ADVERTISE GENTLY - IN-IMAGE ADVERTISING WITH LOW INTRUSIVENESS*

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ABSTRACT

The new trend of online advertisement is in-image advertising, which is facing the risk of being intrusive. Several works have been done to reduce the intrusiveness. However, intrusiveness is a subjective concept and is difficult to be measured objectively. In this paper, by considering the fact that gentle advertising will not disturb audiences' attention too much but the intrusive ones will, we investigate the relationship between intrusiveness and audience attention. By experiment, we find that two aspects of attention will affect intrusiveness. Firstly, if the inserted advertisement covers the Region of Interest (ROI), it is truly very intrusive. Secondly, if the advertisement distracts audience attention from the original attending point, it is also very intrusive. We measure intrusiveness from the above two aspects. Using this measurement, we insert advertisements into online image collections gently. Given a pair of an image and an advertisement, we detect the suitable place, using attention analysis and visual consistency, to reduce intrusiveness. Given an image set and an advertisement set, we minimize the intrusiveness by searching for an optimal match. Experimental results verify the effectiveness of the proposed measurement of intrusiveness and of the advertising approach.

Index Terms— Visual attention, advertisement

1. INTRODUCTION

With the huge and yet increasing amount of images on the internet, in-image advertising becomes the new trend of online advertisement. Google AdSense [1] and BritePic [2] have provided in-images advertisement services. In AdSense and BritePic, the insertion place and insertion content are determined manually by users. However, it is a labor intensive work for the huge image amount. Several methods have been proposed for automatic in-image/video advertising.

The main problem of in-image/video advertising is that it may annoy audiences. For example, if the inserted advertisement covers the main content of the image/video, it is definitely intrusive. To reduce the intrusiveness the advertisement can be inserted at the region that contains less information [3] or of lower visual relevance [4]. If prior knowledge is available, particular regions of the scene can also be detected as insertion places [5]. In recent literatures, visual attention has been taken into account to determine the insertion place. ImageSence [6], which is an in-image advertising system with the aim to add advertisements into webpage, detects the Region of Interest (ROI) firstly, and then insert the advertisement outside of the ROI. In [7], Lower Attentive Region is defined as the region which attracts less audience attention. It is detected as insertion place by using visual attention analysis.

However, lower attention still can't ensure lower intrusiveness. For example, if the advertisement visually outstands of the image, it will distract audience attention from the original attending point (See Fig. 1 (b)). ImageSence [6] solves this problem by choosing insertion content according to visual consistency. Another method is to harmonize the advertisement to be visually consistent with the original video/image [8].

All the above methods try to reduce intrusiveness. However, there is not an objective measurement of intrusiveness. In this paper, we investigate the relationship between intrusiveness and visual attention. Based on the investigation, we measure intrusiveness from the viewpoint of visual attention. The measurement contains two aspects: ROI interference, which denotes that the advertisement

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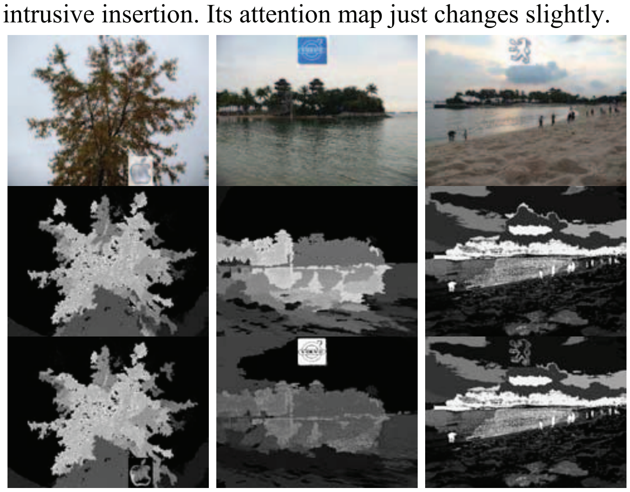
covers the ROI, and distraction, which denotes that the advertisement distracts the viewer's attention from the ROI. Using this measurement, we perform online in-image advertising gently. Given a pair of an image and an advertisement, we reduce the intrusiveness by choosing the insertion position according to visual attention and color consistency. Then given an image set and an advertisement set, we model the problem as an assignment problem and solve it using bipartite graph model.

The rest of the paper is organized as follows. In section 2 and section 3, the proposed measurement of intrusiveness and the online advertising method are presented, respectively. The experimental results will be shown in section 4. Finally, we will discuss and conclude our work in section 5.

2. INTRUSIVENESS MEASUREMENT

As discussed in Section 1, there are two types of intrusiveness, ROI interference and distraction. In this section, we investigate the affect on audience attention caused by insertion. We perform attention analysis, using the method of [7], on the original images and the resulting images. In Fig. 1 there are three examples. The first row displays the advertising result. The second and third rows display the attention maps before and after insertion, respectively. The first column is of ROI interference. Its attention map doesn't change significantly. The second one is of distraction. It can be seen that, the attention map changes significantly. The inserted advertisement is more attentive than the original image. The third one is of non intrusive insertion. Its attention map just changes slightly.



