A REVIEW ON IMAGE RETARGETING TECHNIQUES

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ABSTRACT: *In this digital era, there is rapid growth of mobile technologies and web page layout so, there is need to resize the media content to adapt the preferred display sizefor various layouts of web pages and small size of portable devices such as tab or mobile. Image retargeting method is used to display the original image without changing the important information. It also maintains important and visual major features. There are three main objectives; first preserving important information of original image, secondlimiting visual object in resulting image, third preserving internal structure of original image. Two methods used for semantic preserving deep image retargeting are; first, extracting semantic components which is further used to preserve semantic of the source image. Each semantic component is represented by importance map of source image that preserved in target image and second, the semantic collage method is fed into the carrier to generate the target image and this target image will fit into aspect resolution.*

Key Words: *Image retargerting, Semantic collage, Semantic component, classification guided fusion network, preserve semantic, PixelCNN, GAN.*

I. Introduction

In this digital era, there is rapid growth of mobile technologies and web page layout so, there is need to resize the media content to adapt the preferred display sizefor various layouts of web pages and small size of portable devices such as tab or mobile.Image retargeting is the solution for all of these problems. Image retargeting is used to display the original image by preserving semantic information or important information. To display the image on various devices image should be cropped or resized. The main task of image retargeting is preserving the semantic information of the original image by using pixel wise importance. Each semantic component is represented by map that preserved in target image.
The semantic preserving deep image targetingworks on extracting semantic components (i.e. foreground, background and action context) to preserve important information of an image then semantic collage will combine all components with pixel-wise importance measures.

II. Literature Survey

A. Saliency based image targeting:

L. Wolf, M. Guttmann, and D. Cohen-Or[1] introduced the saliency method for video retargeting. A video retargeting is process of transforming existing video into preferred display size. The algorithm is designed to work efficiently in online manner, in the end leads to real time retargeting of streaming input video several output format. There are two stages of algorithm. First, the frame is analyzed to detect the importance region in the frame. Second, a transformation that respects the analysis shrink-less important regions more than important ones. An optimized transformation of video to downsized version is then calculated that respect the saliency score. Saliency score consist of three basic components: (1) spatial gradient magnitude, (2) a face detector and (3) block based motion detector. The optimization stage amounts of solving a sparse linear system of equations. It considers spatial constraints as well as temporal which leads to smooth temporal user experience. The experimental results compare with seam carving for both L1-norm saliency and L2-norm. The saliency video retargeting method is more rubust than the saliency measure selection. Due to the continuous nature of saliency method. The advantages saliency method of optimizing the entire mapping at once are also visible.
L. Marchesotti, C. Cifarelli, and G. Csurka[2] introduced an image thumbnailing consist in the identification of one or more regions of interest in an input image. The salient parts are aggregated in foreground region. A redundant and non-informative pixels become part of background. The thumbnailing and more generally

visual saliency detectors are intrinsically challenging problem such as subjects selectively direct attention to objects in scene using both bottom-up, image based saliency cuses and top-down, task-dependent cuses. A generic framework designed to deal with visual pop-up and task driven saliency using image annoted with salient thumbnail and semantic labels. The framework build on simple idea is images sharing global visual appearance and salient regions. The visual similarity is to detect saliency and to build thumbnails. The saliency detector method compared with three state-of-the-art methods designed for saliency and thumbnail detection: (1) Itti's methodthat leverages a neuromorphic model simulating which elements are likely to attract visual attention, (2) spectral residual method is based on the analysis of the residual of an image in the spectral domain and (3) conditional random field.
The saliency based image retargeting techniques do not preserve visual semantics and delete important content for visual quality.

