Human vision is naturally more attracted by some regions within their field of view than others. This intrinsic selectivity mechanism, so-called visual attention, is influenced by both high- and low-level factors; such as the global environment (illumination, background texture, etc.), stimulus characteristics (color, intensity, orientation, etc.), and some prior visual information. Visual attention is useful for many computer vision applications such as image compression, recognition, and captioning. In this paper, we propose an end-to-end deep-based method, so-called SALYPATH (SALiency and scanPATH), that efficiently predicts the scanpath of an image through features of a saliency model. The idea is to predict the scanpath by exploiting the capacity of a deep-based model to predict the saliency. The proposed method was evaluated through 2 well-known datasets. The results obtained showed the relevance of the proposed framework comparing to state-of-the-art models.

Index Terms— Visual attention, eye movement, saliency, scanpath prediction

1. INTRODUCTION

Human vision is naturally more attracted by some regions within their field of view than others. This natural selectivity mechanism, so-called visual attention, is influenced by both high- and low-level factors; such as the global environment (illumination, background texture, etc.), stimulus characteristics (color, intensity, orientation, etc.), and some prior visual information [1]. It gives the Human Visual System (HVS) an astonishing efficiency for detection and recognition through rapid eye movements called saccades. Predicting visual attention became a staple to improve many image processing and computer vision applications such as indoor localization [2], image quality [3, 4, 5, 6], image watermarking [7], image compression, recognition, and captioning. Visual attention is usually depicted using 2D heat maps, often called saliency maps, representing the most spatial-attractive regions in a given stimulus. The sequential representation of the points follows during the exploration of the image, also called scanpath, is used to derive saliency maps.

Researchers put a lot of efforts in predicting such saliency heat maps, starting with the seminal work of Koch and Ullman [8], later followed by Itti et al. [9] where multi-scale low level features were used. In [10], the saliency is predicted based on the graph theory where Markov chains is defined over different input maps. Several other interesting saliency models have been proposed based on heuristic approaches and low level features [11, 12].

With the recent success of deep learning, many deep-based saliency models have been developed. Pan et al. [13] proposed one of the first Convolutional Neural Network (CNN) models where a deep and shallow networks were used. In [14], the authors proposed a deep convolutional Generative Adversarial Network (GAN) based saliency model with adversarial training. In [15], the authors introduced a method called DeepGaze I where they trained an AlexNet [16] based network on MIT dataset. The authors later introduced a new version, called DeepGazeII [17], where a VGG-19 network [18] was exploited. In [19], the authors proposed a more complex architecture where multi level features extracted from a VGG [18] network were employed. In [20], the authors designed a method to predict the saliency by incorporating an attention mechanism based on the combination of Long Short Term Memory (LSTM) and convolutional networks. In [21], the authors proposed a unified model for saliency prediction, called Unisal, that predicts the saliency for images and videos.

Contrary to the large number of saliency models proposed in the literature, the studies dedicated to the prediction of scanpath are less extensive. In [22], the authors proposed a model where visual scanpaths are inferred stochastically from saliency maps as well as saccadic amplitudes and orientation biases derived from several datasets. In [23], the authors proposed a deep model, called Saltinet, that samples the saccades from a predicted static saliency volume generated by a CNN encoder-decoder network. The authors later proposed a saliency model, called PathGan [24], that predicts scanpath by using LSTM layers and a VGG network with adversarial training. The underlying idea of using LSTM was to predict the current fixation point according to the previous ones to increase the sequential dependence between fixations. In [25], the authors presented a model of scanpath as a dynamic process simulating the laws of gravitational mechanics. The gaze is considered as traveling mass point in the image space, and salient regions as gravitational fields affecting the mass speed and trajectory. In [26], the authors proposed a Deep Convolutional Saccadic Model (DCSM) where the fixation points are predicted from foveated saliency maps and temporal duration while modeling the inhibition of return.

