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Color Recommendation for Drawing Based Image Retrieval on Mobile Devices

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Abstract

Color selection plays an important role in drawing based image retrieval. Frequently, users are overloaded by color options to select while drawing the query. In this paper, a color recommendation method dedicated to drawing-to-retrieve image search is proposed and implemented in our draw-to-retrieve application, which aims at assisting users in choosing colors in order to improve image retrieval efficiency in terms of drawing time and retrieval accuracy. Then, this method is tested in a preliminary experiment designed to explore how the image retrieval efficiency is affected when different colors are provided the palette. In order to illustrate an application of proposed approach, images of natural scenes are used as an example. 23 participants took part in the experiment to perform draw-to-target tasks of 36 images using three different color palettes. There are mainly three results concluded from the experiment: firstly, the image retrieval efficiency drops as the difficulty of target image increases; in addition, providing useful colors in the palette can lead to an more efficient retrieval; finally, the retrieval has better performance using our color recommendation approach than commonly used 20-color palette and a subjective evaluation of the participants is also included.

Introduction

Contemporary image search engines for commercial use are mostly text-based [1]. It manages image database in a traditional fashion using text information. Despite the fact that most typical Web search engines have used text annotations to index the images, text based image retrieval (TBIR) has several obvious limitations. It can be powerful as a technique under the circumstances that proper text labels are available in a database. Nevertheless, annotating images consumes a significant amount of manual efforts and time even though some automatic methods are available to extract text information from images. In order to overcome these weaknesses of TBIR content-based images retrieval (CBIR) was introduced by Kato in 1992 [2].

There are three general applications of CBIR including, search by association, target search and category search [3]. The image retrieval studied in this paper case is specifically narrowed down to the second category where a user searches for a particular image that has been seen by him/her before. We consider a specific scenario where neither text labels nor similar images are available. TBIR is obviously not possible; neither is retrieval using an image query. In this situation, drawing seems to be a more feasible alternative to describe query intent. It is noted by Banfi [4] that using drawing to express search intentions is the most flexible way and can be performed by almost everyone [5]. A picture is worth a thousand words [6].

Mobile devices are considered to be ubiquitous. With the proliferation of these touch-screen devices, drawing becomes a more natural and easier way. Nevertheless, finger touch as an input method is less accurate than mouse clicking on PC screens. Therefore, rough color-block drawing tends to be a more feasible option than silhouette sketching for a draw-to-retrieve (DTR) image search system, which makes color features more important during retrieval than other features. As a result, if users are able to choose colors more accurately when drawing, it might lead to a better retrieval result.

However, designing a color palette with the colors that are best suited for drawing a query to search for a specific target image is hard. Firstly, humans are not very good at discerning similar colors. Moreover, color perception is subjective and the same color may be perceived differently by different individuals and different colors may be perceived as the same. Finally, perceptually matching two colors is hard, this is made even harder when one of the colors is from memory only. Therefore, an intelligent system which can recommend suitable colors to the users would be valuable. In order to develop such a system, we take a user-centered approach where user data is collected through a simple mobile game.

Inspired by the concept of game with a purpose (GWAP), a draw-and-retrieve game has been designed and implemented on android platform. GWAP is defined as the type of games which collects useful data as a side effect during the gaming process. Games such as ESP Game [7], KissKissBan [8], Peekaboom[9], PexAce [10] have been developed as a kind of approach for generating and collecting text labels for images through the entertaining gameplay. Similarly, this idea is exploited in our research to collect the drawings for recommending colors as well as evaluating retrieval performance.

Instead of exploring the image retrieval algorithm itself, this paper concentrates on improving the retrieval efficiency by providing assistance in choosing colors at the drawing phase. Specifically, the aim of this research is to firstly examine whether providing closely-relevant colors in the palette can enhance the retrieval efficiency; it also investigates how the image retrieval efficiency can be affected by the difficulty of the target image; it also proposes a color recommendation method to assist users in selecting colors. A draw-to-retrieve game with purpose is implemented on the android mobile platform to collect drawings, measure the retrieval performance and users' satisfaction.