B. Semantic based image targeting:

In semantic based image retargeting, major focus is on image information or image contents. J. Luo[3] introduced an image cropping one the most important operation perform to enhance photographs. Digital image system provide ability to crop undesirable content from picture and zoom in desired subject area and better rendering of main subject. A robust automatic cropping algorithm is based on: (1) a performance-scalable, probabilistic main subject detection algorithm and (2) an efficient global optimization search procedure. A probabilistic measure of the saliency of different image regions associated with different subjects in unconstraint scene. The outcome of main subject belief map, an efficient global search algorithm using the concept of integral image to locate the best cropping window that satisfy multiple constraint such as aspect ration, head room and composition rules while maximizing the subject content within the cropping window according to main subject belief map.
Z. Lihi[4] introduced the content aware saliency detection is an image region that represent the scene. The goal is to other identify fixation point or detect dominant object. The content of the dominant objects is just as essential as the object themselves. The salient region should contain prominent object and the part of background that convey the context. The content aware saliency detection method compares between three cases. The first case, it includes images that show a single salient object overan uninteresting background. The object's pixels will be identified as salient. The background is excluded, however, many pixels on the salient objects arenot detected as salient. The secondcase, it includes images where the immediatesurroundings of thesalient object shed light.The third case includes images of complex scenes.
S. Ding [5] introduced the content aware retargeting maintain visual information of the covered scene viewed from certain angle. To preserve important content close to the original and unimportant pixels should distorted. To minimize the preserve important content to constrain the retargeting process directly using the original image itself such that all information global and local can be used together to enable the optimal overall quality. The important filtering algorithm is used for content aware image retargeting. It consist of three major steps: (1) compute the image saliency using an importance map. An importance map that represent saliency with structure of original image. It is achieve using guided filter, (2) the resulting structure consistent importance map provide the key constraint to determine up to which extent pixels allow to shift from original to target image. The pixels with high importance should not shift much with respect to the neighboring pixels with similar importance so, the shape remain same as original, and (3) Integrate the shift gradient across the image to construct a smooth shift map and render the target image. The integrated pixels shift to be smooth along with dimensions and consistent across image. The important filteringalgorithm compared the RetargetMe dataset.
These semantic based image retargeting method does not work on multiple object scene based image.

C. Convolution based image targeting:

In convolution based image retargeting, it uses convolution neural network technique for deep learning. Jain[6] introduced an end to end learning framework for segment generic object in both images and videos. Deep convolution network is used to assign label to each pixels which may be in background or object. It applies to extract all prominent object whether they move or not and how it leverages varying strengths of training annotations. The generic method compare with saliency and object method deep learning techniques that is shown in table 1.

Methods	MIT dataset (subset)			MIT dataset (full)		
	Airplane	Car	Horse	Airplane	Car	Horse
# Images	82	89	93	470	1208	810
Joint Segmentation						
Joulin et al. [89]	15.36	37.15	30.16	n/a	n/a	n/a
Joulin et al. [39]	11.72	35.15	29.53	n/a	n/a	n/a
Kim et al. [40]	7.9	0.04	6.43	n/a	n/a	n/a
Rubinstein et al. [30]	55.81	64.42	51.65	55.62	63.35	53.88
Chen et al. [41]	54.62	69.2	44.46	60.87	62.74	60.23
Jain et al. [42]	58.65	66.47	53.57	62.27	65.3	55.41
Saliency						
Jiang et al. [8]	37.22	55.22	47.02	41.52	54.34	49.67
Zhang et al. [6]	51.84	46.61	39.52	54.09	47.38	44.12
DeepMC [11]	41.75	59.16	39.34	42.84	58.13	41.85
DeepSaliency [12]	69.11	83.48	57.61	**69.11**	83.48	**67.26**
Object Proposals						
MCG [14]	32.02	54.21	37.85	35.32	52.98	40.44
DeepMask [18]	**71.81**	67.01	58.80	68.89	65.4	62.61
SalObj [10]	53.91	58.03	47.42	55.31	55.83	49.13
Ours	66.43	**85.07**	**60.85**	66.18	**84.80**	64.90

Table 1: Quantitative results on Object Discovery data set.

Fan[7] introduced the foreground map evaluation which is crucial for measuring the process of object segmentation algorithm. A predicted foreground map against a ground truth annotation map is crucial in evaluating and comparing. An evaluation measure classify into two types: (1) the binary map evaluation with common measure being F-Beta measure and PASCAL VOC segmentation measure and, (2) non-binary map evaluation. The foreground map contain entire structure of object. Thus, evaluation measures are expected to tell which model generates more complete object and structure map will rank these map. Establishing that structure-measure offers a better way to evaluate salient object detection models, it compare 10 state-of-the-art saliency models on 4 datasets (PASCAL-S, ECSSD, HKU-IS, and SOD).