In this study, we propose an end-to-end deep-based method, called SALYPATH (SALiency and scanPATH), that efficiently predicts the scanpath of images by leveraging features from a trained saliency model. The idea is to predict the scanpath of a given image by exploiting the capacity of a deep-based model to predict the saliency. Inspired by SalGan [14], we first construct a saliency model that integrates an attention module. Feature maps are then extracted from the designed saliency model and fed as input to a second CNN model that aims to predict the scanpath of the image.

The rest of the paper is organized as follows: Section 2 describes the proposed method in details. We then discuss the results obtained in Section 3. Finally, we provide some conclusions in Section 4.
2. PROPOSED METHOD

As illustrated by Fig. 1, we propose a novel fully convolutional neural network architecture for predicting saliency and scanpath of static natural images. Our model is composed of a VGG-based encoder as well as two predictor networks to predict the corresponding saliency and scanpath, respectively. An attention module is also used to adaptively refine the features extracted from the encoder part. Each part of the proposed model is described in this section.

2.1. Saliency Prediction

In order to predict the scanpath of a given image, we design a deep-based saliency model. The idea is to predict the scanpath of a given image by exploiting high level features of a deep-based saliency model. The proposed model is constituted by a VGG-based encoder-decoder similar to the generator part of SalGan [14]. The encoder part is composed of (3x3) convolutional layers and (2x2) max-pooling layers, while the decoder part is composed of (3x3) convolutions and (2x2) up-sampling layers with a (1x1) final convolutional layer activated by a Sigmoid function. The encoder aims to generate high dimensional feature maps from the input image by aggregating them on multiple levels, while decoder aims to merge the obtained feature maps to a single image that represents the saliency map.

2.2. Scanpath Prediction

From the model’s bottle-neck, we extract the high level representational features to predict the scanpath through a fully convolutional network. It is composed of 10 convolutional layers while gradually decreasing the depth of the feature maps to 8 channels, corresponding to the length of the predicted scanpath. The latter has been fixed according to a statistical analysis of the lengths of scanpaths provided by the dataset used to train our model (see Section 3.1). The central tendency indicates that a length of 8 fixation points is appropriate. The output of the module is represented by the following equation:

\[ z = X \otimes \text{Att}_{S}(X \otimes \text{Att}_{Ch}(X)) \]  

where \(z\) is the output of the module, \(\text{Att}_{S}\) and \(\text{Att}_{Ch}\) are the spatial attention and the channel attention blocks, respectively. \(X\) is the input feature maps and \(\otimes\) represents the element-wise multiplication.

The input \(X'\) of the decoder and the fully convolutional network branches is then computed as follows:

\[ X' = X + z \otimes \gamma \]  

where \(\gamma\) is a learnable parameter.

2.4. Training

Two different loss functions have been used to train each branch of our model. The saliency branch was trained using the following loss function:
function $L_1$:

$$L_1 = 0.6 \times KLdiv(y, \hat{y}) + 0.3 \times MSE(y, \hat{y}) - 0.1 \times NSS(y, \hat{y})$$  \hspace{1cm} (4)$$

where $KLdiv$ is the Kullback-Leibler Divergence, $MSE$ is the Mean Squared Error and $NSS$ is Normalized Scanpath Saliency. $y$ and $\hat{y}$ are the predicted and the ground truth saliency maps, respectively.

Each term of the designed loss function has its own impact on the convergence of our model [32]. Indeed, $KLdiv$ function aims to compare the distributions of the output and the corresponding ground truth, while $MSE$ function regularizes the loss by comparing the predicted saliency map and its corresponding ground truth on pixel level [33]. We also introduced the NSS value which is usually used as metric to evaluate saliency prediction [34]. It allows to capture several properties that are specific to saliency maps. This branch was trained with a learning rate of $10^{-7}$ and a step LR scheduler with a multiplicative factor of 0.9 per epoch.

