Towards Enabling Synchronous Digital Creative Collaboration: Codifying Conflicts in Co-Coloring

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ABSTRACT

Humans are unique in working collaboratively by sharing and understanding intentions. However, digital collaboration is daunting, especially in creative design life cycles, due to non-linear workflows and lack of micro-alignments coupled with the need for robust network connectivity. We present a formative study with creatives to identify key themes in conflicts that arise in this space. We introduce CollabColor, a user interface that aids in resolving conflicts for two users synchronously collaborating on a low-touch creative task. More specifically, given an uncolored line-art on a canvas and a set of reference images from the users as input, we arrive at design goals for an intelligent system that can enhance our interface. We find that such a system must provide non-obtrusive interventions during real-time collaboration to ensure that the final colorization of the art is coherent, and all the users' aligned preferences are incorporated.

CCS CONCEPTS

• **Human-centered computing → User interface design**; *Collaborative interaction.*

KEYWORDS

collaboration, creativity, conflict resolution, support system

ACM Reference Format:
Suryateja BV, Jeet Patel, Atharva Naik, Yash Parag Butala, Sristy Sharma, and Niyati Chhaya. 2022. Towards Enabling Synchronous Digital Creative Collaboration: Codifying Conflicts in Co-Coloring. In *CHI '22: ACM Conference on Human Factors in Computing System, Apr 30–May 06 2022, New Orleans, LA.* ACM, New York, NY, USA, 7 pages. https://doi.org/10.1145/3491101.3519789

CHI '23, Apr 30–May 06, 2022, New Orleans, LA

ACM ISBN 978-1-4503-9156-6/22/04…$15.00
https://doi.org/10.1145/3491101.3519789

1 INTRODUCTION

Collaboration is a process of accumulating shared information, aligning on choices, and acting on it together [38]. Collaboration happens everywhere – ranging from music bands to business meetings, and in co-editing documents. In nature, we find several examples of species of ants or bees that live in large colonies and cooperate with optimal work division to collect food and survive [17]. Ever since the Covid-19 pandemic raged, companies and institutions have accelerated towards a "digital-first" approach of collaboration. However, due to lack of alignment of daily intentions, excessive hidden work, bad network connectivity, and an overall lack of common view, collaboration has shifted from unifying and exciting to time-consuming and daunting [1].

The perils of digital collaboration are worsened in creative design workflows [35]. Art directors provide reviews across the entire creative life cycle leading to a non-linear workflow with significant back-and-forth between ideation, creation, and the feedback phases. In particular, the creation phase involves lots of conflicts among co-creators when choosing appropriate colors, fonts, shapes, etc. wherein simple merging would lead to unpleasant outputs. Carefully delegating individual tasks to creators and forgoing collaboration could be a solution, but a recent work by Parikh and Zitnick [29] found that individual creators provide value, whereas collaboration leads to more novel and surprising designs. This motivates us to focus on easing collaboration in the creation phase.

Prior to 1962, machines were largely seen as tools for solving heavy numerical problems. In 1962, Douglas Engelbart's [5, 8] proposal of using machines to augment human intelligence propelled researchers to think of them as real-time interactive systems. Today, humans and machines collaborate in various disciplines to produce highly creative outcomes [11, 14, 31]. Recent studies on human-machine co-creativity [16, 25] discuss the perception and utility of automated tools in supporting creative work, especially in the discovery stage of design projects. However, the situation of two or more humans collaborating on a creative task with software support is still in nascent stages of exploration. A genre of creative support tools called Casual Creators [1] [7, 26, 30, 36] have only been deployed recently as test-beds to understand this scenario better. Building an intelligent system that aids two or more users not only in casual co-creative explorations, but also in solving creative tasks

[1]Casual Creators are tools that allow users to pursue their creative intentions casually without any pressure of achieving certain goals

poses several challenges: (i) the system must understand the creative motivations of all users in context of the current state of artwork and arrive at a *high-level* shared perspective that adds value; then, (ii) the system must promote *low-level* conflict-resolving actions during the co-creation process while not obstructing or limiting the imagination of users.

