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A Photomosaic Image Generation Method using Photo Annotation in a Social Network Environment

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Abstract With the growing use of social networking services, various applications have been developed to utilize their vast capabilities. Photomosaic techniques, which combine many images to create a new rendering of an input image, can benefit from the capabilities of social networks. In this study, we propose a method that generates a photomosaic image by considering social network context. Our algorithm creates a photomosaic that incorporates photos posted by other users in the user's network . We enable the matching function to easily select photos from the albums of users who are connected to the owner of the input image, by computing the closeness of those connections. Moreover, our technique allows the photos in the albums of friends who are annotated in the source image to be matched more effectively.

Keywords photomosaic · social networks · Non-photorealistic rendering

1 Introduction

Photomosaic techniques [Silvers(1997a)] combine many images from a given database to create a new rendering of an input image. Because it can build an image that consists of other images with a certain theme, a photomosaic effectively conveys the subject of the work. As a result, this technique has been employed in various fields, including advertising and broadcasting [Silvers(1997b)]. Typically, photomosaic images are generated using the following steps. First, an input image is divided into equally sized small blocks. Next, the

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image database is searched to locate an image that matches each block. Finally, each block is replaced by the matching image. In general, the more images in the image database, the better the quality of the photomosaic. Therefore, in order to generate a high quality photomosaic, a large and varied database is required.

With the popularization of digital photography and the growing use of social networking services such as Facebook, Flickr, and Twitter, social networks have been closely connected with photography. Many people upload their photos to online albums instead of using physical photo albums. When users upload a photo to a social network, they attach a description to the photo by writing a post. Moreover, they annotate their photos with place and event information, as well as the names of friends appearing in the photo. Their social network connections can leave comments on the post. These overall social network contexts provide invisible additional information, as well as physical information such as Exif data. These social network contexts can be utilized for analyzing photos on social networks; the vast number of photos contained on social networks form large and complex data sets, which can be characterized as big data . Therefore, social network context is an abundant source of new content that includes photos and their higher-level information. The photomosaic technique is a practical example of a new content type that includes social network context.

In this study, we propose a method that generates a photomosaic image consisting of photos in social network albums, while integrating relevant social network context. In our method, we generate a photomosaic image for an image containing social network annotations. At this time, we use images in the albums of social network users as our image database. We design our algorithm to more frequently select the photos of users who have a close relationship with the user associated with the input image. Therefore, a user can obtain a photomosaic image that reflects their social network activity.

The remainder of this paper is organized as follows. In Section 2, we provide an overview of related works that analyzed photomosaic techniques. Next, in Section 3, we describe our social network context-based photomosaic method. In Section 4, we present the results of our method. Finally, in Section 5, we conclude with a summary of our method, a discussion of its limitations, and the scope of future development.

2 Related Work

The original photomosaic technique was first proposed by Silvers [Silvers(1997a)]. They divide an input image into small blocks. Then, they search an image database for the image that most closely matches each block, and replace the original blocks with them. Currently, there are various photomosaic algorithms. However, their basic functionality is based on this method.

Finkelstein and Range [Finkelstein and Range(1998)] also proposed a similar technique that uses non-rectangular blocks. They occasionally employ tightly filled hexagonal blocks. In their method, a color correction technique is provided, to produce a photomosaic image that more closely matches the input image.

Kim and Pellacini [Kim and Pellacini(2002)] suggested an extension of the photomosaic method. In their method, instead of using regularly shaped blocks, they use arbitrarily shaped image tiles for generating the photomosaic. In order to tightly pack arbitrarily shaped tiles on the input image, they proposed an energy function-based optimization method.

In addition, there are a number of sibling photomosaic algorithms. Klein et al. [Klein et al(2002)Klein, Grant, Finkelstein, and Cohen] proposed a video mosaic method that constructs video frames consisting of small video blocks. Park et al. [Park et al(2006)Park, Yoon, and Ryoo] suggested a photomosaic method that stacks arbitrarily shaped image layers. Orchard and Kaplan [Orchard and Kaplan(2008)] proposed an efficient photomosaic method that locates the optimal sub-image within an image database. Their method allows optimal color correction and utilizes arbitrarily shaped target tiles.

