Attention-based Assisted Excitation for Salient Object Segmentation

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Abstract

Visual attention brings significant progress for Convolution Neural Networks (CNNs) in various applications. In this paper, object-based attention in human visual cortex inspires us to introduce a mechanism for modification of activations in feature maps of CNNs. In this mechanism, the activations of object locations are excited in feature maps. This mechanism is specifically inspired by gain additive attention modulation in object-based attention in brain. It facilitates figure-ground segregation in the visual cortex.

Similar to brain, we use the idea to address two challenges in salient object segmentation: object interior parts and concise boundaries. We implemented it based on U-net model using different architectures in the encoder parts, including AlexNet, VGG, and ResNet. The proposed method was examined on three benchmark datasets: HKU-IS, MSRB, and PASCAL-S. Experimental results showed that the inspired idea could significantly improve the results in terms of mean absolute error and F-measure. The results also showed that our proposed method better captured not only the boundary but also the object interior. Thus, it can tackle the mentioned challenges.

Introduction

Saliency detection refers to detection of most prominent objects on a visual scene. This is inspired by the ability of human eyes to distinguish salient objects from background. Human visual saliency detection is established by two mechanisms: bottom-up saliency and top-down attention.

The bottom-up saliency is stimulus-driven attention and formed based on the low-level features, including color, intensity, orientation, texture. It is computed in the feedforward hierarchy of visual cortex. The bottom-up processing initializes and contributes toward visual perception during feedforward computations until an early representation of the object is formed. On the other hand, top-down attention is goal-oriented and refers to the internal guidance of attention based on prior knowledge and the viewer’s intention [1]. It consciously allocates attention to certain features, objects, or regions [2].
Inspired by cognitive psychology, Itti et al. [3] suggested the early salient detection model. This model was motivated by Feature Integration Theory by Treisman and Galade [4]. This theory introduced one of the most significant models of human visual attention. It proposes that the attention onto an object involved in separate processes. In the first stage of visual perception, different basic features (color, shape …) are extracted from the visual perceived stimulus, where the features are processed in parallel and separately as a pre-attentive stage. This stage occurs early in perceptual processing before we become conscious of the object. The later stage is the focused attention, where individual features of an object are combined to perceive the whole object. The pre-attentive phase is mainly based on bottom-up processing, while the focal phase relies on the top-down process.

Motivated by the inspiration of biological vision, research on salient object detection and segmentation has been ongoing for the past three decades. Salient object detection (SOD) or segmentation extracts a clear boundary and full object area which captures human visual attention. Despite the great achievements in SOD, there still exist several challenges: distinguishing a salient object, including gathering distinct components of an object, ignoring its interior boundaries while segregating its exterior boundaries from cluttered background. Inspired by visual cortex, SOD works based on bottom-up saliency, top-down attention, and their mixed mechanism [5, 6].

Earlier methods worked based on various low-level handcrafted features. A complete survey of traditional techniques were reviewed in [5, 7]. Convolutional Neural Networks (CNNs) recently achieves impressive performance on SOD over previous methods [8, 9]. Several common successful practices are mostly followed in the SOD literature in the deep learning era [6, 8-10]. A few recent methods [11-13] aim to combine the lower and higher-level features through convolution layers. Another common approach relies on designing specific loss functions to address the challenges of SOD [14, 15]. U-net is one of the influential CNN models, which takes both advantages into account and achieves significant performance improvements in salient object detection and segmentation tasks. The other common approach to SOD and in specific to U-net extension is using visual attention. Different attention-based U-net [16, 17] was recently developed, which incorporates attention into the structure or the loss function of this model.

The feature integration theory [4] and the role of attention is the inspiration source of our proposed method. The pre-attentive phase also happens to some extent in the convolution network. In the bottom-up processing through a CNN, different convolutional filters in the first layers extract different features and thus, transform the image into different feature maps. But CNN does not include an explicit mechanism for feature integration in order to form a unified representation of the whole object.