Cho[8] introduced a weakly and self-supervised deep neural network for content aware image re-targeting. It utilize images and its image-level annotations for structure and content loss computations. The network takes a source image and a target aspect ratio as input, and then directly produces a retargeted image in a shot.A shift layer that maps each pixel from the source to the target grid. The method implicitly learns semantic attention information, and passes it to the shift map. The results of content aware deep image retargeting method compare with benchmark includes cropping and linear scaling.

The semantic preserving deep image retargeting method, predict the soft probabilities. These methods operated implicit assumption that each image contains one salient object. Also, it is able to generate target images containing multiple small objects in diverse scenes.

D. Others:

It crops images to improve visual quality of photographs [9] but it does not preserve important content of an image. A new dataset containing not only score distributions, but also informative attributes and anonymize identities. A new CNN architecture that unifies aesthetics attributes and photo content for image aesthetics rating and achieves state-of-the-art performance on aesthetics classification benchmark. It utilizes mixed within and image pairs for training models. The results of deep learning method compare with the canonical AVA testing partition that is shown table 2. a 1- column CNN baseline yields strong capability in rejecting false positives while attaining a reasonable overall classification accuracy

Previous work	balanced accuracy	overall accuracy
AVA handcrafted features (2012) [49]	-	68.00
SPP (2015) [24]	-	72.85
RAPID - full method (2014) [23]	-	74.46
Peng et al. (2016) [52]	-	74.50
Kao et al. (2016) [58]	-	74.51
RAPID - improved version (2015) [55]	61.77	75.42
DMA net (2015) [24]	62.80	75.41
Kao et al. (2016) [59]	-	76.15
Wang et al. (2016) [53]	-	76.94
Kong et al. (2016) [25]	-	77.33
Mai et al. (2016) [26]	-	77.40
BDN (2016) [56]	67.99	78.08
Proposed baseline using random mini-batches		
DAN-1: VGG-16 (AVA-global-warped-input)	70.39	77.65
DAN-1: VGG-16 (AVA-local-patches)	68.70	77.60
Two-column *DAN-2*	69.45	**78.72**
Proposed baseline using balanced mini-batches		
DAN-1: VGG-16 (AVA-global-warped-input)	**73.59**	74.42
DAN-1: VGG-16 (AVA-local-patches)	71.40	75.8
Two-column *DAN-2*	73.51	75.96

Table 2. Comparison of aesthetic quality classification between our proposed baselines with previous state-of-the-arts on the canonical AVA testing partition.

III. Conclusion

In this work we have studied various image retargeting techniques. These techniques are mainly classified in 4 categories: semantic based, convolution based, saliency based and other. The semantic preserving deep image retargeting method predicts binary maps and soft probabilities. It operates on each image that contains one salient object and generates target images containing multiple small objects in diverse scene as well as action context.

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References

1. L. Wolf, M. Guttmann, and D. Cohen-Or, "Non-homogeneous contentdriven video-retargeting," in Proc. ICCV, Oct. 2007, pp. 1–6.
2. L. Marchesotti, C. Cifarelli, and G. Csurka, "A framework for visual saliency detection with applications to image thumbnailing," in Proc. ICCV, Sep./Oct. 2009, pp. 2232–2239.
3. J. Luo, "Subject content-based intelligent cropping of digital photos," in Proc. ICME, Jul. 2007, pp. 2218–2221.
4. S. goferman, Z. Lihi, "Content aware saliency detection", IEEE Trans.,Pattern anal.,vol.34,otc-2012.
5. Y. Ding, J. Xiao, and J. Yu, "Importance filtering for image retargeting," in Proc. CVPR, Jun. 2011, pp. 89–96.
6. S. D. Jain, B. Xiong, and K. Grauman, "Pixel objectness," in Proc. CVPR, 2017, pp. 1–18.
7. D.-P. Fan, M.-M. Cheng, Y. Liu, T. Li, and A. Borji, "Structuremeasure: A new way to evaluate foreground maps," in Proc. ICCV, 2017, pp. 1–10.
8. D. Cho, J. Park, T.-H. Oh, Y.-W. Tai, and I.-S. Kweon, "Weakly- and self-supervised learning for content-aware deep image retargeting," in Proc. ICCV, 2017, pp. 4568–4577.
9. Y. Deng, C. C. Loy, and X. Tang, "Image aesthetic assessment: An experimental survey," IEEE Signal Process. Mag., vol. 34, no. 4, pp. 80–106, Jul. 2017.