Related Work

Modelling color perception has been widely studied by researchers from various areas: psychology, perception, computer vision, image retrieval and graphics. Some of them resulted in well-defined color spaces, such as RGB, HSV, CMYK, CIE, etc. These intellectual fruits are then exploited in CBIR engines not only for color matching but also color selection interfaces since color is one of the most significant features [11]. Nevertheless, there is not enough effort been put into color selection for user interface design [12]. Generally, CBIR engines simply employ a color space in the color chart in the color pick interface [11]. Furthermore, little attention has been focused on assisting users to refine the many color choices through intelligent recommendation.

A relevant work to ours is a user study on palettes for drawing query on the touchscreen by Zhang et al [12]. While the focus of their study is exploring the effects that different user interfaces of the palettes have on image retrieval, we put our focus on the color choices that a palette provides and study whether retrieval performance can be enhanced through recommending useful color in the palette.

There has been some color recommendation systems proposed before, however, they are designed for other purposes. For instance, [13] proposed a color recommendation system that combines design concepts with interactive customers preference in order to help them select colors. To the best of our knowledge, this work represents the first effort towards designing a color palette with color recommendation to support users in picking colors for draw-to-retrieve image search.

System User Interfaces

System Overview

The whole system is implemented with the Client-Server structure: the Client side allows users to interact with the application on the mobile devices; on the Server side, it 'fetches' different requests from the mobile client end and returns corresponding results as responses to a user's mobile devices.

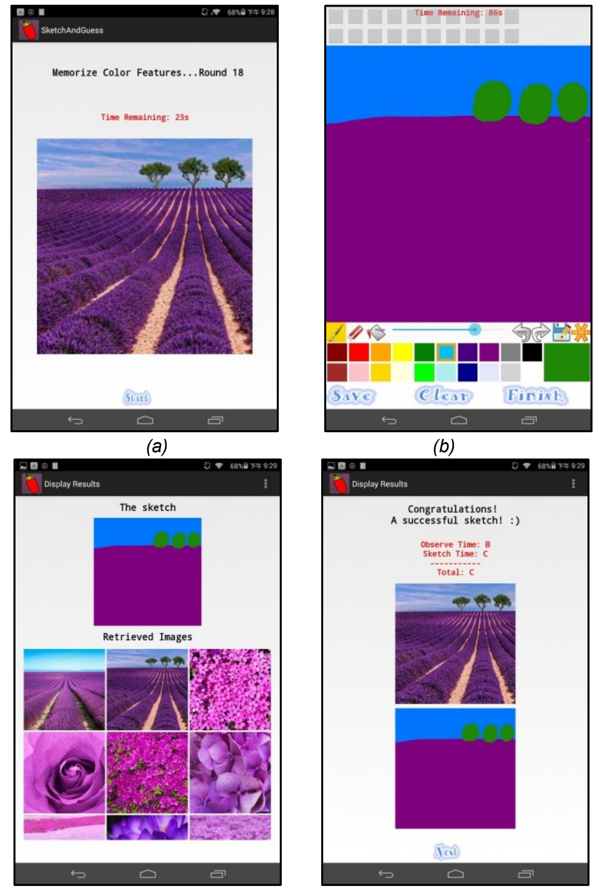
The server side consists of a database and three subsystems i.e. color recommendation system, image retrieval system and game system. Firstly, the Image Retrieval System takes in a query image, search through the image database and returns a list of images according to an image retrieval algorithm. In addition to that, a Game System is built to control the game process, store game information from the client side and respond accordingly to the requests from the client side. It utilizes the concept of game with a purpose to collect data from users through a fun game so that the fatigue or tedium of the users can be reduced during the data collection process. Finally, a Color Recommendation System takes in a chosen color and recommends a list of relevant colors based the color recommendation approach proposed by us, which will be further elaborate later in the paper.