In this paper, we introduce an attention-based approach in U-net model to address the challenges in SOD. The object-based attention and feature binding in the second stage of FIT inspire us to explicitly use it in the CNN model and in specific U-net model. We excite certain activations in
convolutional feature maps in order to help the network learn to better distinguish salient objects from background. We call the proposed method attention-based assisted excitation. From vision neuroscience, our method acts similar to attention modulation. It enhances synchrony and improves the activity of neurons corresponding to the inner surface of the objects relative to the surroundings. It also helps the model to perceive the object as a unified whole regardless of its components, similar to the concept of feature binding and perceptual grouping in the brain.

In the following, we first describe the proposed method from the CNN learning viewpoint. The neuro-inspired aspects of our contribution is then explained. We evaluate the attention-based AE in U-net model for SOD and finally discuss and conclude the paper.

2. Proposed Method

We introduce a method to address the challenges in SOD: distinguishing a salient object, including gathering distinct components of an object, ignoring its interior boundaries while segregating its exterior boundaries from cluttered background. We previously suggested the similar approach in general object detection [18]. Our method only works in the learning process. We neither change the U-net architecture nor the segmentation process. We manually excite the activations of object locations in the feature maps. This auxiliary excitation is applied at the beginning of learning, while gradually reduced with the learning proceeds. It is reduced to zero in the final epochs of learning to adapt the model to work without assisted excitation in the testing phase. The assisted excitation of activations helps the network to distinguish the foreground and salient objects from background. We extract the locations of objects from segmentation ground-truth and excite their corresponding activations in the feature maps.

These excitations guide the model through the segmentation of objects from background. We call our proposed method as Assisted Excitation. However, Ground-truth is only available during training, and thus our final trained model should not count on it. We adapt the model to work without the need for assisted excitation inspiring by curriculum learning [19]. The curriculum learning framework suggests that learning begins with easier tasks while the more complex ones are gradually considered. It is inspired by human developmental learning where human infant first learns easier tasks and gradually acquires the ability to perform complex tasks. Interestingly, the same applies to neural network learning, curriculum learning suggests. When the problem is non-convex, and the stochastic gradient may fall into a bad local minimum, this learning framework argues that begin with easier tasks and continue with more complex ones. It yields better convergence in terms of the quality of local minima and generalization.
2.1. Assisted Excitation using Ground-Truth

Assisted excitation works as a built-in module in CNN. It manipulates neural activations in the feature maps of a CNN as follows:

\[ a^{l+1}_{ci,j} = a^l_{ci,j} + \alpha(t)e_{ci,j} \]  

(1)

where \( a^l \) and \( a^{l+1} \) are activation tensors at layers \( l \) and \( l+1 \) and \( e \) is excitation matrix broadcasted to all feature maps in a tensor, and \( \alpha(t) \) is the excitation factor works as a function of epoch number \( t \). Also \( (c; i; j) \) refer to channel number, row, and column. During training, \( \alpha(t) \) begins with a nonzero value while gradually decays to zero. Our proposed excitation, \( e \), is a function of activations and ground-truth computed based on the following procedure. We first create a binary segmentation map from ground-truth, as follows:

\[ g(i, j) = \begin{cases} 
1, & \text{object exists in cell}(i, j) \\
0, & \text{no object exists in cell}(i, j) 
\end{cases} \]  

(2)

Next, the matrix \( e(c, i, j) \) averages out all channels of \( a^l(c, i, j) \). We compute excitation tensor \( e \) as follows:

\[ e_{ci,j} = \frac{1}{d} \sum_{i=1}^{d} a_{ci,j} \]  

(3)

where \( d \) refers to the number of feature channels.

Figure 1 illustrates our AE module in more detail. Moreover, Figure 2 presents how we use the AE module in U-net.