Prior to building such a system, it is critical to understand what are the exact conflicts that occur in digital synchronous creative collaboration. In this paper, we present a formative study to quantify such conflicts conducted on a novel user interface built to support Co-coloring for creatives. Specifically, we consider flat line-art colorization as the creative task of interest. We believe, such a interface supported with intelligent algorithms based on the outcome of our formative study can help support the research in humanities and social studies towards leveraging creativity for improved societal mental health.

We introduce, CollabColor, an user interface that allows two users to synchronously collaborate on flat line-art colorization. We then conduct user studies to derive insights into key conflicts that occur during co-creative task of flat line-art colorization. The user interface design, the studies, and the insights are detailed in this paper.

2 RELATED WORK

We discuss prior art around studies on support systems that enhance creativity here. CoDraw [19] presents two AI-based neural models called drawer and teller that interact to generate a clipart-based scene. Each of these models can be used in isolation to assist humans in generating creative scenes. While this provides us a framework to reason about, we build a system that has a model to assist *two* humans collaborating on a creative task. There are several works that consider this teller-drawer architecture to design assistive tools. For instance, Creative Sketching Partner [16] presents an AI drawer that sketches variants for ideation based on user inputs of visual and conceptual similarity. Casual Creators such as GANimals [9] foster data collection for human-human co-creativity but do not consider ways to resolve conflicts.

There are other examples of interactive support systems such as Vocal Shortcuts for designing [20], StreamSketch for livestreaming [24], Ideawall for collaborative ideation [34], and Scones [15] for sketching via natural language commands but none of them build strong intuitions for processing long sequences of user interactions or help reduce conflicts.

While no previous work defines metrics for creative conflicts during colorization, Gu et al. [12] devise techniques for understanding and aiding conflicts in the text domain. Kuiter et al. present variED [21] and define conflicts and data structures for collaborative editing in the context of coding software. Similarly, Owhadi-Kareshk et al. [28] devises features out of GitHub code versions to predict merge conflicts. We note that text conflicts are easier to quantify as compared to creative conflicts that are ambiguous and subjective.

2.1 Interactive Colorization

Several works in Computer Vision literature tackle the problem of colorization of raster images [10, 18, 23, 40, 41]. Zhang et al. [40] devise a convolutional neural network that colors grayscale images into RGB images. Barnes et al. [3] point out the vast design space of creative tasks like colorization and posit that user interactivity is paramount to good colorizations. Motivated by this, Zhang el al. [41] further fine-tune their architecture to allow for interactivity wherein users can pick pixels in the image and enlist their color preferences. However, none of these work in the context of co-creativity that we approach in this paper.

3 FLAT COLORIZATION OF LINE-ARTS: DATASET CREATION

Our key goal is to identify and understand the conflicts that occur in synchronous online collaborative colorization. In order to do so, we first create a user interface, CollabColor, that allows two users to color the same line art together. We also need to find a uniform dataset of such line art images that can be shared across users for the synchronous colorization task. In order to ground the final colored images w.r.t how users usually color a given image, we need a dataset that not only has line arts (uncolored) but also contains a corresponding colored version of the same image (which becomes a reference when deriving insights) [2]. Further, the dataset also needs to have sufficient number of semantic segments so that multiple users can collaborate. Easy images won't really suffice.

We obtain flat colored raster images from the web and convert them to SVG images. Inspired by automatic generation of fake images using Photoshop Scripting [37], we process a large batch of raster images and convert them to SVGs using built-in tracing functionality of a popular image editing tool. Although raster-to-vector tracing is a hard task [22], flat colored images with closed line segments are easier to trace. We thus obtain our dataset of 255797 SVG images of 4418 unique line-arts, boiling down to nearly 58 alternate colorings per line-art. This captures the inherent multimodality of the coloring process [6] and ensures that our images cater to a diverse set of users. Figure 2 shows a schematic diagram of our data preparation pipeline. Figure 3(a) shows an uncolored line-art with six alternate colorings and associated tags. From Figure 3(b), we can see that our images in our dataset contain 30 segments on average, making it feasible for two users to iteratively color and impart their preferences. These images are pre-loaded into our user interface for users to start coloring them together. Any image outside this can also be potentially be used, however to maintain a consistency in our formative study, we only use this dataset. Our dataset is not publicly available as of now but we hope the detailed steps presented above can aid in reproducing dataset.