The scanpath branch was trained using only the $MSE$ as loss function $L_2$ (see eq. 5). It was used since scanpath prediction are characterized by the locations of their fixation points and thus their prediction can be seen as a regression problem. It worth noting that the scanpaths are predicted through features of the designed saliency model. To better predict the scanpath, we here focused more on improving the intermediate representational space, optimized through the more complex saliency loss function $L_1$ (see eq. 4). This branch was trained with a learning rate of $10^{-5}$ and a step LR scheduler with a multiplicative factor of 0.9 per epoch.

$$L_2 = \frac{1}{N} \sum_i (p - \hat{p})^2$$  \hspace{1cm} (5)$$

where $p$ is the predicted scanpath and $\hat{p}$ is the ground truth scanpath, while $N$ is the number of the fixation points.

3. EXPERIMENTAL RESULTS

In this section, we evaluate the capacity of our method to predict the scanpath of a given image. After presenting the datasets used, the saliency prediction branch as well as the scanpath prediction branch are evaluated. Both are also compared to a set of representative state-of-the-art methods.

3.1. Datasets

In order to evaluate of our method, two widely used datasets have been employed: Salicon [35] and MIT1003 [36]. Salicon dataset is the largest natural image saliency dataset and it was built for the Salicon challenge. More precisely, we used a subset of 15000 images from the dataset for training (i.e. 9000), validation (i.e. 1000) and testing (i.e. 5000). MIT1003 dataset is one of the most used natural image saliency datasets and it was employed during the MIT300 challenge [34]. It is composed of 1003 natural images with their corresponding saliency maps and scanpaths. The whole dataset has been considered in this study for cross-dataset testing.

3.2. Saliency Prediction

In this section, we evaluate the saliency prediction branch using common metrics [38]: Area Under Curve Judd ($Auc\_Judd$), $Auc\_Borji$, NSS, Correlation coefficient ($CC$), Similarity ($SIM$) and kullback Leibler Divergence ($KLD$). Table 1 shows the results obtained on the MIT1003 dataset. The results obtained are also compared to some state-of-the-art saliency models (i.e. Salgan [14], Salicon [35] and MLNet [19]). As can be seen, our model achieves the best results compared to the other models in 4 different metrics including $Auc\_Judd$, $CC$, $SIM$, and $KLD$. In particular, we obtain a significant improvement in terms of $KLD$ compared to Salgan and MLNet. We reach close second place to SalGan in terms of $Auc\_Borji$ metric, while the obtained $NSS$ values are close to Salicon and MLNet.

3.3. Scanpath Prediction

In order to evaluate the performance of the scanpath prediction branch, three metrics have been used:

- MultiMatch (MM) [39]: It compares the scanpaths through multiple criteria scores (i.e. shape of the vectors, the difference in direction and angles between saccades, the length of the saccades, the position of the fixation points and duration between fixation points). In this study, only the first four criteria have been considered since the temporal aspect has not been yet integrated.
- NSS [34]: It compares a fixation map generated from the predicted fixation points with the ground truth saliency map.
- Congruency [40]: It measures the percentage of predicted fixation points within a thresholded saliency map.

Table 2 shows the results obtained on Salicon dataset. Our results are also compared to a set of representative state-of-the-art methods, including handcrafted-based models (i.e. Le Meur [22] and G-Eymol [23]) and deep learning-based models (i.e. PathGan [24], DCSM-VGG and DCSM-ResNet [25]). As can be seen, our model achieves the highest values for the shape and direction criteria of the MultiMatch metric. It obtains a very close score to PathGan and G-Eymol on the length and the position criteria, respectively. However, our model obtains the state-of-art results on the mean score. For NSS, our model achieves the third place behind Le Meur and G-Eymol. However, this result can be justified by the fact that models like Le Meur use a predicted saliency map to predict fixation points and thus the fixation points are generally within the salient regions. For the Congruency, our model obtains the second best result close to Le Meur.