Game Procedure

The game is designed based on the target-retrieval task and includes game elements such as timer and rank so that users can accomplish the tasks in a playful mood. This drawing game includes four steps which are displayed in **Figure 1**. Firstly, a target image is displayed to the player along with a countdown timer. The image will disappear when a preset time is up. At this step, the player is instructed to memorize the color features and layout of the target image. Then the player needs to draw to the target image as closely similar as possible based on memory. Once the player finishes the drawing, he/she could click the finish button to view the retrieval results. A group of 30 images are displayed to the player. If the retrieved results contain the target image the player needs to select it out, otherwise, he/she just shall select a similar image to the drawing. The game score is displayed afterwards. A winning game is when the target image is successfully retrieved, otherwise, the game is considered to be lost. The game score is based on the observation time and sketching time to stimulate players to observe and draw as quickly as they can so that the time efficiency can be evaluated.

Drawing Interface

The basic tools for drawing are provided in the drawing interface. These tools include a brush, an eraser, a seek bar which can adjust the width of brush or eraser, a flood filler, 'Undo', 'Redo', 'Clear', 'Save' and 'Finish' button that finishes drawing and starts searching. Most importantly, the palette is provided to allow users to select colors directly and a color picker dialogue which allows more colors to be chosen.



(a) (b) (c) (d)

***Figure 1.** The user interface and the gaming process. (a) A target image is shown to the player, a timer clock is clicking away. (b) The user is drawing a query image based on memory of the target image using colors from the palette. (c) Retrieved image list. (d) Found the target.*

Color Recommendation System

There are several differences between our Color Recommendation System (CRS) and traditional Recommendation Systems (RS) that recommend shopping items, movies, music, etc. The user story here is that each time a user selects a color in the palette then a set of relevant colors are recommended. In this case, we can treat a chosen color as 'a user' and the target colors as 'the items' preferred by 'the user'. Similar to the idea that RS recommend items to similar users; CRS recommends target colors to similar chosen colors. Another major difference is that it is much easier to acquire the similarity distance of two colors than two human users as the distance of two colors can be calculated by Euclidean distance of two colors in CIE Lab color space. Our CRS employs a combination of collaborative filtering algorithm and K Nearest Neighbors (kNN) algorithm. The merits of kNN are simplicity and reasonably accurate result [14].

Color Recommendation System Process

The work process of the Color Recommendation System is illustrated in **Figure 2**. Once our system collected paired-up target and drawing images, a drawing color from the drawing and its corresponding target colors can be extracted from the target to build up what we call a color matcher. The algorithm takes all the drawing-target images as input, builds up a table of color matchers as output and stores it in the database.

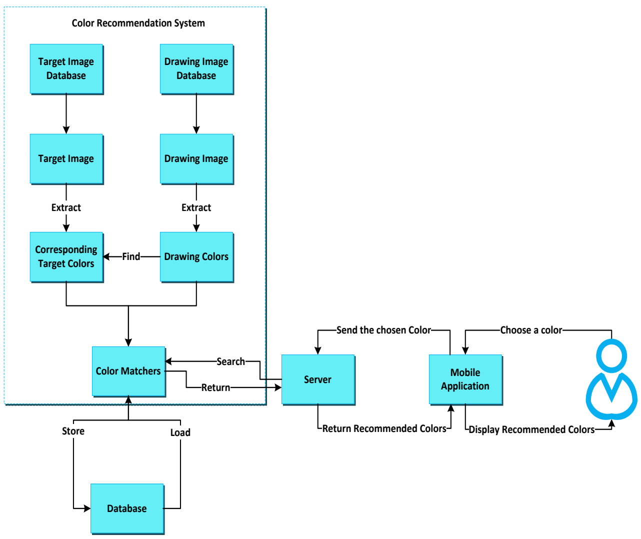


Figure 2. *Color Recommendation System Process Overview*

Algorithm

Generating color matchers

An example of the process of extracting color matchers from a paired-up of drawing and target image according to our algorithm is presented in **Figure 3**. This process includes several steps:

(a) Extract the salient colors from drawing image, filter out color noises by leaving out colors that are less than 1% of the color histogram

(b) Go through the extracted colors, for each of them, find the colors in the target image at its corresponding positions in the drawing image

(c) Match the drawing color with its corresponding target colors in the similarity order and take top-10 of them.

