Composing Mood Board with User Feedback in Concept Space

Shin Sano[1] and Seiji Yamada[2]

[1,2]Department of Informatics, Graduate University for Advanced Studies (SOKENDAI), Tokyo, Japan
[1]Institute for Creative Integration, Oakland, CA, United States
[2]Digital Content and Media Sciences Research Division, National Institute of Informatics, Tokyo, Japan
Email: [1]ssano@creative-integration.com, [2]seiji@nii.ac.jp

Abstract

We propose the Mood Board Composer (MBC), which supports concept designers in retrieving and composing images on a 2-D concept space to communicate design concepts visually. The MBC enables users to search images intuitively. Its algorithm adapts the query vector for the next search according to the user's rearrangement of images on the 3×3 grid. The next image search is performed by obtaining the most similar words from the adapted mean vector of the images on the grid thus obtained and using them as a new query. Our participants' experiment with 211 cases of mood board creation confirmed the effectiveness of adaptive iterations by the Creativity Support Index (CSI) score.

Introduction

Mood boards are visual artifacts often used as design development tools to communicate and share design ideas, such as emotions, feelings, or "moods" between stakeholders(Lucero 2012). They are often used in design practice and education, such as thinking externalization, meaning acquisition, and conceptual reasoning (Li and Zhao 2021). Mood boards are also used as qualitative design research tools facilitating creative thinking, presenting and communicating products (Cassidy 2011), communicating the designers' imagination and ideas they are pursuing (Edwards, Fadzli, and Setchi 2009). Bouchard et al. (2005) discuss the role of mood boards as intermediate representations (IR) in design at different levels of abstraction.

A mood board-composing task involves a variety of algorithmic problems to solve, such as image retrieval, search strategies, computer vision, semantic feature engineering, natural language processing, and query expansion and modification based on user feedback. Setchi et al. (2011) attacked the problem of the semantic gap of content-based image retrieval, and proposed a semantic-based approach that relies on textual information around the target image to avoid low-level and literal labels from given images. The method extracts the most relevant words in a document utilizing TF-IDF and a general-purpose ontology to expand the queries to find more of relevant images. Koch et al. (2019) created an interactive digital tool to support designers in creating a mood board, utilizing exploration-exploitation strategy optimized by a cooperative contextual bandit reinforcement learning algorithm. They further advanced the digital mood board tool(Koch et al. 2020), utilizing Google's Vision API to assign semantic labels to each image. The above two studies incorporates user feedback while engaged in the mood board creation task. Yet, no prior research has used the positions of images on the mood board to adjust queries for new images, and assumed a semantic space model on a quadrant system on which designers can position their ideation relative to the Design Concept Phrases (DCP) (Sano and Yamada 2022) of a target design concept.

Method

The MBC is an AI-assisted interactive web application designed to be used by concept designers who wish to explore and communicate their design concepts visually. It also intends to build on the idea of the Character Space (CS) and the Design Concept Phrase (DCP) (Sano and Yamada 2022), on which users explore design concepts in a lexicosemantic space. Mood boards composed by MBC are constructed in a grid of $n \times m$ tiles. Although no prior research specifically found the optimum number of images on a mood board, a few recent studies have indicated that participants in their studies typically handle 5 to 12 images per mood board(Koch et al. 2020; 2019; Zabotto et al. 2019). Aliakseyeu et al.(2006) experimented with different sizes of digital image piles to compare human performances on navigation, repositioning, and reorganizing tasks and found significant differences in task performance between two different pile sizes (15 and 45). In our development and experiment, we chose nine images with a 3×3 grid to facilitate users in quick glancing and iterations while maintaining the capability to represent an original design concept with combinations of the images. The size of the mood board was also considered in terms of the participants' experiment logistics and task load as we planned to conduct a large-scale experiment. The MBC uses a DCP as queries and searches images from Adobe Behance(Wilber et al. 2017). The UI renders the upper right quadrant of the Character Space (CS), consisting of word 1 and word 2 as attributions on the semantic axes (Fig.1-C,D). The proposed MBC system is designed to encourage users to iterate the exploration of images till they are satisfied with the overall mood board composition. Various cost factors can hinder these iterative processes, such as the time and effort to collect materials, trying different search queries and re-

