scientists believe that these illusions have a net benefit by helping people interpret complex scenes even though they sometimes produce wrong interpretations.

By developing the fast Laminart algorithm, I hope to create an algorithm able to mimic basic human vision behavior. My motivation is to provide a tool that could help computer visions methods have better recognition performance and perhaps better scene understanding algorithm. Today state-of-the-art deep learning methods provide outstanding results in object recognition, but scene understanding algorithms shows inferior performances. Beyond pure performance, an algorithm that emulates human behavior might be able to leverage humans' excellent recognition skills combined with ingenuity for scene interpretation.

(a) (b)

Figure 1: (a) Famous Little Prince drawing of a snake having eaten an elephant; it resembles a hat (b) Picture of a bird into the sky that can be interpreted as a rabbit making a long jump in sky.

When viewing the two illustrations in figure 1, one may recognize the famous Little Prince drawing of a boa snake eating an elephant that "grown-ups" recognize as a hat. The right image shows, a simple sky picture with a bird, but one can imagine a rabbit making a long jump on skies. These two illustrations show how a human is able to use what he perceives to make jokes. In the second picture, the sky makes a strong context dependence of recognizing a bird, but the ears of the "rabbit" and the shape of a skier makes a funny interpretation, especially as it seems impossible.

2 Aim of the Fast Laminart Algorithm

The fast Laminart algorithm is far from achieving such ability, but by using a pre-processing segmentation, we could explore how it enhance deep learning performance. Firstly segmentation could help recognition of a hidden object in a bottom-up approach. Secondly, we hope to use this algorithm in a top-down approach combined with deep learning methods to segment an object and use the additional information that could be made by the fast Laminart algorithm in order to help scene understanding.