4 USER INTERFACE DESIGN

To understand the pain points of creative collaboration, we build a user interface (UI) that enables two users to color a line-art simultaneously. Figure 1 shows screens of two users (S1 and S2) coloring the line-art of an elephant. Our UI is inspired from collaborative interfaces such as Miro, Figma [3], etc. to provide a realistic experience to the users. We use Twilio's[2] real-time state synchronization API to enable synchronous coloring. Collecting reference/inspiration

[2]Note that we did not find publicly available datasets that matched our requirements, hence the need to first create our own uncolored images.
[3]https://miro.com/, https://www.figma.com/

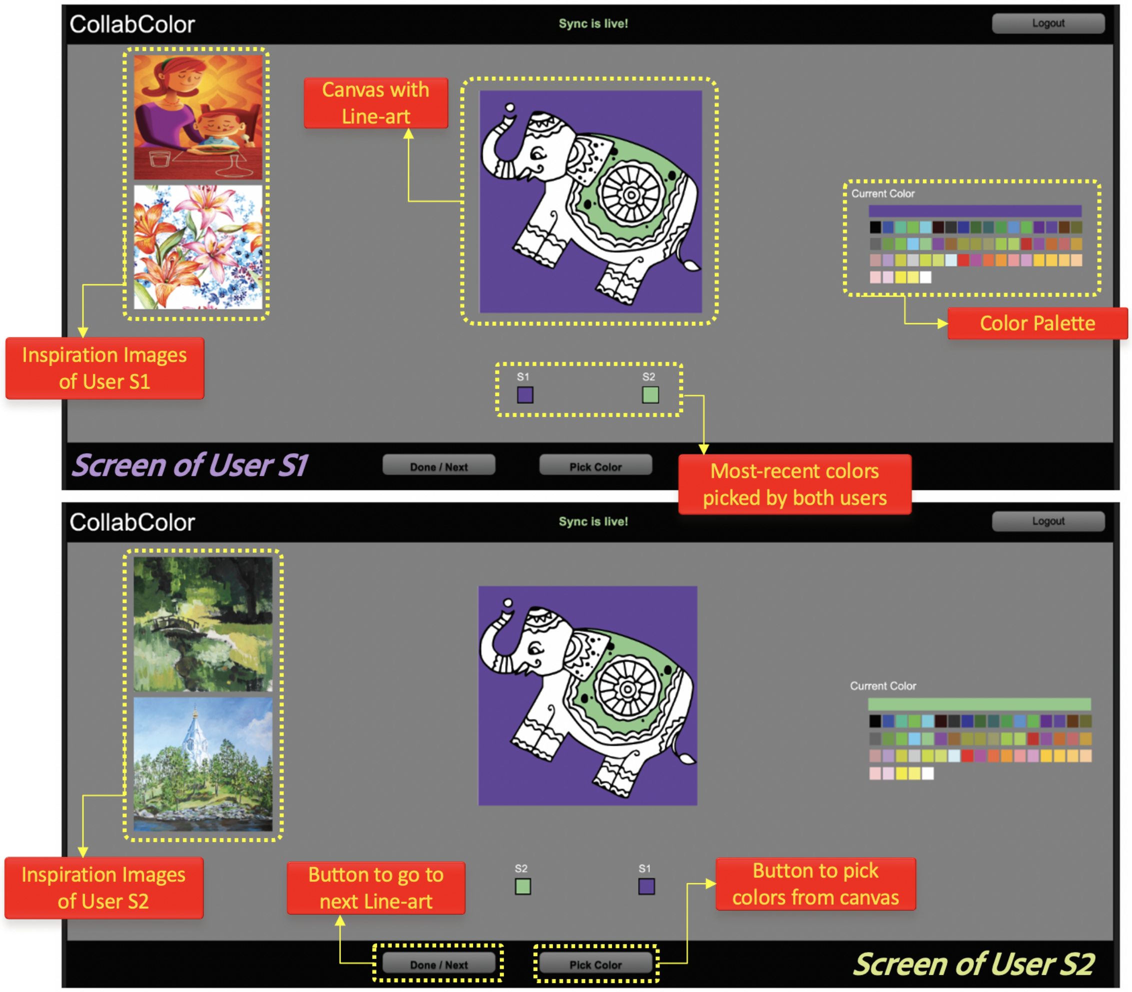

Figure 1: CollabColor: Screens of two users S1 (top) and S2 (bottom). Users can pick colors from the palette based on their inspiration images to color the line-art displayed in the canvas. The various components of our UI are labelled in the red boxes. User S1's inspiration images present a happier emotion with bright hues; User S2's images present a peaceful emotion with light green hues

images into a moodboard to diversely color an artwork is a standard practice in designer's toolbox [25]. We mimic this scenario by providing two inspiration images to each user that cater to certain emotions, using the Behance Artistic Media (BAM) dataset [39]. Here, user S2 gets peaceful/calm images in the form of sceneries, large green fields, etc. Colors can be picked either from the palette or from the canvas. We also display the most recent color