Several studies focused on the performance of photomosaic methods. Tran [Tran(1999)] suggested methods to measure the effectiveness and cost of a photomosaic technique. In his study, effectiveness is measured by analyzing the similarities between the input image and the resulting photomosaic image. Cost is determined by measuring the photomosaic algorithm's execution time. In his experiments, he showed that a large image database is required to produce an effective photomosaic, because the probability of finding an image that is similar to the input image block increased according to the growth of the database. Therefore, searching for the best matching image from a large database is the primary bottleneck in general photomosaic algorithms. In order to reduce the cost of photomosaic processing, Blasi and Petralia [Blasi et al(2005)Blasi, Gallo, and Maria] employed an antipole tree structure [Blasi and Petralia(2005)] and Kang et al. [Kang et al(2011)Kang, Seo, Ryoo, and Yoon] developed a GPU-based photomosaic framework.

Mosaic which is the arrangement of tiny tiles to form artistic image is one of sub-topics in stylization field [Kyprianidis et al(2013)Kyprianidis, Collomosse, Wang, and Isenberg]. Hansner [Hausner(2001)] packed rectangular tiles to simulate decorative mosaic. Kang et al. [Kang et al(2012)Kang, Ohn, Han, and Yoon] extended Hansner's method to animation by using motion between video frames. While these approaches used uni-colored shapes as tiles, we employ only photographic images as tiles.

3 Proposed algorithm

3.1 Photomosaic framework

In this study, we propose a method that generates a photomosaic image based on a photo in a social network photo album. Our method employs photos in a user's social network as a photomosaic image database. Users who appear in social network photos can be annotated. We assume that any photos directly uploaded by the user, and any photos uploaded by the user's connections (in which the user has been annotated) belong to the first user's album. Photos that have annotations of other users are shared with those users, as shown in Figure 1. When a photomosaic image is generated for a user, our method uses albums belonging to the user and the user's connections as the photomosaic image database. Because we collect many images from the albums of the user's connections, we can easily obtain the large and varied database that is necessary for generating a photomosaic.

In our algorithm, we divide the selected photomosaic input image into small blocks with a fixed size, as shown in Figure 2. Because each block in the photomosaic is replaced by an image from the database, the smaller the size of the block, the better the detail of the resulting photomosaic. Our algorithm searches for the image that best matches the sub-image of each block. In order to reflect the activity of social network users, we add social network context to the matching function that is generally used to search for similar images in a database. The details of this process are explained in section 3.2.

The matching function replaces each block of the input image with the best matching image from the database, to produce the photomosaic image. However, it is possible to select redundant images from the database. As a result, the same image replaces many blocks. Because blocks are very similar to each other in low-contrast regions, it is easy to use the same image repeatedly over a large area. As mentioned by Tran [Tran(1999)], redundancy is one of the factors used to evaluate photomosaic techniques. To reduce redundancy, we eliminate images that were previously selected for other blocks. We can remove all redundancy by eliminating each best matching image from the database, before searching for the best matching image for the next block. However, this method eliminates too many images, and may decrease the quality of the photomosaic. To prevent this situation, we only eliminate previously selected images within adjacent blocks. Therefore, we achieve a balance between reducing redundancy and maintaining quality.

3.2 Matching function

To allow the photomosaic algorithm to incorporate social networking activity and relationships between users, we define the matching function to search for the best matching image as equation (1).

$$F(I_q^y, I_p^x) = F_1(I_q^y, i_p^x) + w_1 F_2(I_q^y, I_p^x), y \in Y, I_q^y \in I^y, i_p^x \in I_p^x \tag{1}$$

Let us denote Y as users with connections to a user x (including user x), I^y as the album of a user y, and i_p^x as the sub-image of I_p^x in the album I^x. Our algorithm divides user x's image I_p^x into many small blocks as mentioned in section 3.1. For each divided block, it finds the best matching image fromI^y, which is the album belonging to the connections of user x , by maximizing equation (1). The first term of equation (1) evaluates the similarity between

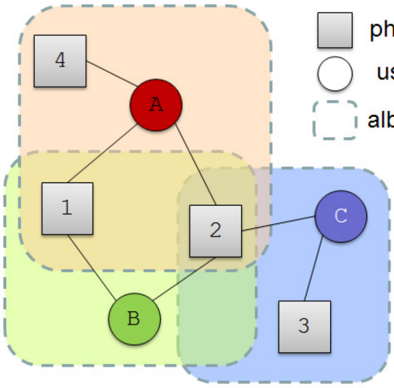


Fig. 1 Social network photo album framework used in this study. Solid lines indicate annotation. The photo annotated by multiple users is shared among user albums.

