A User-Adaptive Image Browsing System with Summarization Layout for the Personal Photo Collections

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ABSTRACT

Users spend much time organizing photos into small groups as part of photo management. Selecting good quality photos and organizing them is burdensome, as photographers amass large number of photos. This paper presents a new photo layout system with representative photos considering multiple features. Our approach consists of three steps to deal with hundreds of photos. First, we construct photo clusters by user-adapted criteria: temporal context, the number of faces, blur and luminance metrics. Then, we construct a bipartite graph that consists of photo nodes in a partite set and the constructed cluster nodes in other partite set. The representative photos of each cluster are selected by a maximal matching algorithm based on user-controlled multiple criteria. Finally, our system places the selected representative photos on a 2D grid using the placement algorithm of PHOTOLAND. Other photos in each cluster are displayed in an upper layer of a screen when the user clicks the representative photo. We conducted an experiment based on a user study; it used nine photo sets taken on a trip. The experiment showed that our system conveniently managed hundreds of photos, summarizing and visualizing them.

Keywords: digital photo, photo layout, maximal matching.

1 INTRODUCTION

The digital camera has become an indispensable commodity for people. The low price of memory encourages people to take a large number of photos. Since a digital camera is convenient and does not need extra cost to take photos, except for memory space, which is getting cheaper, people tend to take more photos than when using an analogue camera [3, 9]. Therefore, it is usual for users to take hundreds of pictures. Moreover, several users can take photos concurrently at the same event. These digital photo files can be easily exchanged by various means, such as flash memory, e-mail, ftp, and messenger. The number of photos is more increasing. People have to spend much more time organizing and browsing them.

We face several issues in managing digital photo collections due to the acquisition of large number of photos. These include:

- Poor accessibility - Low efficiency in selecting a photo in the current layout scheme. It is hard to find a specific photo amongst massive data.
- Classification of photos - We need to classify input photos based on user preference, e.g., date, event or persons in a photo.
- Preference of clustering criteria - Photos are increasing in volume and variety, since memory is cheap. Photos can be clustered using various criteria.

Photo browsing and clustering are crucial features to manage and organize many photos. Most users find what they want through a browser interface, and they spend most of their time classifying the photos into meaningful sets. In this sense, the interface to manage a large number of photos has been emphasized in recent studies. Most photo browsing systems present the images as a grid of thumbnails that the user can scroll through with a scroll bar; they can see the original version of the selected photo [8].

Meanwhile, many redundant or low quality photos occupy much space in the display area. This makes it difficult to understand the overall content of the photos. These low-priority photos do not need to be preserved in the original form. We introduce a method to select representative photos from the user's unrefined input photos based on customizable categories and visualize classified photos in a smart layout.

2 PREVIOUS WORK

Many studies related to photo management have been undertaken recently. Many useful applications have been developed to manage a large number of photos.

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Table 1: Previous work and systems for digital photo management and visualization

Method (reference)	Layout	Main features	Extra info.	Spatial info.
ACDSee [1]	Grid	Viewing only	EXIF	None
Agrafo [2]	Grid	Grouping and browsing	EXIF	Use (hybrid)
PhotoMesa [3]	Grid	Viewing (quantum treemap)	Directory info.	None
Kang [11]	Grid	Viewing (simple search)	Annotation	None
Picasa [17]	Grid	Viewing only	EXIF	None
Incremental board [18]	Grid	Viewing (similarity-based)	None	External input
Rodden [21]	Grid	Similarity-based arrangement	Annotation	Use
PhotoTOC [9]	Hierarchical	Clustering by temporal info.	timestamp	None
Kustanowitz [12, 13]	Hierarchical	Layout scheme	User input	None
Chen & Chu [4, 5]	Slide	Slideshow with layout [13]	EXIF	Use
Photo Navigator [10]	Slide	Slideshow for tracing scenes	Creation time	Use (3D)
Moghaddam [14]	Non-Grid	Layout for image retrieval	Annotation	Use
MediaGLOW [8]	Graph	Zoomable interface	EXIF	Use (graph)
Naaman [15, 16]	Geometric	Clustering based on place	GPS	Use
Quack [20]	Geometric	Community photo mining	GPS+annotation	Use

The most popular layout scheme of visualization systems is the grid layout to visualize a massive number of photos.