Figure 1 – Illustration of AE module. An activation tensor is input to this module in which all activation maps are averaged out. Then, it masks the average result based on binary segmentation ground truth. The excitation matrix is computed by multiplying the masked matrix and curriculum factor. The excitation matrix is finally broadcasted and added through each feature map in the tensor and passed on to max-pooling and next stage.
2.2. AE module in U-net during Training

The AE module can be incorporated on each tensor map of a CNN. We used this module in encoder and concatenation parts of U-net model during training. The schematic overview of the proposed model is depicted in Figure 2.

![Figure 2](image)

Figure 2. Attention-based AE module in U-net architecture. This module is incorporated between encoder stages and concatenation stages.

2.3. Our proposed U-net in practice

We set the excitation factor $\alpha = 0$ as if the AE module is removed in the inference phase. Since we gradually decrease the factor during the last epochs of training, our model learns to work without the help of segmentation ground-truth.

In practice, our model architecture is identical to U-net during inference. Our trained model differs from the standard U-net model only in the trained weights. Moreover, the inference time remains identical to the U-net model; however, we achieve better accuracy.
3. Attention-based Assisted Excitation, from vision neuroscience perspective

In this section, we describe the similarities and differences of the proposed method with the mechanisms involved in the visual cortex of the brain and visual attention. Our proposed method does not model the visual attention system but inspired by it. We first provide an overview of main similarities of the proposed method with its inspiration. We also get a closer look at these similarities and analyze the correspondence between the components of assisted excitation module and the mechanisms in the visual attention. According to this functional similarity, we complete the name of our proposed method as attention-based assisted excitation. Finally, we explain the main differences between the real mechanism in brain and ours.

General Similarities

Based on high-level analysis, the feedforward process in CNN is similar to the overall performance of the primary visual cortex. In both models, edge and contour detection, contour grouping, and object boundary formation occur in bottom-up computation. Receptive fields of visual neurons get gradually larger and gradually merged through the hierarchy to include the whole object within. Accordingly, a neuron in the highest layer can view the whole object, classify, and identify it. CNNs work this way; however, visual cortex applies more diverse mechanisms to perceive objects. These mechanisms include perceptual grouping [20], feature binding[21] , and object-based attention [22], and their entanglements [24 ,23]. The Gestalt’s view [25-27] to these mechanisms describes objects are perceived not simply as a set of different parts but as a holistic entity in the brain.

The feature integration theory [4] and the role of attention is the inspiration source of our proposed method. As mentioned before, the pre-attentive phase also happens to some extent in the CNN. In bottom-up processing, different convolutional filters extract different features separately. However, CNN does not include an explicit mechanism for feature integration in order to form a unified representation of the whole object.

In the high-level analysis, our proposed method introduces the explicit mechanism into CNN. When we manipulate the activations of whole object regions, similar to the process involved in object-based attention, it helps the CNN to group different object parts into a unified whole. The mechanism called perceptual grouping [20] in cognitive neuroscience. Excitation of the objects regions resembles the object-based attention mechanism and its role in figure-ground segregation. It distinguishes between the foreground objects and background in the visual scene.

Moreover, the visual cortex employs two auxiliary mechanisms for better figure-ground segregation, including lateral connection and top-down feedback [28, 29], while this mechanism is neglected in CNNs. We incorporate the explicit object-based feedback mechanism that distinguishes the activity of object-viewer neurons from peripheral ones. We manually excite the
relative activity of the object-viewer neurons. It helps the higher-layer neurons to better understand and distinguish between the inner and outer regions of the object.

**The Functional and detailed similarities**

From a closer look, we discuss the similarities of the proposed method with neuronal mechanisms at the algorithmic level. In the learning phase of the model, a local feedback module is incorporated into the mid-layers of the model. Inspired by object-based attention, this module excites the object-viewing neurons to modify their activations to increase the separability of objects and background. The proposed method assumes that object-based attention information is available from the location of objects in a binary map.