Fig. 2 Divided blocks for photomosaic. We divide an input image into regular small blocks with fixed size.

an image in the database, denoted by I_q^y, and a sub-image i_p^x from the input image. We describe the details of this process in section 3.2.1. The second term of equation (2) is a social network context term that is related to users' social networking activities. We describe the details of this term in section 3.2.2.

3.2.1 Image similarity

There are numerous methods that calculate the similarities between images in the image processing and computer graphics fields. However, image similarity computations are the primary bottleneck of the photomosaic algorithm; as a result, a simple, low-cost method is typically used [Blasi and Petralia(2005), Kang et al(2011)Kang, Seo, Ryoo, and Yoon, Kang et al(2013)Kang, Seo, Ryoo, and Yoon]. In this paper, we employ a simple method [Kang et al(2013)Kang,

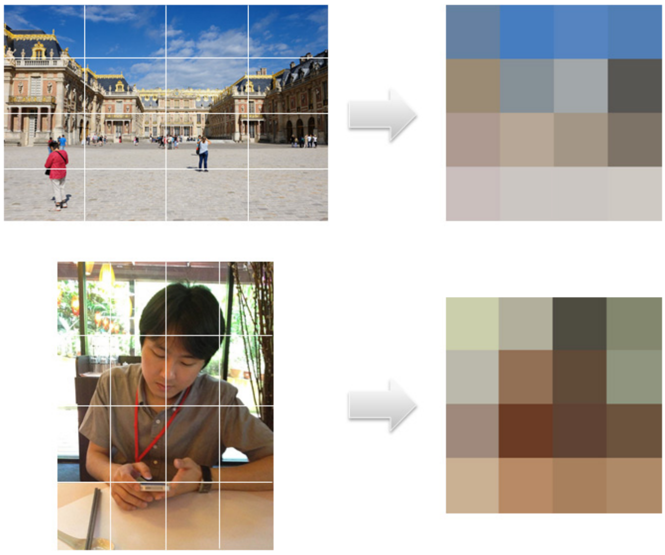


Fig. 3 Normalized downsampling for calculating image similarity.

Seo, Ryoo, and Yoon] that calculates image similarity by summing the differences between the pixels of downsampled images. If we use original sized images for similarity calculation, then we can obtain more precise result that is more similar to input image. However, the tile of photomosaic is much smaller than input image, downsampled image is enough to represent each tile in similarity calculation. As described in Figure 3, we downsample two given images into smaller images with the same aspect ratio, and calculate image similarity using equation (2).

$$F_1(I_a, I_b) = \frac{1}{N} \sum_x \sum_y (1 - ||I_a(x,y) - I_b(x,y)||) \tag{2}$$

Here, $I(x,y)$ indicates a RGB vector of pixel (x,y) in image I, and N indicates a normalized term which is the number of pixels in I. When two images are similar to each other, the value of $F_1(\cdot)$ is increased.

3.2.2 Social networks context

A social network context term that reflects social activity and its relation to a photomosaic is represented by the following equations.

$$F_2(I_q^y, I_p^x) = F_4(I^y|x)F_4(I^x|y) + w_2(F_3(I_q^y|y) + 1)F_3(I_p^x|y) \tag{3}$$

$$F_3(I|x) = \begin{cases} 1 & x \text{ is annotated in } I \\ 0 & \text{else} \end{cases} \tag{4}$$

$$F_4(I^y|x) = \sum_{I_p^y \in I^y} F_3(I_p^y|x) / \sum_{z_i \in z} \sum_{I_p^y \in I^y} F_3(I_p^y|z_i) \quad (5)$$

Equation (4) is an indicator function that shows whether user x is annotated on image I. In equation (5), z denotes the users connected to user y. Consequently, equation (5) shows the ratio between the number of annotations from user x's connections in images from album I^y and those of user x. Therefore, the first term of equation (3) shows the ratio between the cross annotation counts of the owners of two images. This is based on an assumption that closer connections frequently annotate each other in their social network photos. Therefore, if the photos of closer connections are in the database, the photos will be selected as the best matching image more frequently.

The second term of equation (3) multiplies two indicator functions. When user y is annotated in a photo belonging to user x, I_p^x, the value of this term is increased. At this time, cases in which user y is annotated on I_q^y cause a greater increase in this term's value compared to other cases. Therefore, the photos from albums belonging to users who are annotated on the photomosaic input image are selected as the best matching image more frequently. Moreover, if the photos in the albums of users who are annotated on the input image include the user associated with the photo, this photo will be selected as the best matching image more frequently than others. If the search for best matching image depends largely on the annotation, less similar photos can be replaced with the photomosaic blocks. This will decrease the quality of the photomosaic. To avoid this problem, we adequately adjust the value of w_2.