Many image application including ACDSee, Picasa and others use thumbnails of photos on grid layout [1, 17]. Generally, a user selects a specific photo on a grid, and then the original size photo is shown on the full screen. It is a very simple but useful method to show photos when there are less than several hundred photos. However, grid view has problems when there are too many photos. Redundant photos may occupy much of the display area. A long scroll bar is needed to explore the entire photo set.

Some enhanced grid layout schemes were proposed to overcome defects. Bederson introduced the section based grid view, PhotoMesa. It can show each directory as a section of layout [3]. PhotoMesa displays hierarchically organized photo clusters based on a file system using treemaps. It uses a simple layout for image clusters called bubblemaps. PhotoMesa emphasizes presenting large numbers of photos on a limited screen. At the top level view, photos of a specific directory are shown as tiny thumbnails. Zoomed photos with larger space are shown by selecting a section. Pinho proposed grid-based incremental board [18]. This uses an infinite grid by attaching tiny image thumbnails. Using a pre-processed photo similarity, an identical photo is located in close position to similar existing photos. It can visualize abundant photos on the screen at low cost by attaching many tiny photos to grid view. However, it is too small to see each photo, so this is not an efficient way to understand the content of input photos.

A hierarchical layout using uniform thumbnails was proposed for convenient recognition in visualizing photos. Kustanowitz proposed an organized layout scheme with different image sizes [12, 13]. The most important image, which shows the concept of the photo set, is located at the center of display area. The other photos surround the center photo aligned according to the classification. However, the method requires identifying photos by users. In addition, it is practically limited to one sheet of display screen due to the center image. Thus, it is not suitable to use the scroll bar or to show a massive number of images. Chen & Chu applied the method on their slideshow method [4, 5]. Photos in each slide are arranged using a hierarchical layout.

Graham exploits Calendar and Hierarchical image browsers to allocate the time-intensive annotation for the photo groups [9]. He exploits the timing information to construct the collections and to automatically generate meaningful summaries. These studies help the user give a more practical structure to the photos, but they cannot provide implicit browsing regarding temporal and spatial information simultaneously. A graph-based photo layout system, MediaGLOW, uses the spring model to determine a layout in which the spring system is in a state of minimal energy [8] . This graph-based interface determines the distance between each photo node according to a variety of distance measures, such as temporal, geographic, and visual distance (tagged data). It can also deal with lots of user interaction. This interface is very useful to organize photos. Table 1 summarizes representative studies.

3 CLUSTERING WITH MULTIPLE FEATURES

In digital life, people want to cluster photos using several features; they also want to browse the corresponding summarized view with each feature. For example, let us assume the following case. Users grouped pho-

Figure 1: Result of clustering by multiple features. For convenience, we randomly pick 33 photos from the photo set. The total number of clusters with multiple features is 23. (a) Temporal clustering by time [6]. $|C_T| = 10$. (b) Clustering by the number of faces (We use *cvHaarDetectObjects* function of OpenCV library to detect the face in a photo). $|C_F| = 4$.(c) Clustering by blur metric[7]. $|C_B| = 4$. (d) Clustering by luminance in Lab color space. $|C_L| = 5$.

tos by time taken. Then, after some time has passed, they wish to find the corresponding photos that satisfy the following conditions: 1) Photos taken with his two friends, 2) A good quality photo without blur, 3) The light atmosphere of photos. In this case, he spends much time to find the corresponding photos having these conditions (Users compare the selected photo with most of the photos in each cluster). Besides, when the photos to be arranged are getting numerous, these tasks become burdensome. A user-adaptive photo browser that can provide a summarized view by multiple user clustering criteria would be very useful in this case.

We deal with a variety of similarity measures to overcome these problems. These include time photo taken, the number of faces, blur and luminance metrics. In this section, we discuss with how to cluster each photo. For discussion, let us define the following notation:

- U : $U = < P_0, P_1, ..., P_n >$ denotes a sequence of photos taken, where P_i is each photo image.
- $face(P_i)$: the number of faces in P_i.
- $blur(P_i)$: a perceptual blur metric of P_i [7]. $(0 \leq blur(P_i) \leq 1.0)$
- $lumi(P_i)$: a luminance metric in Lab color space for P_i. $(0 \leq lumi(P_i) \leq 1.0)$
- $time(P_i)$: a timestamp extracted from EXIF of P_i.