In the proposed method, the process of averaging the activity of the feature maps is similar to the neuronal synchrony arising from lateral interconnections [30] in the feedforward pathway. The method synchronizes the object-viewer neurons in different feature maps, and their information is accumulated in an extra memory (analogous to visual working memory). Each neuron in the memory-like unit receives, aggregates, and normalizes the accumulated information of its corresponding neurons (with the same receptive field). This memory-like unit is then modulated and multiplied by the binary map information of the approximate location of the objects (top-down feedback). The resulting unit is then aggregated with each feature map in this layer. In this way, the activity of the object-viewer neurons in the channel is enhanced.

In other words, the similarity can be explained by the process: the neurons whose objects are in their receptive fields are synchronized together [32,31] and their information in the corresponding working memory of this layer [33] is accumulated [34]. This process resembles the visual working memory [34,29,28]. The memory is the place where lateral connection and top-down attention feedback interact with each other.

Moreover, the proposed method is similar to top-down feedback based on object-based attention that affects the lateral communication of the lower layers. This feedback specifically modulates object-viewer neurons and increase their amplitude responses [35]. Based on the attention modulation theories, this modulation changes neuronal responses additively.

To sum up, the general mechanism of the proposed method is similar to the interaction of bottom-up and top-down attention in the brain [36]. Accordingly, top-down attention can influence bottom-up one by enhancing the correlation and synchrony of specific neurons.

**Also Inspired by Developmental Learning**

Our proposed assisted excitation is implemented only during the learning phase of the CNN model and does not exist in the test phase. This is the fundamental difference between our approach and human vision. We adapt the model to transfer from the training phase to the test using the curriculum learning [19] in developmental learning [37]. The process of human developmental
learning is from easy to difficult so that the human infant learns simple tasks as he grows up and gradually becomes able to learn more complex cognitive and behavioral tasks.

**A Novel Implementation of Curriculum learning**

In particular, we propose a novel implementation of curriculum learning, different from the literature. In basic curriculum learning, input data are presented to the model in order of simple to difficult. In our proposed approach, however, moving from simple to difficult is simulated not by changing the order but by modifying the amount of auxiliary information. Introducing the auxiliary knowledge to the model facilitate its learning at the beginning, but it is gradually diminished while learning proceeds. In the application we investigated, the auxiliary information is related to the object locations (binary segmentation).

The introduced information facilitates the localization of objects at the beginning of training in object detection and segmentation problem. We gradually reduce this auxiliary process in the training phase and thus adapt the model to work without it in the test phase. Because the knowledge extracted from ground-truth will not be available during the test phase. This is the fundamental difference between ours and the brain, where visual attention actively and permanently guides the eyes for a better understanding of the visual scene. But there is no attention module in our model in the testing phase.

At the algorithmic level, reducing the curriculum coefficient may be explained by familiarity or novelty detection [38], engaging the attention and learning based on neuromodulators in the brain [39, 40]. Reinforcement learning in the brain is based on the theory of unexpected reward (reward prediction error) and involving the neuromodulators, especially the dopamine system. The dopamine system engages in novelty detection mechanism and thus get more memory, attention, learning involved [41].

Neuromodulators and feedback are two important factors in learning, where both involved, most learning occurs in these conditions [42]. However, neuromodulators and especially dopamine, are released globally in the brain, but feedback acts selectively. Therefore, based on synaptic tagging and/or bi-lateral connection, the corresponding synapses are selected and stimulated to excite synaptic plasticity [43,42]. During infancy, when most environments and objects are unfamiliar to the infant, maximum learning occurs according to the theory. When almost all things are novel, more attention and memory get involved in learning.

To sum up, the similarity of the proposed method to the above discussion is based on the gradual decrease in the rate of curriculum factor when learning proceeds and the novelty of the objects decrease. As if the factor simulates the interaction of dopamine during novelty detection and thus involving attention and learning.
The differences

There is a fundamental difference between real attention mechanism and ours. Our attention-based AE module works during the training phase of CNN while we removed it in practice. However, attention is actively involved in the visual cortex.