Table 3 shows the results obtained on MIT1003 dataset which is used as a neutral comparison dataset (i.e. we did not fine-tune our model on it). For MultiMatch metrics, our model scores the highest on the shape and direction criteria, while it achieves a very close second place on the length criterion just behind Le Meur. For the position criterion, our model achieves a better score than Le Meur.

| Model    | $Auc\_Judd$ | $Auc\_Borji$ | NSS | $CC$ | $SIM$ | $KLD$ |
|----------|-------------|--------------|-----|------|-------|-------|
| Salicon  | 0.8686      | 0.8443       | 1.9460 | 0.5836 | 0.4908 | 1.0470 |
| Salicon  | 0.8630      | 0.8135       | 2.1240 | 0.6013 | 0.4923 | 0.9051 |
| MLNet    | 0.8599      | 0.7714       | 2.1678 | 0.5787 | 0.4815 | 1.3083 |
| SALYPATH (Our method) | 0.8745 | 0.8290 | 2.1152 | 0.6182 | 0.4982 | 0.8750 |

Table 1. Results of saliency prediction on MIT1003.
and G-Eymol, and reasonably close score to PathGan and DSCM-VGG. We still obtain the best overall score for the mean MultiMatch metric. For NSS and Congruency, our method obtains a lower score than Le Meur and G-Eymol but still outperforms PathGan.

In Fig 2, we present scanpaths and saliency maps generated by our model as well as their corresponding ground truth scanpaths and saliency maps for two natural images of the MIT1003 dataset. As can be seen, the visualization demonstrates the efficiency of our model for both branches.

### 4. CONCLUSION

In this paper, we proposed a novel fully convolutional neural network architecture for predicting saliency and scanpaths of natural images. Our model is composed of an encoder-decoder to predict the saliency and a second branch from which the scanpath is predicted. The latter takes advantage of the features provided at the bottle-neck of the designed saliency model. An attention module was also used to refine the image encoded feature space, improving thus the saliency and scanpath prediction. The proposed model outperformed a good representative set of state-of-the-art models for saliency and scanpath prediction on both MIT1003 and Salicon datasets. Besides the quantitative comparison, the qualitative results prove the effectiveness of our model.

As future work, we plan to integrate the temporal dimension. We will also modify the loss function used to train the scanpath prediction branch in order to consider the saliency and the interdependence between both saliency and fixation points. Finally, we will test more advanced architectures instead of VGG.

### 5. REFERENCES

[1] Anne M Treisman and Garry Gelade, “A feature-integration theory of attention,” *Cognitive psychology*, vol. 12, no. 1, pp. 97–136, 1980.

[2] W. Elloumi, K. Guissous, A. Chetouani, and S. Treuillet, “Improving a vision indoor localization system by a saliency-guided detection,” in *2014 IEEE Visual Communications and Image Processing Conference*, 2014, pp. 149–152.

[3] Aladine Chetouani and Leida Li, “On the use of a scanpath predictor and convolutional neural network for blind image quality assessment,” *Signal Processing: Image Communication*, vol. 89, pp. 115963, 2020.

[4] Ilyass Abouelaziz, Aladine Chetouani, Mohammed El Hassouni, Longin Jan Latecki, and Hocine Cherifi, “Convolutional neural network for blind mesh visual quality assessment using 3d visual saliency,” in *2018 25th IEEE International Conference on Image Processing (ICIP)*, 2018, pp. 3533–3537.

[5] Ilyass Abouelaziz, Aladine Chetouani, Mohammed El Hassouni, Longin Jan Latecki, and Hocine Cherifi, “No-reference mesh visual quality assessment via ensemble of convolutional neural networks and compact multi-linear pooling,” *Pattern Recognition*, vol. 100, pp. 107174, 2020.

[6] Aladine Chetouani, “A blind image quality metric using a selection of relevant patches based on convolutional neural network,” in *2018 26th European Signal Processing Conference (EUSIPCO)*, 2018, pp. 1452–1456.