The first criterion is temporal context. We use Cooper's clustering method to evaluate the similarity of each photo, as below [6] :

If K increases, we can get a coarser clustering result of the photos' timestamps. For smaller K, finer dissimilarities between groups of timestamps become apparent.

The second criterion of content based clustering is the number of faces in a photo. In the photo, we can grasp the number of faces using the OpenCV face detection algorithm based on a Harr transform. Our system simply classifies photos into small groups based on the number of faces. We use the similarity of face feature as below:

$$Sim_F(P_i, P_j) = 1 - \frac{|face(P_i) - face(P_j)|}{\max_{P_k \in U} \{face(P_k)\}} \quad (1)$$

We construct a classified photo group considering some visual features such as blur and luminance metrics. The similarity of blur metrics is determined by

Frederique's method [7]. The key idea of his method is to blur the initial image and to analyze the behavior of the neighboring pixels variation. We also consider the luminance features, which are calculated from the average of L values in Lab color space. These two metrics are normalized in a defined range from 0 to 1, their similarity measures are given below:

$$Sim_B(P_i,P_j) = 1 - |blur(P_i) - blur(P_j)| \quad (2)$$

$$Sim_L(P_i,P_j) = 1 - |lumi(P_i) - lumi(P_j)| \quad (3)$$

Figure 1 shows the result of clustering by four features. The input photos are selected from our past photos taken on a trip without any special intent. For convenience, we randomly select 33 photos from the photo set in this study, since most photo sets have hundreds of photos. As a result of this clustering, we can get several small groups, $C_x^{(k)}$, where $x \in T,F,B,L$ classify four features (Temporal, Number of Faces, Blur metric and Luminance in Lab color space):

1. $C_T^{(k)}$ denotes the k-th photo cluster using Cooper's algorithm [6].
2. $C_F^{(k)} = \{P_j \,|\, face(P_j) = k\}$
3. $C_B^{(k)}$ denotes the k-th photo cluster in terms of the blur metric.
4. $C_L^{(k)}$ denotes the k-th photo cluster in terms of luminance value.

4 SELECTING REPRESENTATIVE PHOTOS

Now, we have many small groups clustered by multiple features. We select each representative photo to summarize each photo clusters. In this paper, we present a selection method of representative photos using a maximal matching graph algorithm. First, we construct a bipartite graph, whose node consists of the photos in a partite set, and the created photo clusters of section 3, in another partite set, as shown in Figure 2.

The cluster nodes on the right hand side of this graph can have multiple edges, since the photos are assigned into clusters through multiple features. However, since each cluster has just one representative photo, we have to determine which photos are assigned into which clusters in this graph. We use the maximal matching algorithm to select the representative photos of each cluster to satisfy user's clustering preference as much as possible.

Let us consider a bipartite graph $G(V,E)$, as shown in Figure 2. Placing weight $w(P_i,C_x^{(j)})$ on edge $e(P_i,C_x^{(j)})$, ($P_i \in V$, $e \in E$, V and E are the set of all vertices and edges in this graph, respectively) gives us a weighted bipartite graph with partite sets $Photos = \{P_0,P_1, ..., P_n\}$ and $Clusters = \{C_T^{(0)}, C_T^{(1)}, ..., C_F^{(0)}, C_F^{(1)}, ..., C_B^{(0)}, C_B^{(1)}, ..., C_L^{(0)}, C_L^{(1)}, ... \}$. The weights of each edge are given below:

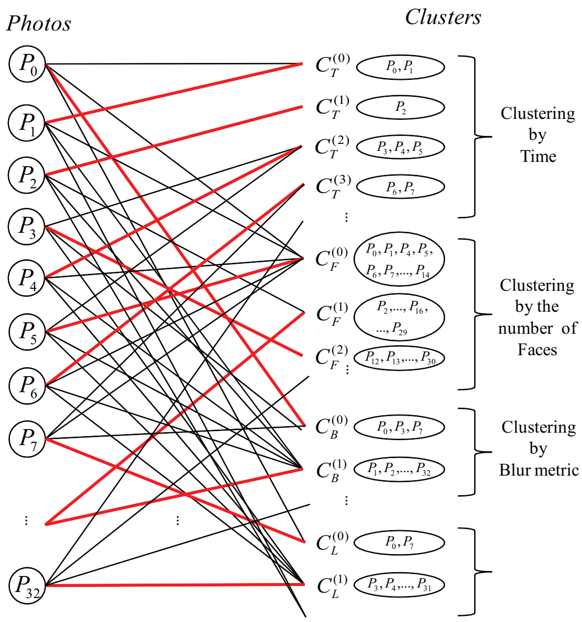

Figure 2: Maximal matching process for a selection of representative photos.

$$w(P_i,C_F^{(j)}) = \frac{1}{|E(C_F^j)|} \cdot \sum_{P_x \in C_F^j} (u_x \cdot Sim_x(P_i,P_x)) \quad (4)$$

, where $Sim_x(P_i,P_x)$ is the similarity function for each clustering feature, $\{Sim_T(P_i,P_x)$, $Sim_F(P_i,P_x)$, $Sim_B(P_i,P_x)$, $Sim_L(P_i,P_x)\}$, defined as Section 3. $u_x = \{u_t,u_f,u_b,u_l\}$ is one of the user-defined parameters to control each clustering feature.

A maximal matching M of a graph G is maximal, if every edge in G has a non-empty intersection with at least one edge in M. Our system selects each representative photo of clustered groups based on the relationships of these matching M. The maximal matching of this graph means the most similar relations globally between clusters and photos, when we consider the user's intent.

Figure 3 shows a portion of the relationships between several representative photos (P_{15}, P_{23}, P_{31}) and their corresponding clusters in Figure 1. In this figure, if we consider the number of faces, three photos are respectively clustered into different clusters (bold red edges in the Figure). At the same time, they are also clustered into different clusters considering the luminance of photos (bold blue edges in the Figure). In this case, the user can control which features are used to select the representative photos using u_x in Equation 4. If the user sets u_f = 1.0 and other features are less than 0.1, then our system selects the red edges for the representative photos of each cluster in this Figure. If the user

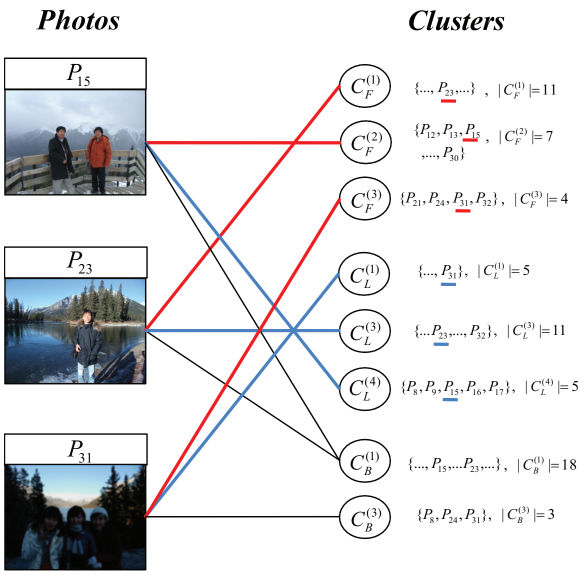

Figure 3: A portion of the graph constructed from the clusters in Figure 1. The user can control which features are used to select the representative photos using u_x in Equation 4. Bold red edges depict maximal matchings when we consider the number of faces. Bold blue edges depict maximal matchings when we consider the luminance value of each photo.

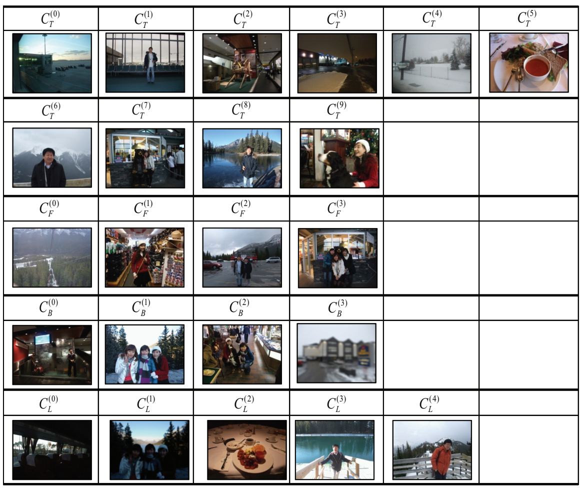

Figure 4: Corresponding result with photos selected in Figure 1. We set parameters as u_t = 0.9, u_f = 0.7, u_b =0.6, u_l = 0.6.

also sets u_l = 1.0 and other features are less than 0.1, likewise our system selects the blue edges for their representative photos.