Another difference is related to the supervised binary segmentation map in our proposed method. We extract the object locations from segmentation ground-truth while this supervised knowledge is not available in the brain. Instead, several saliency maps are distributed and computed in different regions across the cortex and in specific visual cortex. These saliency maps guide our attention towards salient objects in the visual field.

More precisely, we explain the answer to the question: does the binary saliency maps correspond to salient objects forms in the brain? Some cognitive theories of visual attention in the brain suggest that the binary saliency maps are formed [45,44]. These maps are formed corresponding to the location of salient objects in the visual scene. However, the recent theories of attention believe that different and distributed areas in brain (but not a particular one) are involved in saliency maps formation. Indeed, the considerable studies suggested that the significant role of the prefrontal cortex as a top-down controller in the attention and working memory processing [47,46]. However, there is also a general similarity between the role of prefrontal cortex and ours in visual attention control.

4. Experimental Results

In this section, we conduct experiments to evaluate the performance of our proposed AAE+U_NET on the salient object segmentation benchmarks in terms of F-measure and MAE.

Datasets

Three widely used saliency detection datasets are used to demonstrate the effectiveness of the proposed method.

HKU-IS [11] dataset has 4,447 images with complex scenes. Most of the images in the dataset contain multiple disconnected salient objects with relatively diverse foreground-background appearance.

MSRA-A [48] dataset has 20,840 images. Each image has a clear, unambiguous object. MSRA-B is a subset of MSRA-A and has 5000 images. Compared with MSRA-A, MSRA-B [49] is selected from the consistent bounding box labels of the original dataset. Most of the images have only one foreground salient object and clear background, thus has less ambiguity.
PASCAL-S [50] dataset has 850 natural images selected from the validation set of PASCAL VOC2010 segmentation challenge. It contains cluttered backgrounds and multiple foreground objects and thus more difficult for the salient detection task than the others.

**Implementation Details**

We used the implementation of U-net in [51]. Different architectures were used in the encoder parts of U-net, including Alexnet, VGG, ResNet [52-54].

**Evaluation Metrics**

There are several ways to measure the agreement between model predictions and human annotations. We evaluate the quantitative performance based on these measures: Precision-Recall, F-measure, and Mean Absolute Error (MAE). These measures are calculated as follows:

\[
\text{Precision} = \frac{TP}{TP + FP}, \quad \text{Recall} = \frac{TP}{TP + FN}
\]

, where TP, TN, FP, FN denote true positive, true negative, false positive, and false negative, respectively. Precision-Recall is calculated based on the binarized saliency mask and the ground-truth.

F-measure [55] considers both Precision and Recall by computing the weighted harmonic mean:

\[
F_\beta = \frac{(1 + \beta^2) \text{Precision} \times \text{Recall}}{\beta^2 \text{Precision} + \text{Recall}}
\]

, where \( \beta^2 \) is empirically set to 0.3 to emphasize more on precision. An adaptive threshold is first used to segment the saliency map \( S \) and obtain the Precision-Recall, and the F-measure score is finally calculated. Although this measure does not explicitly consider true negative pixels. To address this problem, MAE is also commonly used. MAE is calculated based on the average pixel-wise absolute error between normalized map \( S \) and ground-truth mask \( G \).

\[
\text{MAE} = \frac{1}{W \times H} \sum_{i=1}^{W} \sum_{j=1}^{H} |G(i, j) - S(i, j)|
\]

, where \( W \) and \( H \) denote width and height of the saliency map, respectively. MAE is complementary to F-measure, which calculated the absolute distance between the results and the ground truth.
Results

We evaluated the performance of our proposed method attention-based AE in U-net model in MSRB, HKU-IS, and PASCAL-S datasets. The results are reported and compared in Table 1. Moreover, the qualitative results are also compared in Figure 3.