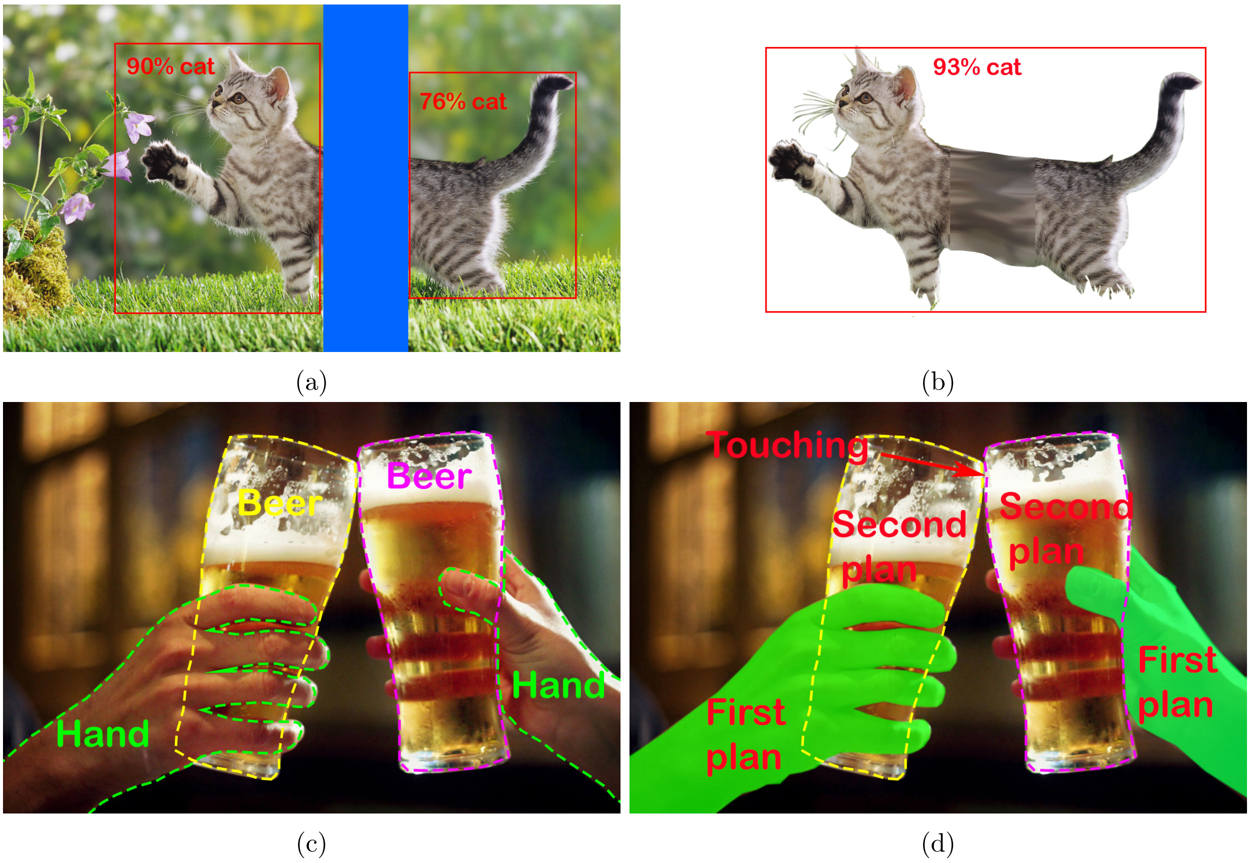

Figure 2: (a) Illustration of a cat obstructed by a blue rectangle, the red boxes represent hypothetical deep learning classification results, (b) Segmented and reconstructed cat to increase classification result, (c) picture of two beers cheering, (d) possible additional information given by a top-down approach made of a deep learning segmentation process and the Laminart model, the algorithm by segmenting an object before another could give information of which objects are in front (first plan), and which ones are in the back (second plan)

The current fast Laminart algorithm performance is far from being able to segment a cat, the implementation works only for black and white images and is only able to reconstruct straight lines. Nevertheless, figure 3 shows how the algorithm can mimic human vision on basic shapes. The result shown by the algorithm are what the author believe to be close to how someone would describe the shape when ask to explain what he sees for the gray color shape. The four examples show how the algorithm deals with the segmentation process of a first object followed by a second one touching it. In example 1, 3 and 4, one would probably think that the white shape is hiding a part of the gray color shape. In this cases, the algorithm reconstruct the hidden object, such as a human could have done. In example 2, as the gray shape could be a simple square touching the white rectangle, or a rectangle partially hidden, the algorithm simply reconstruct the easiest possible shape.