Figure 4 shows the result of representative photo selection based on each cluster in Figure 1. We implements this maximal matching algorithm using the LEDA library.

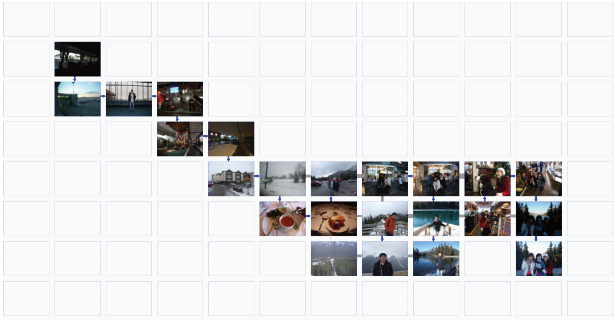

Figure 5: Result of placement for representative photos in Figure 4. We consider only the temporal context of selected representative photos in placing them.

5 LAYOUT FOR PHOTO VISUALIZATION

Our earlier paper on PHOTOLAND outlined a system that visualizes hundreds of photos on a 2D grid space to help users manage their photos [22]. This system considers spatial and temporal context simultaneously when photos are placed on a grid. We used a similar placement algorithm to visualize photos. This paper summarized the placement algorithm as below:

1. PHOTOLAND places the first photo in the center of a 2D grid.

2. It places the next photo considering temporal information and spatial context :

$$S(P_i,P_j) = (t_\alpha \cdot S_T(P_i,P_j) + (1-t_\alpha)\cdot S_C(P_i,P_j)) \quad (5)$$

,where t_α is a user-defined parameter to control spatial and temporal weight, it ranges from 0 to 1.0. S_T and S_C denote the temporal and spatial similarity, respectively.

3. It also considers global geometric constraints, such as center of weight for placed photos and aspect ratio for a screen.

4. The temporal similarity is calculated by the logistic function of the time gap between two photos.

We use two hierarchical layers that display the representative photos and the clustered photos related to them in order to display photos. First, we consider only temporal context to place the representative photos. As mentioned before, since it is related to the user's event, the temporal context has to be considered as being most important. Figure 5 shows the result of placement for representative photos in Figure 4. Then, the user can click on a representative photo; our system displays other photos related to it in an upper layer, as shown in Figure 6. When the clustered detail photos are displayed, we rendered a semi-transparent gray background on the lower layer for representative photos.

Figure 6: Other photos related to the selected representative photos in a upper layer. We rendered a semi-transparent gray background on the lower layer for representative photos.

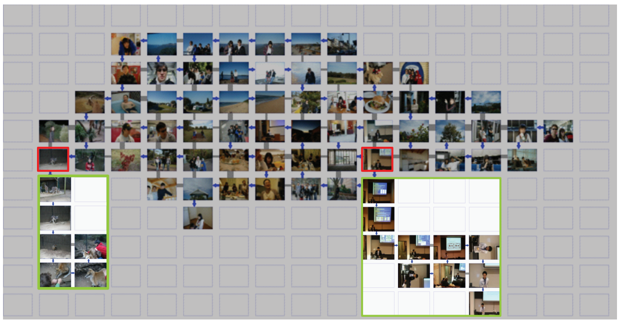

Figure 7: Photo placement result of another representative photo. Input photo set is one of the type ‘C’ sets. There are 66 clusters. They consist of 457 photos taken in Banff, Canada. We set parameters as u_t = 0.5, u_f = 0.7, u_b =0.7, u_l = 0.5.

Figure 7 shows the result of placement for representative photos selected from one of the type ‘C’ photos taken in Banff. There are 66 clusters. The blue arrows near the grid cell depict their temporal sequence. Spatial similarity between their neighboring photos is presented by the gray line border. The thicker line depicts that the photos have colors that are more similar in 25 perceptual colors [19].