Image References:

https://www.behance.net/gallery/113437545/CSW/modules/648144727

https://www.behance.net/gallery/82167757/COSH-series-of-armchairs-for-Boliacom/modules/476202235

https://www.behance.net/gallery/90111067/The-Hoffmann-Collection/modules/520974885

https://www.behance.net/gallery/145381227/Kioto/modules/821319521

https://www.behance.net/gallery/114951215/Wesley-Faux-Leather-Lounge-Chair-Set-3D-Model/modules/656201147

https://www.behance.net/gallery/13899989/Re-turned/modules/96236775

https://www.behance.net/gallery/149515177/Silky-(2022)/modules/844396881

https://www.behance.net/gallery/147913281/Dedas-public-seating-system/modules/835536071

https://www.behance.net/gallery/114951215/Wesley-Faux-Leather-Lounge-Chair-Set-3D-Model/modules/656201147

Figure 1: The proposed MBC system UI. It allows users to move any image within the 3×3 matrix. Moving images upward (G) will weight more of the semantics of the word 1 (C), "ergonomic", and moving images to the right (H) will weight more of the semantics of the word 2 (D)"comfortable" when it performs the next search.

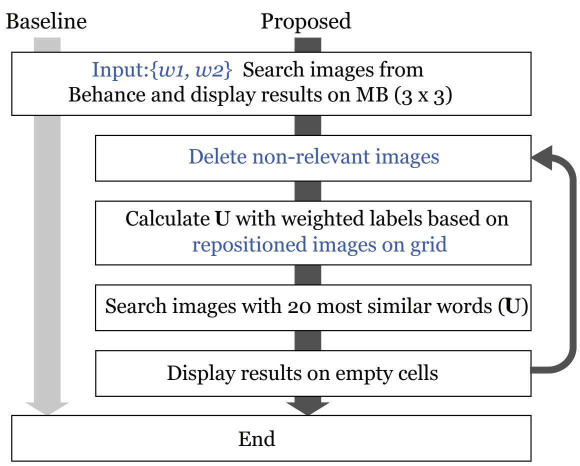

Figure 2: Variations of Mood Board Composer (MBC) algorithms. Text in blue shows the user's operations

sources, and figuring out the compositions. Edwards et al. (2009) discussed that the iterative process could be discouraged due to the vast choice of images offered by digital resources. They further argued that once images are selected, confidence is built so that users feel the continuous search for new material would be futile. To confirm the positive effect of iterative processes and overcome this iteration cost, we designed our experiment in the following ways. We first set up a comparative experiment between a baseline system that does not involve users' iterations for composing a mood board and the proposed system, which allows users to iterate as many as they like. We aimed to implement low-cost and high-engagement interaction so that the users can effortlessly try the optimum number of iterations to get the best experience in mood board creation tasks. We developed two separate systems, the baseline system, which does not support iterations, and the proposed system. Figure 2 shows the overall differences in the algorithms each system takes.

Baseline Search Algorithm

The baseline tool first receives the user's query (Q) input as two adjectives, (w_1, w_2), in the two search windows (Fig.1-A). When the "START" button is pressed, the system will search images on Behance in three "Fields," which are "Industrial Design," "Architecture," and "Fashion," which are likely to contain more of style elements such as form and CMF (Color, Material, and Finish) than, for instance, "web and graphic design" does. The candidates of images are ranked by relevancy and sorted per field. The top nine images are then randomly assigned to an empty grid of the 3×3 image set (D) of the mood board. This single session concludes the algorithm, and the user can export the mood board as a PNG file.