picked by each user to aid in understanding each other's preferences. Here, users S1 and S2 have last picked violet and green colors respectively. Once both the users are done with iterative coloring the current line-art and click the "Done/Next" button, we proceed to the next line-art.

This is a browser-based interface and can be easily accessed in any standard browser.

5 FORMATIVE STUDY

We conduct a formative study in three modes by altering the type of reference images displayed (no images, ground-truth (GT) images,& inspiration images) with 20 user pairs consisting of novices (undergraduate STEM students of age 18-20 in India) and experts (senior designers in an industrial lab of age 28-40 in India). We ask the users not to communicate via any other medium beyond the canvas (user interface). While several collaborative platforms provide users with options to video/voice-call or chat via text, we intend to study scenarios wherein users do not have means to communicate either due to poor network quality or lack of cognitive bandwidth [13]. At each click (action / turn) t for a given SVG image, we record a triplet (u_t, s_t, c_t) corresponding to the user $u_t (u_1$ or $u_2)$ coloring a segment s_t (segment ID in the SVG image) with color c_t. We also restrict the number of turns per user to $T = 100$. Additionally, we conduct informal interviews and query users about their experience and

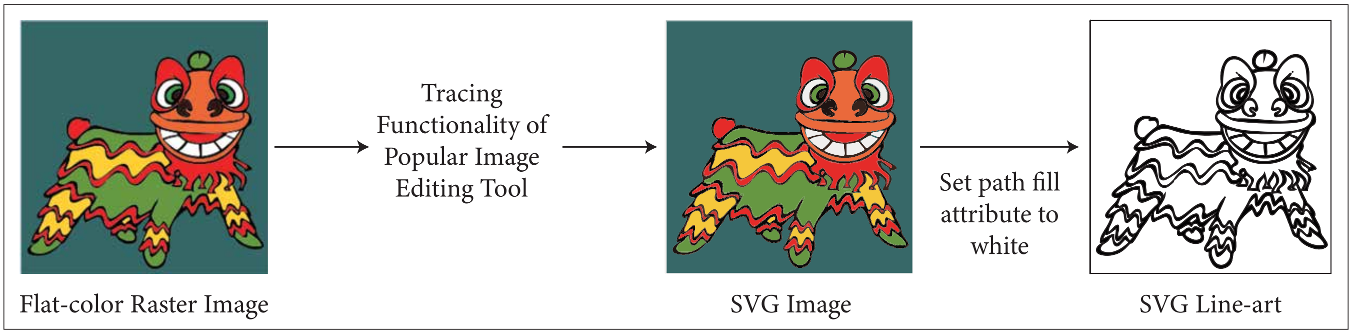

Figure 2: We use a popular image editing tool's built-in tracing functionality to extract SVG image (colored) and uncolored line-arts.