4 Experimental results

In this study, we conducted our experiment using Facebook. Because Facebook's API does not provide the authority to access other users' photos, we collected annotated photos from connected users by using a crawler that we developed, and simulated our algorithm offline. Our crawler visited users' Facebook page, and collected all of photos and user annotation information by analyzing HTML source code of Facebook's user page. Because HTML is well structured, our software easily extracted photos with annotations. We simulated our algorithm using the photos of 52 users who allowed us to use their social network content to conduct this experiment. The number of photos used for the photomosaic database was $2,506$.

The block size of the photomosaic in our experiment was set to 64×64 pixels. If the size is too small, then user cannot recognize each image. On the contrary, if the size is too large, then the quality of result is decreased. In our observation, we found that 1/50 - 1/60 of input image size offered good balance between them. When we calculated image similarity between the blocks and the images in the database, we downsampled each block and every image in the database to 4×4 pixels as used in [Kang et al(2013)Kang, Seo, Ryoo, and Yoon], and compared the corresponding pixels of the downsampled images. In this experiment, we typically used 1 and 0.01 as the values for w_1 and w_2,

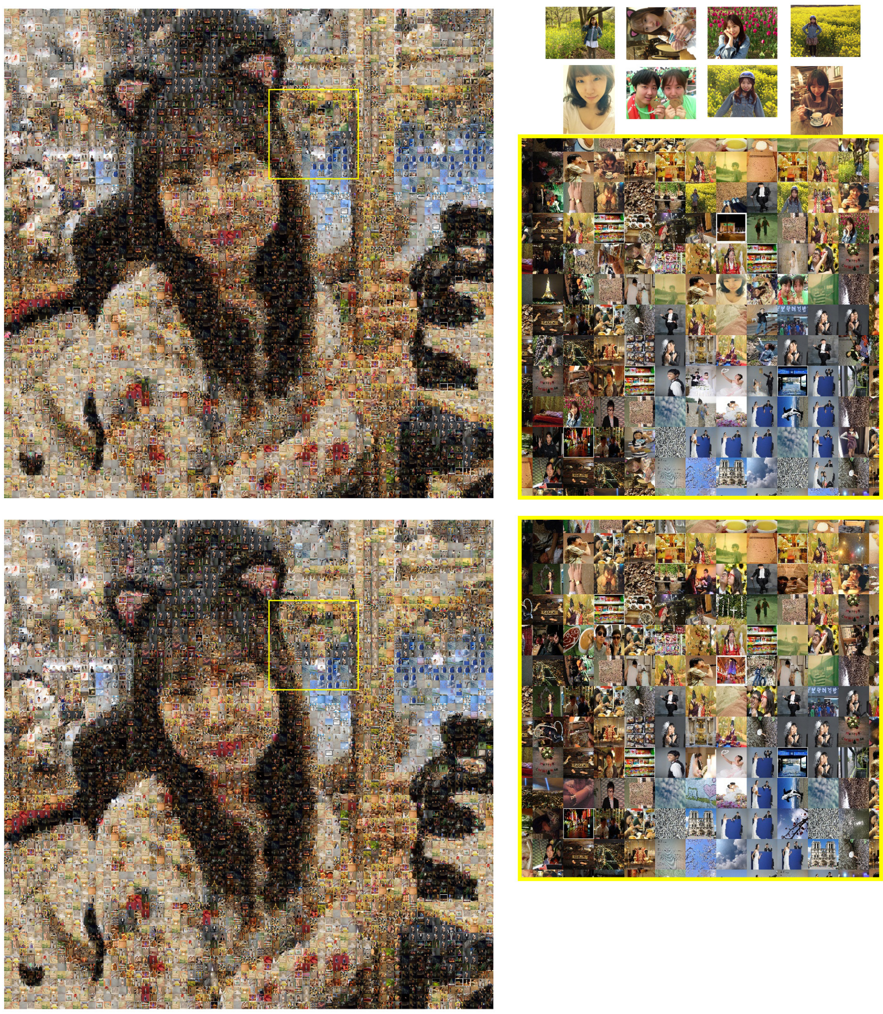
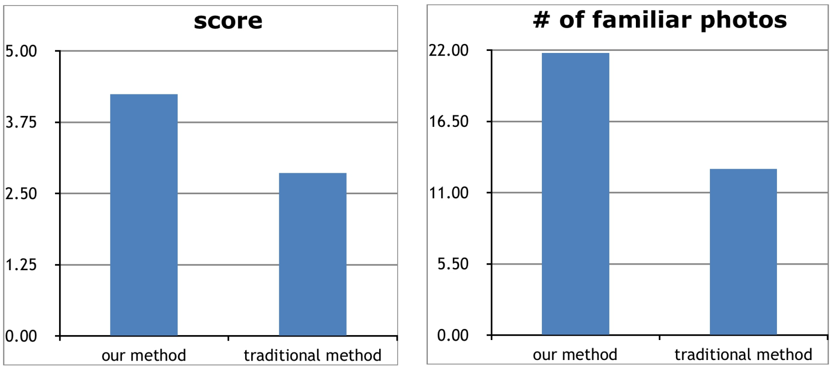