Proposed algorithm - Query update with average vector calculation

The proposed algorithm (Algorithm 1) involves query modifications based on user feedback. For each image on the current mood board, the system acquires semantic labels from the Google Vision API (Chen and Chen 2017). The Vision API uses pre-trained machine learning models, assigns labels to images, and classifies them into millions of predefined categories. The proposed system obtains the top five labels for each image on the mood board, ranked by the confidence score. Let $D\,(d_1, d_2, ..., d_m)$ be the image set on the current mood board, where d_i is the i-th image on the mood board, $L^i\,(l^i_1, l^i_2, ...l^i_k)$ be the labels for each image, where l^i_j is the j-th label for image d^i, and $S^i\,(s^i_1, s^i_2, ..., s^i_k)$ be the confidence score from the Vision API assigned to each label, where s^i_j is the score of the j-th label for image d^i. For each image label l^i_j in the set of image labels L^i nested under each image d_i on the mood board D, the system assigns label vectors using Concept Net Numberbatch word embedding. Let $\boldsymbol{V}^i\,(\boldsymbol{v}_1^i, \boldsymbol{v}_2^i, ..., \boldsymbol{v}_k^i)$ be the vectors of the labels $L^i\,(l_1^i, l_2^i, ...l_k^i)$, where $\boldsymbol{v}_j^i$ is the vector of the j-th label for image d^i. A mean vector $\overline{\mathbf{v}}_i$ of the image d_i can be calculated as follows:

$$\begin{aligned}\overline{\mathbf{v}}_i &= \frac{(s_1^i \boldsymbol{v}_1^i + s_2^i \boldsymbol{v}_2^i +, ..., s_k^i \boldsymbol{v}_k^i)}{k} \\ &= \frac{1}{k}\sum_{j=1}^{k}\{s_j^i \boldsymbol{v}_j^i\}\end{aligned} \tag{1}$$

where k is the total number of labels for image d_i.

Algorithm 1 Proposed (updating query)

```
 1: function NEWQUERY
 2:     Q^new := []
 3:     L, S, V := []
 4:     Wt := []
 5:     v̄_i := [], Weighted v̄_i := []
 6:     U := []
 7:
 8:     for each d_i in D do
 9:         L.append(VisionAPI(d_i))
10:         S.append (VisionAPI(d_i))
11:         Wt.append (OnDropWeight(x, y))
12:         for each l_i in L do
13:             V.append (ConceptNetVector(l_i, s_i))
14:             if cosSim(l^i, w_1) > cosSim(l^i, w_2), then
15:                 Weighted v̄_i = v̄_i × Wt(β)
16:             else
17:                 Weighted v̄_i = v̄_i × Wt(α)
18:             end if
19:         end for
20:         U := Mean (Weighted v̄^i)
21:     end for
22:     Q^new.append (MostSimilarWords (U))
23: end function
```

The proposed system lets users reposition images on the mood board's 3×3 matrix. This operation determines which of the labels on images should be enhanced towards the semantics of either word 1 or word 2 by classifying the image labels into two classes, w_1_labels, and w_2_labels. Then, only one of the pairs of position weights, $Wt(\alpha, \beta)$ (Fig.3), assigned to each grid is multiplied for the labels that are classified as the class of label. This classification is performed by comparing the cosine similarity ($CosSim$) of each label to the vector of w_1 and w_2 (Algorithm 1-14). For example, if a label vector is more similar to the meaning of w_1, the label is classified as a w_1 label, and the label vector is multiplied only by the β value (w_1 on y axis side) of the pair of position weight $Wt(\alpha, \beta)$. This way, the user's repositioning an image towards a particular direction on the matrix will provide feedback to the system (Fig.1-G,H). The system, in effect, will detect the users' intention to enhance a particular semantics in the following search without having to modify the query explicitly. The position-weighted average vector $_{Weighted}\overline{\boldsymbol{v}^i}$ of the repositioned image d_i will be updated as described in Algorithm 1 (14 -17). As for the paired weight for each position in the 3×3 grid, which will be multiplied by a label vector, we have tested two options with several initial queries. Figure 4 shows the weight array we implemented. It keeps the images fairly close to the user's intention while expanding the semantic space to explore.