6 EXPERIMENT

We conducted three consecutive experiments to evaluate the usability of our system. These user studies were designed to understand the user’s subjective reaction to our system. Our user studies deal with the following three perspectives:

1. How much time can we save using our system in photo clustering?
2. How nice is the representative photo selection algorithm compared to random selection?
3. How quickly can users find the desired photos in each photo sets?

Sixteen people participated in our experimental sessions. The participants were six beginners, seven experts and three evaluators. We define a beginner as a user whose major is not related to computer engineering. The beginner group does not deal with computers in everyday life (Ages ranged from 25 to 36). In contrast to the beginner, the expert group consists of users whose major is related to computer engineering. The final group of participants (evaluators) consists of people who take each photo set directly.

The input data consisted of three levels of photo sets, A, B, and C based on the number of photos, described in Table 2. Each photo sets consists of evaluator’s photos taken during a trip without any special intent. We classified photos into several categories with the person who took each photo set before the experiment to compare the result of clustering. Then, these categories are embedded in the custom field of their EXIF (“On the mountain” and “Number of Face 3”). The clustering features considered were temporal context, the number of faces and luminance in Lab color space.

Table 2: Description of the input photos, A, B and C. depicts the evaluator for each photo set

Type	# of Photos	# of Evaluator	# of photo sets
A	80 ∼ 100	3	4
B	150 ∼ 180	2	3
C	420 ∼ 460	3	2

Experiment 1. We investigated the clustering task completion time. We compared our system to a traditional scrolling interface based on a 2D grid, ACDSee Photo manager, as a benchmark [1]. The photo sets were classified by evaluators in advance to construct the true sets for this experiment. We determined the true cluster information to be the number of clusters, the number of photos in each cluster, the categories of each cluster. We term this as “cluster information”.

We organized the new tester group for experiment 1 from the sixteen participants in the experiment. Since clustering is very subjective, we want to pick out the person who shares the memory of each photo set with the evaluator as testers, to investigate the satisfaction with the clustering results impartially. In this experiment, they consisted of the photographer’s traveling companions. We computed the satisfaction level of clustering results comparing the file names of photos in clustering folder to the cluster category label.

The precision indicates the proportion of true positives clustered as below:

$$E_p = \frac{|\{\text{true photo sets}\} \bigcap \{\text{user-clustered photo sets}\}|}{|\{\text{user-clustered photo sets}\}|} \quad (6)$$

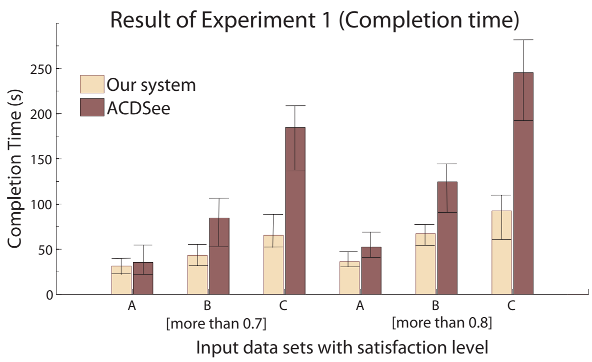

Figure 8: Average completion time to classify each cluster. The input photo sets are A, B and C as described in Table 2.

The recall measure is the number of correct results divided by the number of all relevant results. It measures the proportion of true clustered photos :

$$E_r = \frac{|\{\text{true photo sets}\} \bigcap \{\text{user-clustered photo sets}\}|}{|\{\text{all of relevant truth photo sets}\}|} \tag{7}$$

We use an average of precision and recall that was respectively measured as more than 0.4 in this experiment to decide if it is sufficient to satisfy the clustering result.

Now we wrapped up preparation for experiment 1. First, each tester selects one photo set from every type of photo set described in Table 2. Then, we gave the testers the cluster information of the selected set with a simple program that can divide photos into groups by a constant time gap. They were asked to divide each photo set already by the evaluator. During the experiment, the testers can know the corresponding satisfaction level of their clustering results by clicking the ‘evaluation’ button on the program we presented them. This simple program can report how much the current photo clustering satisfies the evaluator’s clustering results, considering precision and recall. We iterate the above steps until the clustering results can be recognized as reaching the satisfaction level to compare the completion time.