Fig. 4 Comparison between a photomosaic result with (upper left) and without (lower left) social network context. Right column shows magnified version of the yellow boxes on the resulting images. The upper right corner contains the photos of the user who is annotated on the input image.

respectively. The resolution of the input image used in this experiment was set to $4,096 \times 4,096$ pixels. To reduce redundancy, we did not reuse previously selected images within three adjacent blocks.

Figure 4 shows a comparison between photomosaics created with and without social network context. By considering social network context, the figure shows that the photos of users who have more social activity with the owner of the input image (and who are annotated on the input image) are frequently selected. However, the figure shows that the quality of the photomosaic cre-



(a) Satisfaction score (b) number of familiar photos in the results

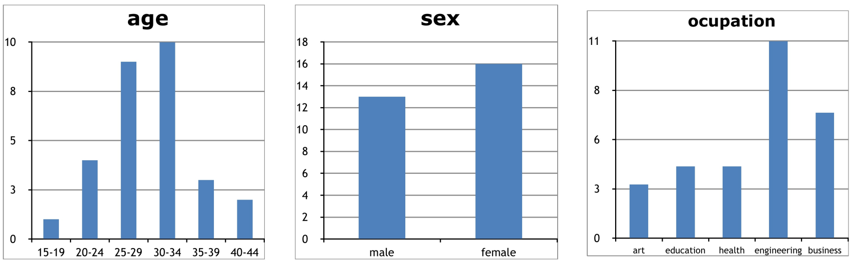
Fig. 5 Evaluation to determine the effectiveness of the proposed method: (a) users were more satisfied with our results compared to those of the traditional photomosaic; (b) More photos were identified as familiar in our method.

ated without social network context is slightly better than the photomosaic created with social network context. This occurred because a higher number of similar images were eliminated, owing to the influence of social network context. However, the visual difference is very minor, and social network context can provide a new photomosaic amusement factor. Therefore, the value of w_2 should be adequately adjusted to achieve the optimum balance between quality and the social network context effect. Figure 7 shows other results generated by the proposed photomosaic algorithm.

To evaluate the effectiveness of our method, we conducted two experiments. We showed photomosaic images generated by the proposed method and a traditional method to 29 volunteers among 52 users who allowed to use their photos for our experiment. The detail information of them is shown in Figure 6. The results of both methods consisted of photos on the users' social networks. However, the traditional method did not employ social context. In the first experiment, we asked users to provide a score that rated their satisfaction with the results. As shown in Figure 5(a), our method gave users the most satisfaction. From the score, we concluded that users enjoy the results of our method more than those of the traditional method. In the second experiment, we asked users to determine how many familiar photos they identified in each result (Figure 5(b)). Although the same photo sets were used for generating the photomosaics, users could more easily identify familiar photos in our result. From these results, we concluded that social network context greatly contributed to the effectiveness of the result.

5 Conclusion

In this paper, we proposed a new photomosaic method that considers social network context. Our algorithm generated a photomosaic using photos be-



(a) sex distribution (b) age distribution (c) ocupation distribution

Fig. 6 The information of volunteers who participated in our evaluations.

longing to users who were connected to each other through a social network. We proposed a matching function that could accurately select photos from albums of other users who had close connections to the user, and who were annotated in the input image; this was accomplished by computing the social networks context. Consequently, our algorithm generated a photomosaic result that was very similar to a traditional photomosaic but reflected the activity and relationships on social networks.

In this study, we only used photos and annotations as the social network context. However, posts with photos and comments can be useful sources of social network context. We are planning additional research to analyze posts with photos and comments, to generate photomosaics that can utilize them.

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(a)

(b)

Fig. 7 Various results of our collage.