[7] Mohamed Hamidi, Aladine Chetouani, Mohamed El Haziti, Mohammed El Hassouni, and Hocine Cherifi, “Blind robust 3d mesh watermarking based on mesh saliency and wavelet
transform for copyright protection," *Information*, vol. 10, no. 2, 2019.

[8] Christof Koch and Shimon Ullman, “Shifts in selective visual attention: towards the underlying neural circuitry,” in *Matters of intelligence*, pp. 115–141. Springer, 1987.

[9] Laurent Itti and Christof Koch, “Computational modelling of visual attention,” *Nature reviews neuroscience*, vol. 2, no. 3, pp. 194–203, 2001.

[10] Jonathan Harel, Christof Koch, and Pietro Perona, “Graph-based visual saliency,” in *Advances in neural information processing systems*, 2007, pp. 545–552.

[11] Robert Peters and Laurent Itti, “The role of fourier phase information in predicting saliency,” *Journal of Vision*, vol. 8, no. 6, pp. 879–879, 2008.

[12] Chenlei Guo, Qi Ma, and Liming Zhang, “Spatio-temporal saliency detection using phase spectrum of quaternion fourier transform,” in *2008 IEEE Conference on Computer Vision and Pattern Recognition*. IEEE, 2008, pp. 1–8.

[13] Junting Pan, Elisa Sayrol, Xavier Giro-i Nieto, Kevin McGuinness, and Noel E O’Connor, “Shallow and deep convolutional networks for saliency prediction,” in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2016, pp. 598–606.

[14] Junting Pan, Cristian Canton Ferrer, Kevin McGuinness, Noel E O’Connor, Jordi Torres, Elisa Sayrol, and Xavier Giro-i Nieto, “Salgan: Visual saliency prediction with generative adversarial networks,” *arXiv preprint arXiv:1701.01081*, 2017.

[15] Matthias Kümmerer, Lucas Theis, and Matthias Bethge, “Deep gaze i: Boosting saliency prediction with feature maps trained on imagenet,” *arXiv preprint arXiv:1411.1045*, 2014.

[16] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton, “Imagenet classification with deep convolutional neural networks,” *Communications of the ACM*, vol. 60, no. 6, pp. 84–90, 2017.

[17] Matthias Kümmerer, Thomas SA Wallis, and Matthias Bethge, “Deepgaze ii: Reading fixations from deep features trained on object recognition,” *arXiv preprint arXiv:1610.01563*, 2016.

[18] Karen Simonyan and Andrew Zisserman, “Very deep convolutional networks for large-scale image recognition,” *arXiv preprint arXiv:1409.1556*, 2014.

[19] Marcella Cornia, Lorenzo Baraldi, Giuseppe Serra, and Rita Cucchiara, “A deep multi-level network for saliency prediction,” in *2016 23rd International Conference on Pattern Recognition (ICPR)*. IEEE, 2016, pp. 3488–3493.

[20] Marcella Cornia, Lorenzo Baraldi, Giuseppe Serra, and Rita Cucchiara, “Predicting human eye fixations via an lstm-based saliency attentive model,” *IEEE Transactions on Image Processing*, vol. 27, no. 10, pp. 5142–5154, 2018.

[21] Richard Drosté, Jianbo Jiao, and J Alison Noble, “Unified image and video saliency modeling,” *arXiv preprint arXiv:2003.05477*, 2020.

[22] Olivier Le Meur and Zhi Liu, “Saccadic model of eye movements for free-viewing condition,” *Vision research*, vol. 116, pp. 152–164, 2015.

[23] Marc Assens Reina, Xavier Giro-i Nieto, Kevin McGuinness, and Noel E O’Connor, “Saltinet: Scan-path prediction on 360 degree images using saliency volumes,” in *Proceedings of the IEEE International Conference on Computer Vision Workshops*, 2017, pp. 2331–2338.