Table 1. The performance of AAE-based U-net with the different encoder architectures are compared to original U-net in MSRB, HKU-IS, and PASCAL-S datasets. The results are also compared to several state-of-the-arts results.

| Method                  | MSRBP | HKU-IS | PASCAL-S |
|-------------------------|-------|--------|----------|
| Model                   |       |        |          |
| Encoder                 | MAE   | F-measure | MAE | F-measure | MAE   | F-measure |
| AlexNet                 | 0.144 | 0.813  | 0.081   | 0.804  | 0.149 | 0.719   |
| U-Net                   | 0.107 | 0.859  | 0.059   | 0.849  | 0.126 | 0.762   |
| ResNet                  | 0.112 | 0.850  | 0.060   | 0.846  | 0.123 | 0.767   |
| AlexNet                 | 0.132 | 0.822  | 0.077   | 0.811  | 0.140 | 0.730   |
| Attention-based AE U-Net| 0.095 | 0.865  | 0.053   | 0.856  | 0.119 | 0.775   |
| VGG-16                  | 0.111 | 0.853  | 0.057   | 0.850  | 0.121 | 0.771   |
| VGG-16                  | 0.048 | 0.911  | 0.048   | 0.902  | 0.099 | 0.826   |
| NLDF [56]               | 0.036 | 0.933  | 0.046   | 0.912  | 0.095 | 0.845   |

The experimental results confirmed that our proposed AAE could improve the performance of U-net with different encoders. In all benchmark datasets, the F-measure values of AAE-based U-net were increased compared to the original U-net. The MAE values were also reduced by our proposed method. However, the proposed Attention-based AE module could not achieve state-of-the-art compared to [56, 57].

The qualitative results in Figure 3 also approved the contribution of our proposed method in the improvement of U-net model with different encoders.
| Input Image | U-net (AlexNet) | U-net (AlexNet) + AAE | U-net (VGG) + AAE | U-net (ResNet) + AAE | Ground Truth |
|-------------|-----------------|-----------------------|-------------------|---------------------|--------------|
| ![Image 1](image1) | ![Output 1](output1) | ![Output 2](output2) | ![Output 3](output3) | ![Output 4](output4) | ![Ground Truth 1](groundtruth1) |
| ![Image 2](image2) | ![Output 5](output5) | ![Output 6](output6) | ![Output 7](output7) | ![Output 8](output8) | ![Ground Truth 2](groundtruth2) |
| ![Image 3](image3) | ![Output 9](output9) | ![Output 10](output10) | ![Output 11](output11) | ![Output 12](output12) | ![Ground Truth 3](groundtruth3) |
| ![Image 4](image4) | ![Output 13](output13) | ![Output 14](output14) | ![Output 15](output15) | ![Output 16](output16) | ![Ground Truth 4](groundtruth4) |

Figure 3 - The qualitative results of our proposed attention-based AE is U-net with different encoders are visually compared.
Conclusion

Object-based visual attention motivated us to introduce the similar mechanism in CNNs and in specific, U-net model. In particular, we are inspired by the attention gain modulation in the visual cortex and implemented it as attention-based AE. This mechanism implies that the foreground objects are perceived as a coherent region distinct from the background.

However, the difference between brain mechanism and ours is in two folds: 1. Our attention-based AE module works during the training phase of CNN while we removed it in practice. However, attention is actively involved in the visual cortex. 2. We extract the object locations from segmentation ground-truth while this supervised knowledge is not available in the brain. Instead, several saliency maps are distributed and computed in different regions across the cortex and in specific visual cortex. These saliency maps guide our attention towards salient objects in the visual field.

From machine learning viewpoint, the proposed idea is a complement for end-to-end learning based on error backpropagation on the problems related to object localization. In fact, one of our innovations is the use of ground-truth not only as the target of error backpropagation but also as a method for direct modification of the intermediate representations in CNN. The direct manipulation of activations in the feature maps of the CNN leads to better representational learning.

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