The pseudo code of how the color matchers are generated for color recommendation for the whole image database is provided below:

For each drawing image in the drawing image database. D_i
  Extract color set of the D_i, CD_i
  Find the target image T_i that D_i targets for
  For each color in CD_i, C_jD_i
    Find the color set in the target image T_i that the color C_jD_i covers correspondingly. TC_jD_i
    Record that a drawing color C_jD_i targets at the color set TC_jD_i

Making Recommendation

The method for making recommendations is based on the following three steps:

(a) Using the Euclidean Distance in CIE LAB color space, the set of k neighbors for chosen color *c* is produced. The k neighbors for *c* are the most similar colors to *c*.

(b) In order to generate a candidate list of recommended colors *r* on chosen color *c,* the aggregation approach is performed over the target colors of these k neighbors, those colors are within the just-noticeable-difference.

(c) The top-n (in our case, n=20) colors in the candidate list are recommended.

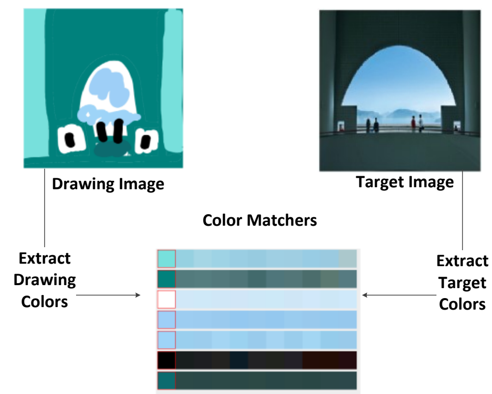


Figure 3. *Creating color matchers from a paired-up drawing and target image (drawing colors in red panes, target colors on the right)*

Experiment

The aim of this study is to enhance the retrieval efficiency of Query-by-Drawing by recommending colors at the drawing phase. The retrieval efficiency or retrieval performance in this paper is mainly evaluated in terms of two aspects: retrieval accuracy and drawing time. Our hypothesis is that if useful colors can be recommended to users when they draw, it will help them select more relevant colors during the drawing process, which may consequently help them to draw a more useful query to improve the retrieval accuracy; in addition, it will reduce the drawing time by saving the time spent on color selection.

In order to verify it, the experiment was proposed to achieve the following aims: firstly, to explore whether the image retrieval performance can be improved by recommending directly relevant colors extracted from the image itself; furthermore, to explore whether the improvement can be achieved by recommending colors using our color recommendation system; lastly, to study how the difficulty of target images affects the retrieval efficiency.

Experiment Design

Three different palettes, shown in **Figure 4** and **Figure 5**,are provided for comparison: Palette 1: quantized 20 colors by median cut [15]; Palette 2: commonly used 20 colors used in Paint of Windows Operating System; Palette 3: a color recommendation palette using our algorithm performed on 439 drawings done by 26 users that were collected through our game, however, the target images are different from the stimuli used in this experiment. Participants are asked to complete 36 draw-to-retrieve tasks, 12 tasks (4 easy, 4 medium, 4 difficult) using each palette; the image database used in this experiment consists 5000 images of natural scenes, flowers and fruits.

Participants

23 participants were recruited from the University of Nottingham Ningbo China, with 40 percent of age of 18-25 years old and 60 percent of age 26-30 years old. None of them are reported color blind, 10 participants have experience with our application.

Device and Stimuli

Two Huawei android tablets with Android 4.4.4 operating system, resolution of 800x1280 and size of 210.6×127.7×7.9mm were used as experiment platform. Both devices were set up to the same level of brightness.

Because the experiment is memory-based, three image groups of similar difficulty are used as stimuli so that each target image is new to the participants. The difficulty levels of images are mainly decided by the salient colors in the image. It is based on our hypothesis that the more salient colors there are, the more difficult it will be for a user to draw because it means more colors he/she needs to memorize. Therefore, the three levels of difficulty of the stimuli are selected in accordance with our hypothesis. The stimuli of 1 to 2 salient colors are categorized into easy tasks; 3 to 4 salient colors for medium tasks and more than 4 salient colors for difficult tasks.