[24] Marc Assens, Xavier Giro-i Nieto, Kevin McGuinness, and Noel E O’Connor, “Pathgan: visual scanpath prediction with generative adversarial networks,” in *Proceedings of the European Conference on Computer Vision (ECCV)*, 2018, pp. 0–0.

[25] Dario Zanca, Stefano Melacci, and Marco Gori, “Gravitational laws of focus of attention,” *IEEE transactions on pattern analysis and machine intelligence*, 2019.

[26] Wentao Bao and Zhennong Chen, “Human scanpath prediction based on deep convolutional saccadic model,” *Neurocomputing*, 2020.

[27] Diogo C. Luiznson, Hedi Tabia, and David Picard, “Human pose regression by combining indirect part detection and contextual information,” *CoRR*, vol. abs/1710.02322, 2017.

[28] Liang-Chieh Chen, Yi Yang, Jiang Wang, Wei Xu, and Alan L. Yuille, “Attention to scale: Scale-aware semantic image segmentation,” *CoRR*, vol. abs/1511.03339, 2015.

[29] Kelvin Xu, Jimmy Ba, Ryan Kiros, Kyunghyun Cho, Aaron C Courville, Ruslan Salakhutdinov, Richard S Zemel, and Yoshua Bengio, “Show, attend and tell: Neural image caption generation with visual attention. corr abs/1502.03044 (2015),” *arXiv preprint arXiv:1502.03044*, 2015.

[30] Sanghyun Woo, Joon-Young Lee, and In So Kweon, “Cbam: Convolutional block attention module,” in *Proceedings of the European conference on computer vision (ECCV)*, 2018, pp. 3–19.

[31] Christopher Thomas, “Opensalicon: An open source implementation of the salicon saliency model,” *arXiv preprint arXiv:1606.00110*, 2016.

[32] Alexandre Bruckert, Hamed R Tavakoli, Zhi Liu, Marc Christie, and Olivier Le Meur, “Deep saliency models: the quest for the loss function,” *Neurocomputing*, 2020.

[33] Alexandre Bruckert, Hamed R Tavakoli, Zhi Liu, Marc Christie, and Olivier Le Meur, “Deep saliency models: The quest for the loss function,” 2019.

[34] Robert J Peters, Asha Iyer, Laurent Itti, and Christof Koch, “Components of bottom-up gaze allocation in natural images,” *Vision research*, vol. 45, no. 18, pp. 2397–2416, 2005.

[35] Ming Jiang, Shengsheng Huang, Junyong Duan, and Qi Zhao, “Salicon: Saliency in context,” in *CVPR*, 2015, pp. 1072–1080, IEEE Computer Society.

[36] Tilke Judd, Krista Ehinger, Frédé Durand, and Antonio Torralba, “Learning to predict where humans look,” in *IEEE International Conference on Computer Vision (ICCV)*, 2009.

[37] Tilke Judd, Frédé Durand, and Antonio Torralba, “A benchmark of computational models of saliency to predict human fixations,” in *MIT Technical Report*, 2012.

[38] Zoya Bylinskii, Tilke Judd, Aude Oliva, Antonio Torralba, and Frédé Durand, “What do different evaluation metrics tell us about saliency models?,” *arXiv preprint arXiv:1604.03605*, 2016.

[39] Richard Dewhurst, Marcus Nyström, Halszka Jarodzka, Tom Foulsham, Roger Johansson, and Kenneth Holmqvist, “It depends on how you look at it: Scanpath comparison in multiple dimensions with multimatch, a vector-based approach,” *Behavior research methods*, vol. 44, no. 4, pp. 1079–1100, 2012.

[40] Olivier Le Meur, Thierry Baccino, and Aline Roumy, “Prediction of the inter-observer visual congruency (iov) and application to image ranking,” in *Proceedings of the 19th ACM international conference on Multimedia*, 2011, pp. 373–382.