Figure 3: Part (a) demonstrates six alternate colorings of the same line-art capturing the inherent multimodality and diversity of colorization process [6]. Part (b) demonstrates a histogram of the number of segments per SVG image in our data. Values are computed over unique line-arts.

ways in which they prefer to be assisted. We identify several key themes in **conflicts** that arise while collaborating on our creative task.

F1: Understanding intentions is hard. Users found it difficult to relay their intentions just using colors on the canvas. Given that our task involves creative decision making, communication becomes paramount to arrive at a coherent colorization. Users could not verbally communicate in our setup, leading to several conflicts. They take multiple actions with excess *recoloring* in an attempt to align their preferences. Table 1 shows the average number of actions taken to color line-arts. We see that when inspiration image were not provided, the number of actions taken were more than twice the average number of segments. Around 12% of all sequences had lengths greater than 80, indicating the long duration of the task. *Cross-recoloring* conflicts are particularly dissatisfying to the users, wherein a user alters the color of the segment colored by the other user. Formally, a recoloring action is recorded when a user alters the color of an already colored segment. Let $S_1, S_2, \ldots, S_{|S|}$ represent segment IDs of a given line-art where the total segment count is $|S|$. Then, the count of recoloring actions is given by $\sum_{t=1}^{T}\sum_{i=1}^{N} I\left(s_t = S_i\right) - |s_1, s_2, \ldots, s_T|$, where $I(.)$ is the indicator function ($I(C)$ is equal to 1 if the condition C is true, else it is equal to 0), and $|.|$ is the count of unique segments in each sequence.

Of these actions, cross-recoloring actions (for user 1) are given by, $\sum_{t=1}^{T}\sum_{i=1}^{N} I\left(s_t = S_i,\ u_t = U_1, f_u\left(S_i\right) = U_2\right)$, where $f_u\left(S_i\right)$ denotes the user that previously colored the segment S_i. We also compute the number of 'reversion' actions wherein users take an undo turn, that is, revert the current action by returning to the previous state. Table 1 also shows the percentage of all these actions. We see that the recoloring actions are lower in the mode where GT images are provided as reference, whereas they are high where no inspiration or reference is available. This may be due to the provision of expected outputs through GT images, which helps in giving a definitive goal for users to pursue at the cost of limiting their novelty and imagination.

F2: Varying pace of actions leads to multiple conflicts. Some users color extremely fast and dominate, giving no opportunity to the other user to think or act. This forces the preferences of one user over the other and leads to skewed turn-taking and inaction from dominated users. To measure this effect, we define a metric called *dominance score*. Formally, dominance of user U_1 over user

Table 1: Formative study of our user interface with three modes varying the reference images (no image, GT images, inspiration images from BAM dataset). The value N indicates the number of SVG line-arts colored by our user pairs. Arrow mark (↑) indicates that higher value is typically better.

Mode	Avg no. of actions (↓)	% Recoloring (↓)	% Cross Recoloring (↓)	% Reversion (↓)	Dominance Score (↓)	Common-sense Score (↑)	Harmony Score (↑)
No Image (N = 77)	62.6	31%	17%	8.0%	0.32	0.11	0.34
GT Images (N = 20)	49.8	28%	10%	11.0%	0.37	0.26	0.41
Inspiration Images (N = 229)	33.7	30%	12%	11.7%	0.47	0.21	0.42

U_2 is given by

$$\sum_{t=1}^{T} exp\left(-\lambda t\right)\left(Count_1\left(u_{1:t}\right) - Count_2\left(u_{1:t}\right)\right)/Z$$

where $Count_k\left(u_{1:t}\right) = \sum_{i=1}^{t} I\left(u_i = U_k\right)$ represents the number of actions taken by user U_k so far and Z_d is a normalization factor. We sum the excess number of actions taken by one user over the other after each action, to capture the cumulative impact of dominance. Note that dominating actions at the beginning of the task are more impactful than those that occur towards the end because early actions determine the overall mood and direction of colorization. We thus multiply an additional $exp\left(-\lambda t\right)$ factor with $\lambda = 0.05$ to capture the decreasing impact of dominating actions. Normalization factor Z_d is the dominance score when only one user takes all the actions (with $T = 100$), given by is 3.84. Table 1 displays the average value of dominance scores over all sequences in each mode. A higher dominance score indicates greater number of conflicts.