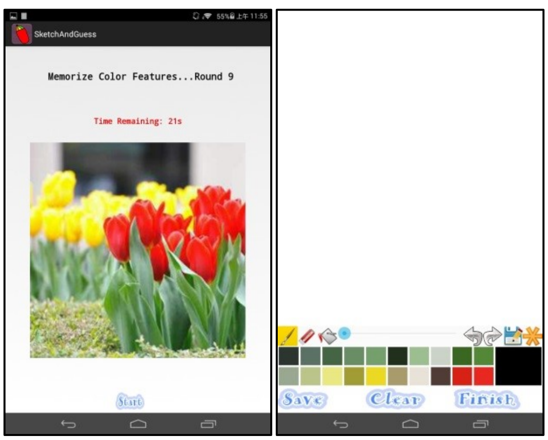


Figure 4: *Palette 1- twenty quantized colors from target image*

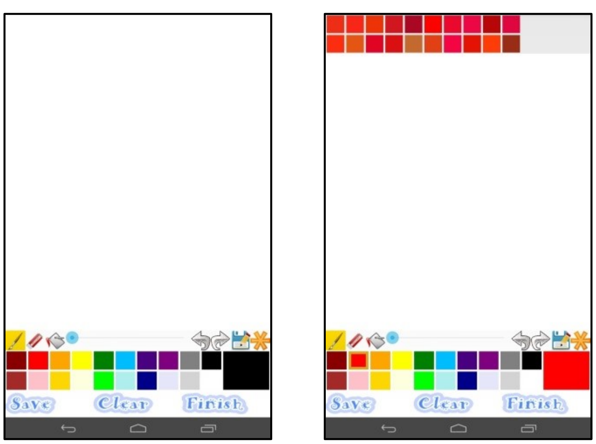


Figure 5: *Palette 2 (left) – twenty commonly used colors and Palette 3 (right) - an extra recommendation palette on top of the screen*

Procedure

A brief introduction about the study is given to the participants and then a printed consent form was handed out for each participant to sign before starting the study. A pre-questionnaire concerning their basic information and experiences with retrieval system is then handled out for them to fill in. Brief information concerning the task procedure was given to the participants, followed by an introduction of the functionalities in the drawing interface. Afterwards they were given some time to sketch freely on the interface until they were familiar with all the functionalities and the game process. Finally, they are informed that they need to accomplish 36 drawings using three different kinds of palettes. After the drawing game session is finished, participants are invited to fill in a post-questionnaire about their experience with the application. During the experiment, the time spent on drawing and the drawings are recorded automatically by the system.

Time Constraints

For each target image, the observation time is restricted to be within 30 seconds while the drawing time is restricted within 120 seconds. However, they are encouraged to move to the next phase as soon as they finish observing or drawing.

RESULTS AND DISCUSSIONS

Only the drawings of the first attempt are analyzed in this section. The independent variables include color palettes, task difficulty and the outcome variables include sketching time, and retrieval accuracy. The image retrieval algorithm for testing retrieval performance is an extended implementation based on the method proposed by Qiu et al [16].

Retrieval Performance Evaluation

The evaluation measure of the retrieval performance is the rank first relevant, which is based on the rank of the target image and the retrieval size is set to be 100 in our case. The following formula is employed to calculate the accuracy.

$$\begin{aligned} accuracy &= \frac{100 - rank + 1}{rank}(rank \leq 100) \\ accuracy &= 0(rank > 100) \end{aligned} \quad (1)$$

According to the formula (1), the accuracy is 100% if the target image ranks 1st in the retrieval result; and 0 if it has not been retrieved in the top-100 list.

The retrieval accuracy is listed in the **Table 1.** As it can be seen in the **Table 1**, Palette 1 achieved the highest average accuracy (71.22%) of the total 12 target images; followed by Palette 3 (49.58%) with slightly higher accuracy than Palette 2 (46.86%).

Table 1: The retrieval accuracy

	Palette 1	Palette 2	Palette 3	Average
Easy	96.76±%	55.49%	68.42%	73.56%
Medium	89.20%	65.93%	48.92%	68.02%
Difficult	27.71%	19.14%	31.38%	26.08%
Average	71.22%	46.86%	49.58%	

Figure 6 is created based on the **Table 1** to investigate how the difficulty of images affects the retrieval accuracy. It can be seen that the average accuracy decreases as the ‘difficulty’ of the tasks increases. The accuracy using Palette 1 and Palette 3 both follow this trend. However, Palette 2 does not quite agree with it particularly in the ‘medium’ image group, the retrieval performance of which somehow reaches the highest.