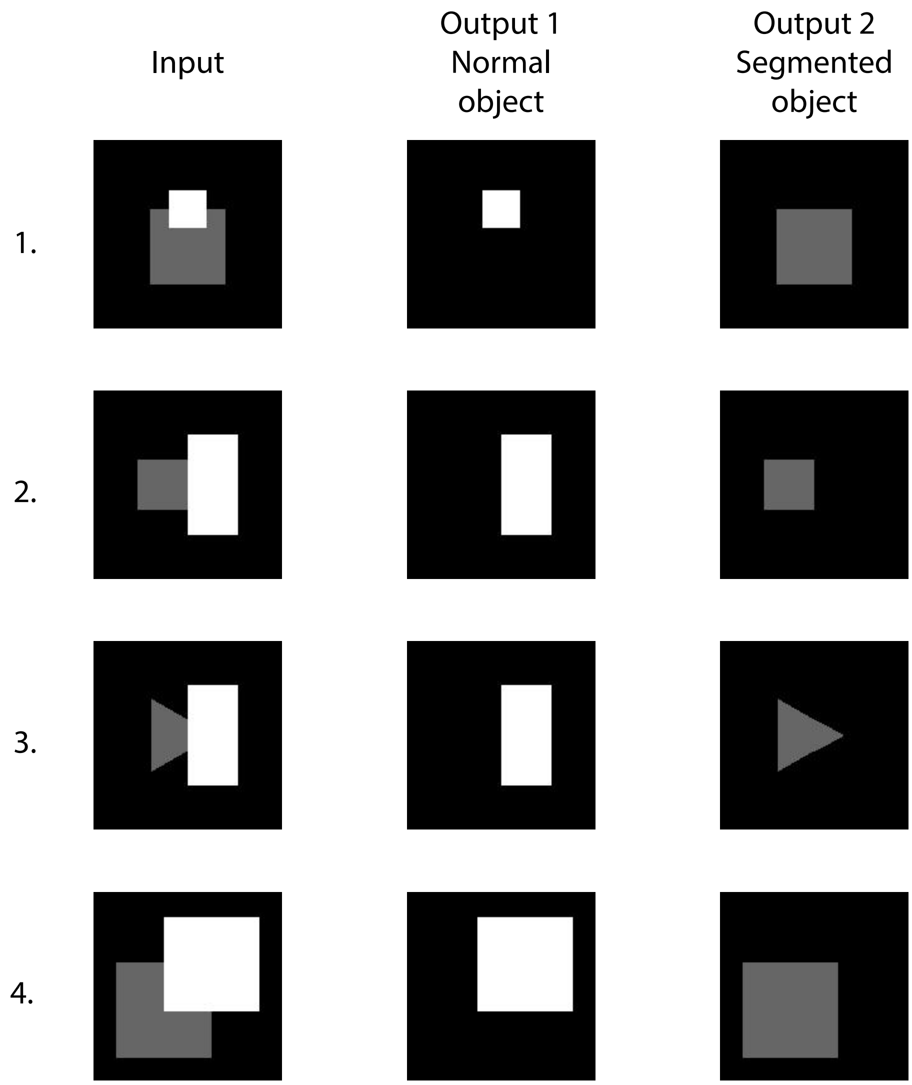

Figure 3

Figure 4: Example of different input feed to the fast Laminart algorithm, the Normal object is reconstructed as it is while the gray object is reconstructed

3 Results

The result of the algorithm is subjective as not everyone would interpret an image the same way, and the author is open to critics. Yet the algorithm was created to serve another purpose, we want to study how human segmentation process may help deep learning methods. In order to study how the algorithm may improve deep learning performance, the author has chosen the MNIST database and decided to obstruct part of the images, see figure 6. A task that would be rather simple for a human but a complete different one for a conventional deep learning method. We have used as deep learning method the TensorFlow convolutional neuronal network tutorial. The performance may not be exactly the last state of the art result, but it is an easy and fast implementation. To access the performance of the fast Laminart, we applied some horizontal lines on top of the numbers. The lines allow to create partial obstructions on each number in such a way that if we combine the training and testing lines, the whole number will be obstructed. The choice is open to critics, but by choosing a simple partial obstruction task that may only affect little a human performance, does affect deeply the one of a deep learning method. We want to use this paradigm to show that in real life, objects often gets partially hidden but our visual system is able to deal extremely well with the tremendous amount of variation in appearance a object may have.

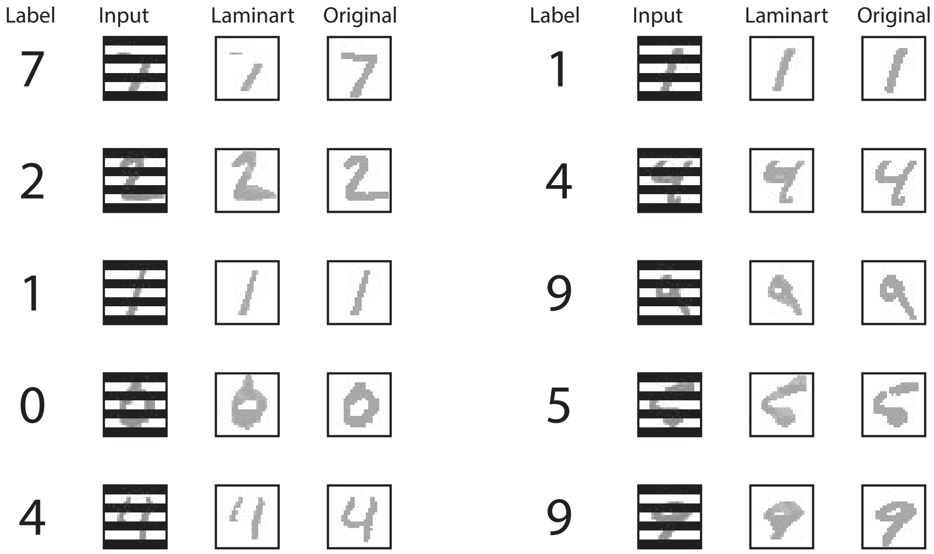

Figure 5: Example of segmentation by the fast Laminart algorithm on the 10 first MNIST test database numbers. The label, the input paradigm used for the deep learning method, the output and finally the original image is plotted in order to show how the fast Laminart algorithm performed.