While our measure is not perfect, we found that it correlates well with users' feelings based on our informal questions. Figure 4(a) shows a qualitative sequence of high dominance score leading to conflicts and overall poor output. Until action turn $t = 10$, user U_1 forces his preference of blue hue while user U_2 barely imparts her greenish hue to the canvas. This leads to a creative conflict and U_2 cannot visualize how to bring about the greenish hue. By action turn $t = 25$, U_1 recolors most of the area colored by U_2, while U_2 is yet to find a possible middle ground. Towards action turn $t = 40$, U_2 decides to help U_1 by altering her preferences and takes up colors with dark blueish/purple hue, recoloring and corrupting some areas that U_1 has already colored. The final output lacks coherence and is misaligned to both their preferences. Moreover, both users have a unpleasant experience collaborating, leading to a lose-lose collaboration [33].

F3: Novice users need help in aligning preferences. Conflicts arise when rules of symmetry are broken, such as, legs of an animal having different colors. Some users found it difficult to match each other's preferences while not violating spatial symmetry. From Figure 4(b), we can see that the body and legs of elephant are colored differently, leading to an incoherent output. We define a metric called *common-sense score* to capture this scenario, given by the average number of color matches for any two segments that have the same ground-truth color. Formally, common-sense score is

$$\Sigma_{t=1}^{T}\Sigma_{i=1}^{|S|}\Sigma_{j=1,\ j\neq i}^{|S|} I\left(C^{GT}\left(S_i\right) = C^{GT}\left(S_j\right), C_t\left(S_i\right) = C_t\left(S_j\right)\right)/T \tag{1}$$

where $C^{GT}\left(.\right)$ gives the ground-truth color of a segment and $C_t\left(.\right)$ gives the color of a segment at turn t. Note that our score is an approximate measure as it is impossible to take all rules of symmetry into consideration. For instance, our score penalizes the case when shirt and trousers of a boy have the same colors in ground-truth image but users in the study have colored it differently, which does not break any rule of symmetry. In our interviews, users felt that there were too many colors to choose from and it was very unclear to arrive at harmonious color combinations. We use the notion of harmony model $\mathrm{H}(c_1, c_2)$ [4, 27, 32] to quantify this scenario, which computes the harmony between two colors by quantifying the hue, luminance, and chroma effects. Formally, *harmony score* is given by

$$\Sigma_{t=1}^{T}\Sigma_{i=1}^{|S|}\Sigma_{j=1,\ j\neq i}^{|S|} \frac{\left\|\left(x_i, y_i\right) - \left(x_j, y_j\right)\right\|_2}{Z_h} H\left(C_t\left(S_i\right), C_t\left(S_j\right)\right)/T \tag{2}$$

where the harmony model's outputs are scaled with the L_2 distance between centroids $\left(x_i, y_i\right)$ of each segment i to capture the fact that the coloring is harmonious over a wide area of the line-art. Normalization factor Z_h is given by $\Sigma_{i=1}^{|S|}\Sigma_{j=1, j\neq i}^{|S|}\left\|\left(x_i, y_i\right) - \left(x_j, y_j\right)\right\|_2$. A low score on either of the above defined metrics indicates a high chance of conflicting experience.

Qualitatively, users found the mode with no inspiration images to be very tricky to deal with, since they were not sure if the overall colorization was heading in the right direction. The mode with GT reference images was too obtrusive and provided no means to think in a novel fashion. The mode with inspiration images was preferred greatly since it provided a reference to compare the canvas with, while also allowing users to be creative and choose novel colors. Overall, many users lacked clarity in dividing the canvas into two meaningful parts, delegate their preferences, and collaborate seamlessly. They were open to assistive systems that can ease their collaborative experience to arrive at a win-win situation [33], while being non-obtrusive. Our qualitative findings coincide with the observation in Main and Grierson [25] that creatives are