(a) ROI interference (b) distraction (c) non intrusive

Fig. 1. Examples of attention changing caused by insertion. 1st row: insertion result; 2nd row: attention maps before insertion; 3rd row: attention maps after insertion.

The above observation prompted us to measure distraction using the difference between attention maps. We performed an experiment to verify this idea. We select 6 photo collections, each of which includes 50 photos, as insertion body. To choose the insertion position, each original image is divided into 5*5 blocks, as illustrated in Fig. 2, and the insertion place is chosen from the 16 surrounding blocks randomly. This is for the consideration that in most images, the main content locates at the image center. For virtual content, we select a set of 75 brands, including Coca Cola, IBM, BMW, and so on. We insert into each photo a brand randomly chosen from the set. The resulting images are displayed to users. The users are required to select the ones which disturb him/her from watching the image. Then for the jth photo in the ith collection, we define its unacceptable degree $I_{i,j}$ as:

$$I_{i,j} = n_{i,j} / N_i \tag{1}$$

where $n_{i,j}$ is the number of users who labeled the result as unacceptable and N_i is the total number of users who watched the ith collection. We label the ones whose unacceptable degree is higher than 1/2 as intrusive.

Fig. 2. Random insertion position choosing.

We invite other users to choose the ones in which the inserted brand covered the attentive content of the image. We found that all of them are among the intrusive ones. This verifies that covering the ROI is definitely unacceptable. According to the user study result, we classify the results into three classes:

A: non intrusive ones

B: intrusive ones of distraction

C: intrusive ones of ROI interference

To compare attention maps before and after insertion, they are normalized to $\sum_{(x,y)} AM(x,y) = 1$ thus they can be looked as probability density function. Several comparison methods are available, such as linear correlation coefficient, Kullback-Leibler divergence, and intersection. In our work, we calculate the consistency between attention maps as their intersection:

$$con = \sum_{(x,y)} \min\left(AM_{before}(x,y), AM_{after}(x,y)\right) \tag{2}$$

In Fig. 3 are the average consistency of classes A, B and C of the 6 photo collections. It can be seen that the average consistency of class C is similar with that of A. But the average consistency of class B is much lower. Since consistency and difference are supplement to each other, we calculate intrusiveness as follow:

$$Intr = \begin{cases} 1 & \text{if the brand covers the ROI} \\ 1 - con & \text{others} \end{cases} \tag{3}$$

According to (3), the intrusiveness locates between 0 and 1. When the logo covers the ROI, the intrusiveness reaches its maximum. This measurement provides a straightforward object for in-image/video advertising. Using it, we obtain the least intrusive advertising and evaluate the result in the following section.

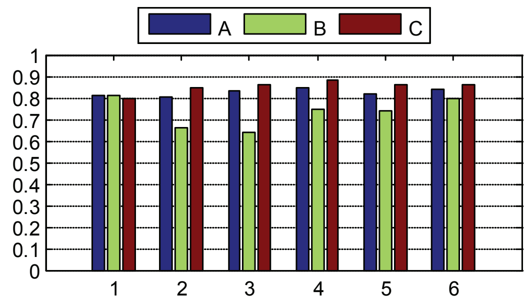


Fig. 3. Comparison of the three classes of the 6 photo sets.

3. ADVERTISEMENT INSERTION

Nowadays, more and more websites provide users to store individual albums. This contains huge potential profit for advertisers. For example, Goolge AdSense pays users according to the visiting frequency to their albums with advertisement [1]. In this section we aim to insert advertisement into online albums. The advertisements adopted are commercial brands, which are usually visually simple and can impress on audiences.

Given a photo and a brand, different insertion place may result in different intrusiveness. Our purpose is to find the best insertion position to minimize the intrusiveness. According to the definition of intrusiveness in Section 2, we firstly detect the ROI of each photo to avoid ROI interference, which leads to the highest intrusiveness. Then we traverse all possible positions outside the ROI to find the insertion position of minimal distraction. Instead of repeated attention analysis on the insertion results, which is straightforward but time consuming, color similarity is utilized as the criterion for position choosing. The region of most similar color with the brand is chosen to reduce the changing of attention maps.

Given an album and an advertisement set, without loss of generality, we insert into each photo no more than one brand, and each brand will not be chosen more than one times. Then the task is modeled as: given an album of size m, a brand database of size n, $k=\min(m,n)$, search for k pairs of match between photo and brand to minimize the total intrusiveness. This task can be formulated as:

$$\min_{\{(x_i,y_i)\}} \sum_{i=1}^{k} Intr(x_i, y_i) \tag{4}$$

where $x_i \in \{1,2,...,m\}$, $y_i \in \{1,2,...,n\}$, for $i \neq j$, $x_i \neq x_j$ and $y_i \neq y_j$. $Intr(x_i, y_i)$ is the intrusiveness caused by inserting the brand y_i into the photo x_i.