Figure 7 is used to compare the retrieval accuracy of different palettes on each image groups of same difficulty. As is shown in **Figure 7**, firstly, in the 'easy' image group, Palette 1 (96.76%) outperforms the other two palettes significantly with the accuracy over 95%. Palette 3 ranks the second in the accuracy (68.42%) with 13 percent higher than Palette 2 (55.49%). In the 'median' image group, while Palette 1 (89.20%) remains the best performance among the three however Palette 2 (65.93%) has a nearly 17% percent higher accuracy than Palette 3 (48.92%). In terms of 'difficult' image group, surprisingly, Palette 1 (27.71%) ranked the 2nd behind Palette 3 (31.38%) with a slightly less accuracy of 3.67% while Palette 2 falls behind Palette 3 (19.14%) with nearly 10 percent less.

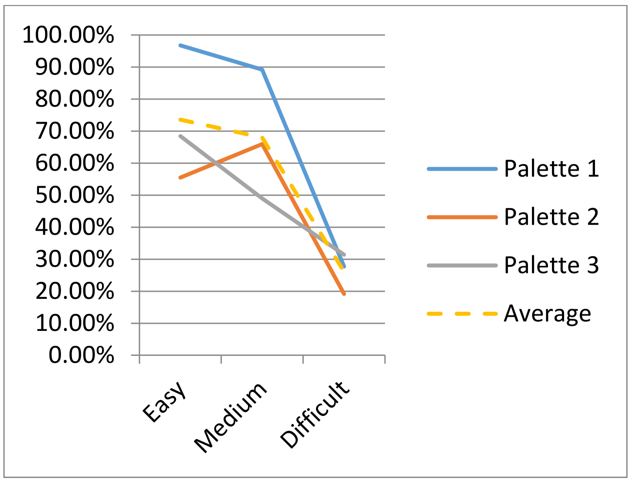


Figure 6. *The line chart of retrieval accuracy*

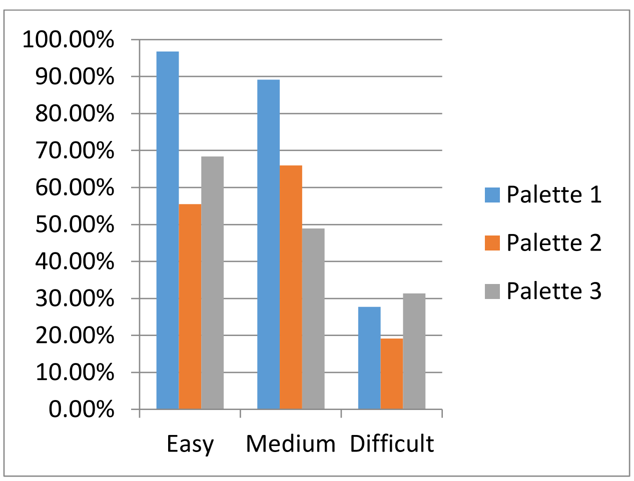


Figure 7. *The bar chart of retrieval accuracy*

Drawing Time

The drawing time during the experiment is recorded in the table 2 and analyzed in **Figure 8**. As it can be seen from **Figure 8**, the participants tend to spend more time on drawing as the difficulty of the image groups increases. The average drawing time using Palette 1 is about 55s, which is the shortest among the three; followed by the average time using Palette 3 with 65.5s; and the time spent on Palette 2 is the longest with an average period of nearly 70s. These ranks remain the same order in despite of the changes in image difficulty.