Figure 8 shows the average completion time for clustering satisfaction, the satisfaction levels are 0.7 and 0.8. It shows that the layout of our system is useful to classify hundreds of photos compared to ACDSee Photo manager.

Experiment 2. We compare the representative photos selected by our system to randomly selected photos from each cluster. These selected photos are given to the evaluators. Then, evaluators were asked to score the satisfaction of each selection. Each experiment was iterated ten times per the photo set randomly selected from sets (A, B and C, respectively), for generality. The scores ranged from 4 to 10. The average score for Experiment 2 is shown in Figure 9. We excluded the blurred features, since it is difficult to identify with the unaided eyes on a document.

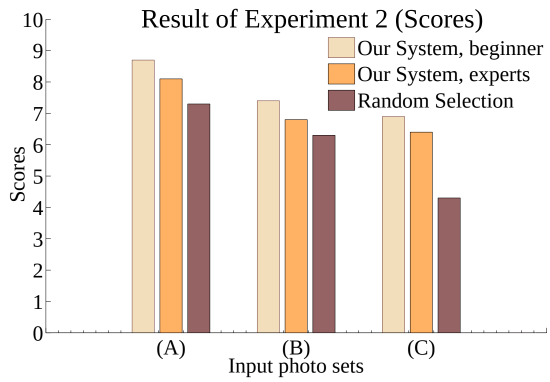

Figure 9: Result of experiment 2. Average scores of participants evaluation.

Experiment 3. The participants were asked to find each corresponding similar photo to the given images when four images were given. We had already selected photos for the correct answer based on its similar images, as a true set. We investigate the number of trials in which that they select all correct answers. Figure 10 shows the average number of trials to find the objective photos. Since the gap of trial results between beginners and experts in Experiment 3 is small, our system can be easily used by Beginners.

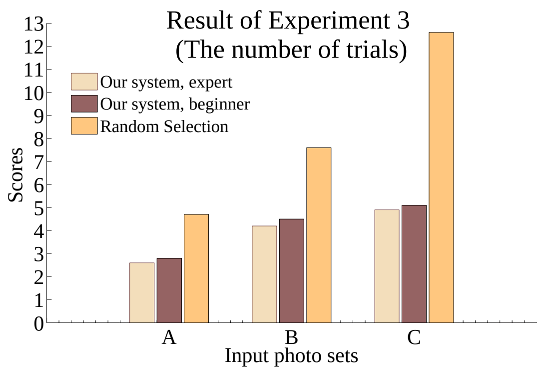

Figure 10: Result of experiment 3. Average number of trials to find all desired photos.

7 CONCLUSION

The digital camera has become an indispensable commodity for people. Tasks related to photo management, such as classification, filtering of a bad quality of photos and their construction, are increasingly part of daily life. The low price of memory allows people to take more and a greater variety of photos. The task of organizing these becomes boring and burdensome. Thus, we propose a representative photo layout system that provides a clustering function for photo collections based on user preference.

Our clustering process used four criteria. First, our system clusters photos into small groups using multiple criteria. Then, we select the representative photo, from each classified photo groups, using a maximal matching graph algorithm. The selected photos are placed on a 2D grid using a similar placement algorithm to PHOTOLAND. The other photos corresponding to the representative photos in the same group are displayed on the upper layer when the user clicks the placed photos in a lower layer. Conclusively, let us summarize the notable contributions of this paper:

1. Our maximal matching algorithm is very useful and efficient in selecting the representative photo.

2. We apply four criteria, such as temporal context, the number of face, blur metric and luminance value in Lab color space, to cluster photos into meaningful groups. Other clustering features can be adopted if that feature is normalized between 0.0 and 1.0.

3. Our system uses two hierarchical layer structure to visualize photo groups based on its representative photos using a method similar to PHOTOLAND's placement algorithm.

The system proposed in this paper was positively received by the participants. They evaluated our system as being an intuitive photo clustering interface. However, the clustered group may at times not be able to find its representative photo. If the edge weight between the group node and its photo node is weak, the pairs are not selected in the process of maximal matching. In this case, we can not display the other photos without the representative photo. We have to develop the solution to this problem.

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