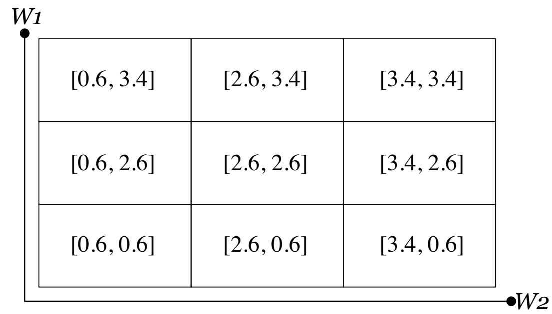

Figure 3: Pairs of position weights $Wt(\alpha, \beta)$ on the mood board matrix. These weights are assigned upon dropping the image to (x, y) coordinates.

The final step before updating the new query is to get the average vector of all the current images on the board, which can be calculated as follows. Let $\mathbf{U}$ be the average of all the weighted vectors for the images $\left\{_{Weighted}\overline{\mathbf{v}}_1, {}_{Weighted}\overline{\mathbf{v}}_2, ..., {}_{Weighted}\overline{\mathbf{v}}_m\right\}$ on the board.

$$\mathbf{U} = \frac{1}{m}\sum_{i=1}^{m} {}_{Weighted}\overline{\mathbf{v}}_i \tag{2}$$

where m is the number of images on the current mood board.

Calculating most similar words To update the query for the next search, the system will get the top 20 most similar words according to the input, in this case, $\mathbf{U}$, the average vectors of all weighted vectors for images on the mood board D. The system computes the cosine similarity ($CosSim$) with the normalized input vectors and outputs the top-N words in $CosSim$. This function is implemented as a method in a Python package, gensim.models(Srinivasa-Desikan 2018).

Experiment Design

The study protocols below have been approved by the Institutional Review Board of the National Institute of Informatics, Tokyo, Japan (Approval number 0042).

Participants and Independent Variables

120 participants, whose job function was "Arts, Design, or Entertainment and Recreation" and who was fluent in English, were recruited via Prolific(Palan and Schitter 2018). 11(9.17%) did not complete the study due to system trouble or unknown reasons. This left us with a total of 109 participants (50 M, 55 F, 4 Non-binary) who completed the study, with a mean age of 33.00 years (σ = 11.34). The participants who completed the study were paid US$12. All

participants were asked to perform the mood board creation task twice with the same type of MBC system. The between-participant factor was the difference in the used MBC system (Fig.2), and the within-participant factor was the two different Design Concept Phrases (DCP) they were given to use as the initial query Q. The factor incorporated in these two DCPs was the $CosSim$ between word 1 and word 2 in the DCP. The near DCP was "Ergonomic Comfortable," and the far DCP was "Relaxed Skillful." The $CosSim$s of those two DCPs were 0.4528 and 0.0053, respectively. The order of the DCP they used in the two tasks was assigned randomly in a counterbalanced order.

Dependent Variables

We used the Creativity Support Index (CSI)(Cherry and Latulipe 2014) as a post-task psychometric measurement to compare four conditions, with a baseline MBC and an experiment MBCs, in terms of supporting creativity in a mood board composition task. The CSI The CSI has a rigorous protocol, which evaluates the result of creation in relation to a user's effort, such as "I was satisfied with what I got out of the system or tool." This is suitable for tools designed for experienced users who know what the creative outcomes are and what the ideal experiences in creation are.

In addition, we employed a single-item measurement for remaining mental resources, the Gas Tank Questionnaire (GTQ)(Monfort et al. 2018), immediately before and after each task. The GTQ attempts to measure users' cognitive load who engage in a task without burdening them by asking multiple questions. The GTQ asks a question, "Think about your brain as an engine. Slide the fuel tank indicator (0 to 100) below to show how much gas you have left now." We took the differences between Gas Tanks before and after the task as a value that indicated the mental resources consumed to perform the task.

Stimuli and Tasks

Participants were randomly assigned to either of the four groups, two counter-balanced groups in different distance DCPs for each baseline and experiment tools and given instructions on the experiment. The MBC tool was provided to the participant as a web link along with the DCP. The participants were asked to download the mood boards they created to their local computers and upload them to the questionnaire on Survey Monkey. They then went through all the CSI questionnaires, followed by the second pre-task GTQ, the second task with the same tool and the other DCP, and the second post-task GTQ. Finally, they responded to a Paired-Factor Comparison that gave weight to each category of CSI evaluations across both tasks.