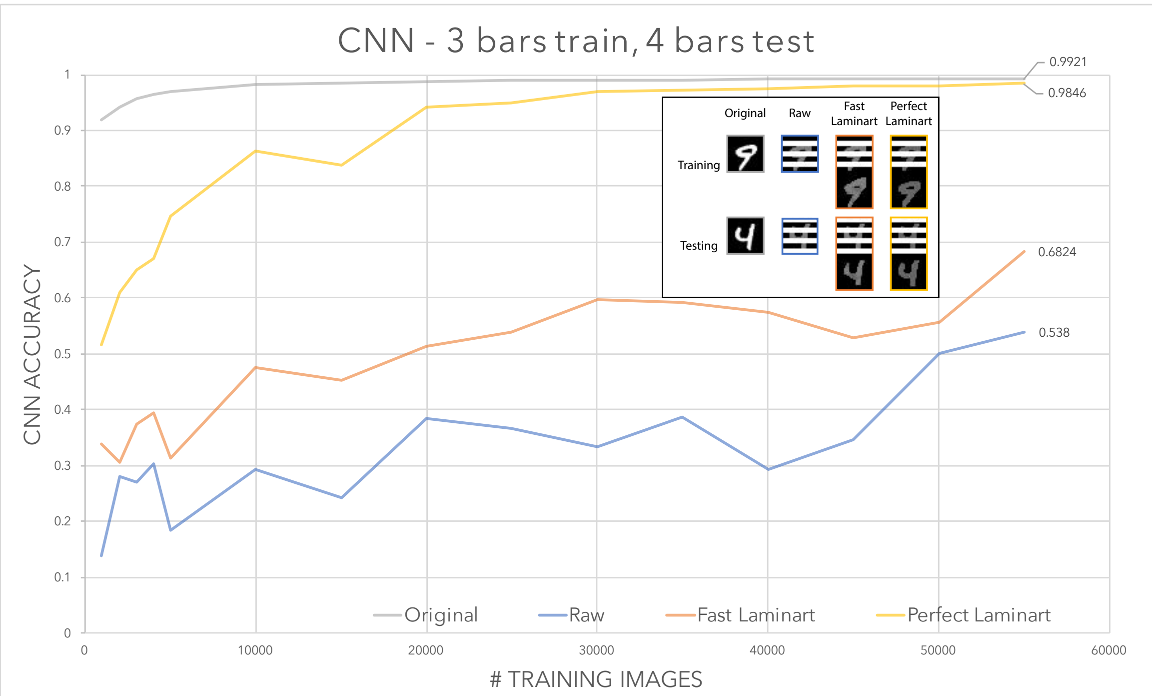

Figure 6: Graph showing the accuracy of the TensorFlow CNN tutorial when using (orange line) or not (blue line) the fast Laminart algorithm as pre-processing in function of the number of MNIST images used to train the neuronal network.

As seen in graph 6, the fast Laminart algorithm does helps to increase the deep learning performance, up to 0.15 points in accuracy when using the full database. It is also interesting to note that when using fast Laminart, almost the same performance is reached compared with the best raw result at only 20'000 images. Thus the fast Laminart improve the overall performance but could also decrease the number of data needed, here about a factor of 2. Moreover, this graph show the results made by the first version of the fast Laminart, we are confident that some increase could be made as a lot of improvement could still be implemented in the fast Laminart alorithm, i.e. better grouping, better inducers calculation, curve completion. Especially we would like to study the effect of combining both a CNN segmentation and the fast Laminart together in order to create a bottom - up - top - down approach on pictures and try to combine the best of the two worlds to segment and find objects in a picture in a even better way.