Table 2: The drawing time

	Palette 1	Palette 2	Palette 3	Average
Easy	43.92	64.73	57.45	55.37
Medium	56.72	68.79	68.45	64.65
Difficult	65.04	76.02	70.72	70.59
Average	55.23	69.85	65.54	

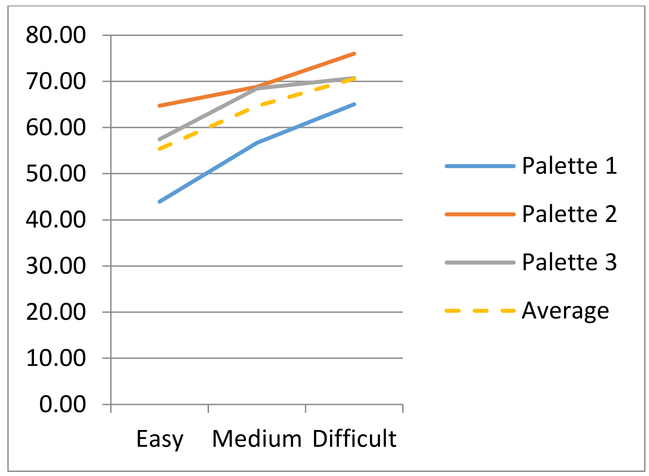


Figure 8. *The Average drawing time (in seconds)*

Subjective Evaluation

Post questionnaires were designed to gather subjective experience from participants about the effort and preference in selecting colors using these three palettes.

Recall of Memory

The question is asked to what extent (from 1 to 5) participants think Palette 3 recalls the memory of colors in the target image. And the result is concluded in **Figure 9**. About half of the participants indicate that Palette 3 largely recalls their memory while a quarter of them note that it somehow remind them of desired colors. Only about 20 percent participants have the opinion that it does not help remember those colors.

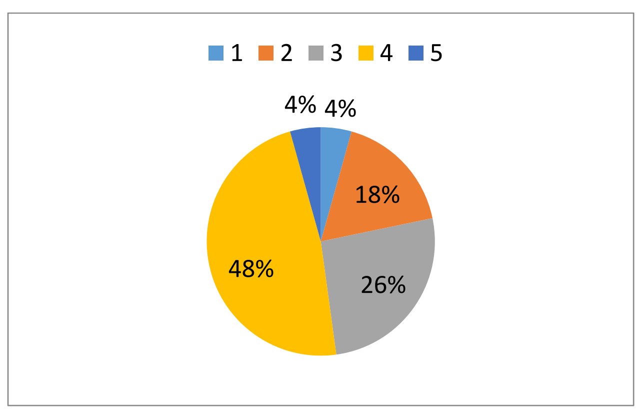


Figure 9. *Subjective Response: recall of memory. 1: not at all; 3 somehow; 5 very much.*

Comparison of Effort and Preference

The post-questionnaires also include questions that to collect their subjective opinions on effort in selecting desired colors and preference between Palette 2 and Palette 3. The results are illustrated in **Figure 10**. Over 85% of the participants find that it takes less effort in finding the desired colors using Palette 3 and nearly 80% indicate that they prefer to use Palette 3 than Palette 2.