Results and discussion

Note that of all the 218 cases, 4 cases were disqualified because their responses to the CSI questionnaire had identical scores all the way through the survey (all 0 or all 10), and 3 cases were excluded because they did not upload valid mood boards, which left us with 211 cases (58 baseline and 49 proposed tool cases) for the final analysis.

Table 1: Mean CSI and Mental Load (GTQ) by tool

	Baseline(σ)	Proposed(σ)	p	Cohen's d
CSI	$21.05(12.36)$	$52.57(24.98)$	$< 0.001^{**}$	1.64
GTQ	$-0.86(9.89)$	$2.85(8.74)$	0.04^{*}	0.40

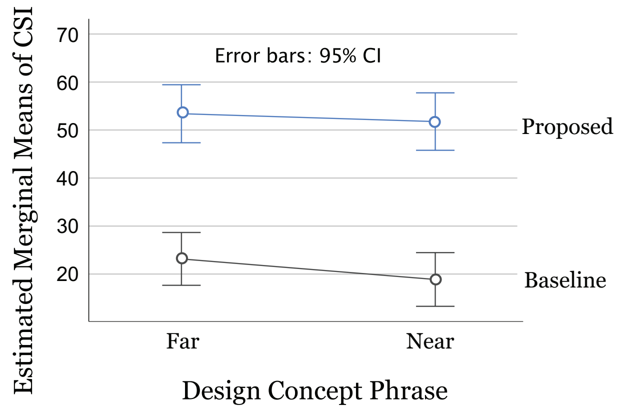

Figure 4: Variance in mean CSI for two different DCPs.

Creativity Support Index

Table 1 shows the mean CSI score and the mental road, measured by the GTQ, between by the tool. The CSI score of the proposed tool was significantly higher than that of the beseline tool, and the mental load of the proposed tool was significantly higher than that of the baseline tool.

Within Participant Factor

Fig. 4 shows the variance in the tool's estimated marginal means of the CSI scores for two different DCPs. The CSI scores with the baseline tool with far and near DCP were 23.15 and 18.87, respectively, which had a significant tendency ($p = 0.064$). With the experiment tool with far and near DCP were 53.40 and 51.76, respectively, which was not significant.

The proposed algorithm, which allowed the participants to iterate the image search interactively, was valid in supporting creativity in the mood board composition task, demonstrated by the CSI score. The values of the pre-task and post-task GTQ between the proposed tools and the baseline tool suggested that the users may have felt exhausted by the operation they had to follow on the proposed algorithm. However, the CSI score clearly shows that the cost is worthwhile. On the other hand, the proposed tool may have left users unclear about how repositioning images on the grid exactly works. Meanwhile, the CSI score difference between far DCP and near DCP seemed to be more apparent with the baseline tool than with the proposed tool. This implies that a potential disadvantage of near DCP may have been compensated by the proposed tool when users are engaged in a visual task.

One limitation of the work is that the way we set up the experiment in comparing the effectiveness of the proposed algorithm to the baseline tool. While we did not find comparable prior studies which uses the grid system to compose a mood board, we had to rely on a rather an artificial baseline tool on our own. In the future we plan to compare variations of iteration algorithms to compare what element of the iterative algorithms, for example, comparing repositioning the images on the board vs. operating the semantic labels on each image directly, and so on. Also, more detailed analysis on the factor scores of the CSI may reveal which aspect of the creativity was supported by what algorithms, which is also our future work.

Conclusion

Through experimenting with the two different MBC tools, we confirmed the effectiveness of the iterative process that allows user feedback, making the mood board creation task more engaging for concept designers. The present study contributes to the field of computational creativity by offering adaptive query updates utilizing the 2-D semantic space where users can rearrange the images on the mood board. Our post-hoc analysis of the CSI and GTQ scores suggest the participants may have been exhausted by the complex process of iterations, yet the effect of the creativity support overcame the cost. We also observed that the characteristics of the initial verbal query may be a strong factor for users to feel creative about the concepts they are operating, but the proposed tool may close such gaps.

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