Function (4) has in total $C_m^k \times C_n^k \times k!$ solutions. For the circumstance in section 2, which include 50 photos and 75 candidate brands, the number of solutions will be more than 1.8×10^{98}. We utilize a weighted bipartite graph to model the matching problem of (4). As shown in Fig. 4, the vertices in one side of bipartite graph represent the images, and the ones in the other side represent the brands. The weight of each edge is the intrusiveness between the photo and the brand. We utilize Hungarian algorithm to find the best match of the bipartite graph [9].

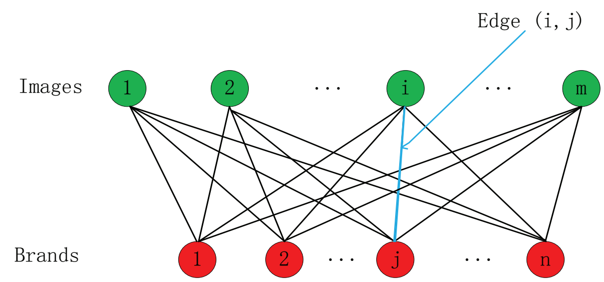


Fig. 4. Weighted bipartite graph model.

4. EXPERIMENT

We evaluate the proposed advertising method from two aspects. Firstly, we compare results with the random results in Section 2. Through this experiment, we will evaluate if the proposed advertisement insertion method is accordant with the intrusiveness definition through objective resulting data. User study is done to show the improvement of user experience brought by this method. Secondly, we test this method on another image set, which is downloaded from the Internet and includes more types of images. User study is taken again to show the acceptable degree of the simulation experiment.

4.1. Comparison with the random results

To compare with the random results, the 6 collections of photos and 75 brands are utilized again. The brands are inserted into the photos through the proposed method. We send the result for user study with the same setting in Section 2. The results are also classified into *A*, *B*, and *C* sets.

Firstly, we calculate the ratios of ROI interference of each album. The results for the 6 album are shown in Tab. 1. It can be seen that the average ratios of ROI interference of the optimized result is about 4% (Opt in Tab. 1), less than that of the random result (Ran in Tab. 1).

Tab. 1 Ratio of ROI interference

	1	2	3	4	5	6	Avg
Ran	14%	8%	4%	16%	2%	2%	8%
Opt	0%	6%	8%	0%	2%	4%	4%

Then excluding the set C, we calculate the average consistency of each album. For the random result, we also calculate the average consistency with the same method. Because the set C is excluded, consistency can well present intrusiveness. The result is shown in Fig. 5. From the figure, we can see that the consistency of the new results is higher than the previous ones. This verifies the effectiveness of our method for reducing intrusiveness.

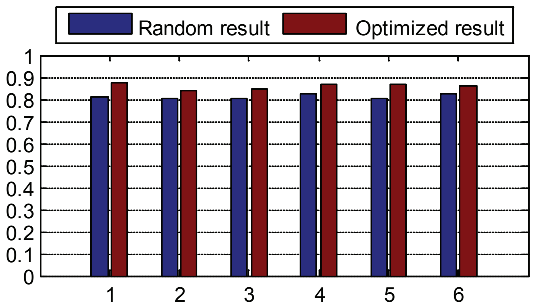


Fig.5 Comparison of average consistency.

Finally, we calculate the ratio of intrusive results for each album. The result is shown in Tab. 2, from which we can see that the optimized results (Opt in Tab. 2) are more acceptable than the random ones (Ran in Tab. 2). For all collections, less than 10% of the optimized results are intrusive while the ratio is about 19% for the random results.

Tab. 2 Ratio of intrusive results

	1	2	3	4	5	6	Avg
Ran	18%	10%	8%	26%	14%	36%	19%
Opt	12%	10%	10%	6%	6%	14%	10%

4.2 Experiment on other image data

We downloaded 106 images from Internet. These images include different genres: scenery, people, cartoon, animal, etc. Then, we perform our algorithm to match the image set with the 75 brands. Finally, we obtain 75 resultant images, each of which is the result of inserting one brand into one image.

We invite users to evaluate the results on this image set. The ratio of unacceptable results is 10%, which is accordant with that of the 6 collection of images. From this we can see that this new method is effective. Some insertion examples are shown in Fig. 6. The purple bounding boxes are drawn for the readers' convenience.

5. CONCLUSTION

In this paper, we investigate the relationship between intrusiveness and visual attention for in-image advertising. The experiment results confirm that if the inserted brand covers the ROI, it will be definitely intrusive. Also, based on the investigation, we find that if the inserted brand distracts the audiences' attention from the original attending point, it is also intrusive. We provide an objective measurement of intrusiveness. By minimizing the intrusiveness, we propose a method to insert advertisement into online albums.


Fig.6 Examples of advertisement insertion.

In the paper, only the consistency between attention maps is taken into account to measure the intrusiveness. However, other statistical measure may take effect too. In future, more statistical measure can also be applied.

6. ACKNOWLEDGEMENT

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