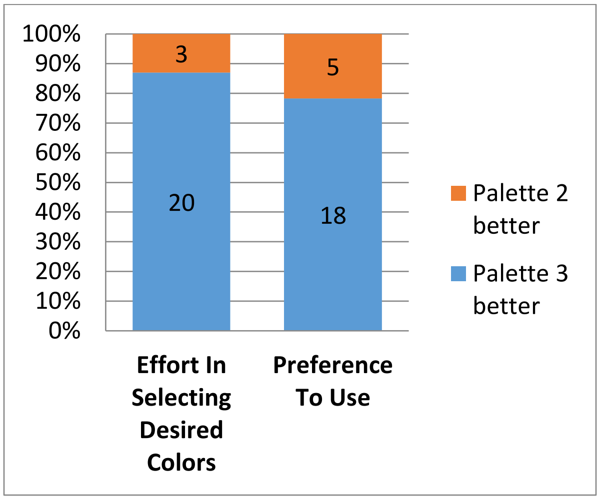


Figure 10. *Subjective Evaluation: Comparison of effort and preference*

Conclusion and Future Work

We explored three different color palettes in a draw-to-retrieve image search mobile game called Draw-And-Retrieve. A user study of 23 participants was carried out, during which the drawing time and retrieval accuracy were recorded to evaluate retrieval efficiency. There are several conclusions we can draw from the study. Firstly, the result shows that there is a trend that the retrieval performance including drawing time and retrieval accuracy decreases as the complexity of the target image increases. This trend persists even when highly relevant colors (Palette 1) are provided at the drawing phase. This indicates that draw-to-retrieve paradigm may be useful in the scenarios where users only need to search for simple images of less 5 salient colors as the target image can be found in the top-50 retrieval list (average accuracy is over 50%). Furthermore, by comparison Palette 1 (20 quantized colors) and Palette 2 (20 commonly used colors), it can be seen that users can perform the retrieval within shorter time and have better retrieval performance when straightforward relevant colors to the target are provided. Nevertheless, in real retrieval scenario, it is more often that the target image is not known by the system beforehand. Therefore, it is difficult to directly recommend these highly-useful colors to users. The future work will investigate how this result can be used in refine procedures where users' feedbacks of retrieval are available for predicting relevant colors. Finally, by comparing Palette 2 and Palette 3 (our color recommendation), it shows that our color recommendation method can help improve retrieval efficiency in terms of retrieval accuracy and drawing time to some extent; and it also meets most users' satisfaction. As is said, this is a preliminary experiment for color recommendation. The future work will study alternative algorithms and methods that can be utilized for color recommendation.

References

[1] H. Jan-Ming, L. Shu-Yu, F. Chi-Wen, W. Yu-Chun, and I. C. Ray, "A novel content based image retrieval system using K-means with feature extraction." pp. 785-790.

[2] T. Kato, "Database architecture for content-based image retrieval." pp. 112-123.

[3] A. W. M. Smeulders, M. Worring, S. Santini, A. Gupta, and R. Jain, "Content-based image retrieval at the end of the early years," *Pattern Analysis and Machine Intelligence, IEEE Transactions on,* vol. 22, no. 12, pp. 1349-1380, 2000.

[4] F. Banfi, "Content-Based Image Retrieval Using Hand-Drawn Sketches and Local Features: a Study on Visual Dissimilarity.," 2000.

[5] G. C. D. Silva, T. Yamasaki, and K. Aizawa, "Sketch-Based Spatial Queries for the Retrieval of Human Locomotion Patterns in Smart Environments," *Advances in Multimedia,* vol. 2009, 2009.

[6] K. Tollmar, T. Yeh, and T. Darrell, "IDiexis: Mobile image-based search on world wide web-a picture is worth a thousand keywords," *Proc of Mobisys*, 2006.

[7] A. Luis von, and D. Laura, "Labeling images with a computer game," *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems %@ 1-58113-702-8*, ACM, 2004, pp. 319-326.

[8] C.-J. Ho, T.-H. Chang, J.-C. Lee, J. Y.-j. Hsu, and K.-T. Chen, "KissKissBan: a competitive human computation game for image annotation," *Sigkdd Explorations,* vol. 12, no. 1, pp. 21-24, 2010.

[9] L. v. Ahn, R. Liu, and M. Blum, "Peekaboom: a game for locating objects in images," in Computer Human Interaction, 2006, pp. 55-64.

[10] J. Simko, and M. Bielikova, "Games with a Purpose: User Generated Valid Metadata for Personal Archives." pp. 45-50.

[11] v. d. E. Broek, L. Vuurpijl, P. Kisters, and v. J. Schmid, "Content-based image retrieval: Color-selection exploited," 2002.

[12] M. Zhang, G. Qiu, N. Alechina, and S. Atkinson, "User study on color palettes for drawing query on touchscreen phone," *Proceedings of MHCI*, 2013.

[13] L. Rodriguez, L. Diago, and I. Hagiwara, "Color recommendation system combining design concepts with interactive customers preference modeling from context changes." pp. 1-8.

[14] J. Bobadilla, F. Ortega, A. Hernando, and A. Gutiérrez, "Recommender systems survey," *Knowledge-Based Systems,* vol. 46, pp. 109-132, 2013.

[15] P. Heckbert, "Color image quantization for frame buffer display," in Proceedings of the 9th annual conference on Computer graphics and interactive techniques, Boston, Massachusetts, USA, 1982, pp. 297-307.

[16] G. Qiu, J. Morris, and X. Fan, "Visual guided navigation for image retrieval," *Pattern Recognition,* vol. 40, no. 6, pp. 1711-1721, 6//, 2007.

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