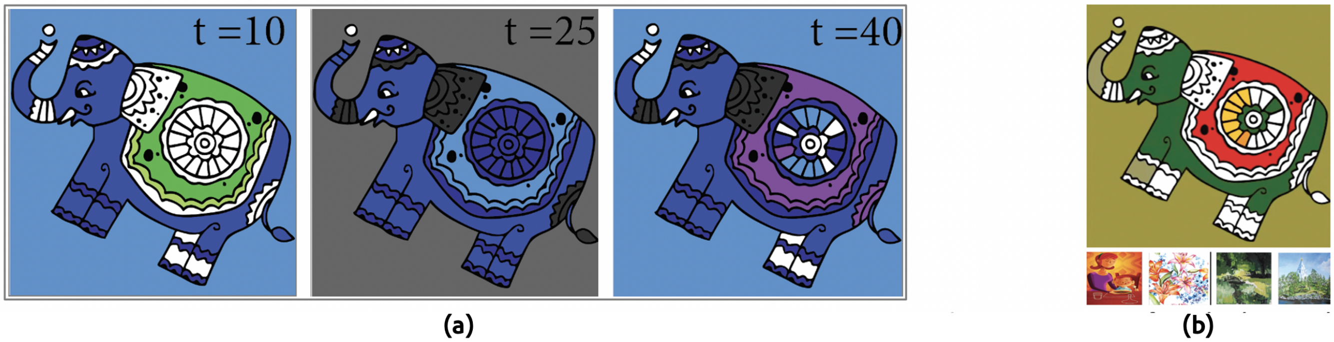

Figure 4: Part (a) demonstrates a sequence showing the conflicts that arise due to varying pace of actions. One user typically takes more moves and dominates the other in terms of overall direction of the colorization. Part (b) demonstrates the line-art of an elephant colored by users in the mode with inspiration images (shown at the bottom). As evident, the quality is poor with incoherent colors for the feet and body of elephant.

open to AI-based support tools provided they do not minimize the role of the creative.

6 DESIGN GOALS FOR INTERVENTIONS

Based on the formative study, analysis, and literature review, we identify the following design goals for a advanced software system to build interventions that can aid in creative collaboration of users during the co-colorization task:

- **G1** *Facilitate communication of intentions and aid in resolution of conflicts*. Users generally want to align preferences and help each other out. They prefer taking fewer steps to color, avoid cross-recoloring [F1], and domination [F2] in turn aiding in building trust. Thus, interventions and features that can imagine the colored image in the context of user preferences and relay intentions from one user to the other can help in converging their perspectives.
- **G2** *Provide feedback on collaborative strength and overall quality of colored line-art*. Users prefer to track their performance on the task which can help in ensuring that they are not too dominant at any stage of coloring [F2].
- **G3** *Provide assistive tools to color harmoniously*. Novice users feel overwhelmed by the multiple segments and color choices provided to them leading to spatial (symmetry) conflicts [F3]. Thus, interventions and features that can sensibly reduce the available choices while staying true to user preferences add significant value.
- **G4** *Interventions should be non-obtrusive*. A common prerequisite of all creative assistance tools [25] is that they should not interfere in the task and hinder the imagination of users. Previous research [29, 33] has shown that initial conflicts can lead to a more creative final product.

Simple hard-coded rule-based methods based on user action counts or segment color counts may help with tracking the state of the image being colored using a CollabColor-like interface, but they do not understand the semantics of the image or how user preferences interact with the image being colored. Moreover, hard-coded algorithms do not take the sequential user history into account beyond simple count statistics. We thus believe that a AI-based learning approach that acts as a facilitator between the two users can help. We plan to take these insights from the studies towards building such a system.

7 CONCLUSION

We introduce CollabColor, a user interface that helps study how creatives collaborate in a synchronous setup, specifically studied via the task of line-art colorization. We identify and define key conflicts that occur in the considered co-creation task using a formative study conducted using the CollabColor interface with both novice as well as expert creatives. We further empirically quantify the findings of the studies using various scores from computational literature and define design goals for a potential advanced computational system to aid collaborative co-creativity. We now plan to extend this work towards building a intelligent system based on the insights of this study to aid digital co-creativity in this virtual world.

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