Make-up FLOW: A Beauty YouTubers' Video Recommendation Method Based on Make-up Flowcharts

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Abstract. Due to the vast number of makeup videos online, finding a suitable one is challenging. To develop a makeup video recommendation service, we must establish a method for calculating the similarities between the makeup processes. This paper proposes a Make-up FLOW system, which represents makeup procedures using a flowchart style structure. We evaluated its effectiveness in recommending videos from 103 tutorial videos based on process similarities. The findings showed a weak correlation using the Levenshtein distance in the first half of the process, suggesting that the process similarity may help recommend multiple information and sort search results.

Keywords: Make-up, Make-up process, Flowchart, Beauty YouTuber

1 Introduction

Beauty information and makeup tutorials are becoming increasingly popular on social network services (SNS). Many people use SNS to research new cosmetics and makeup methods [1, 2]. In addition, several studies have clarified that beauty influencers' reviews significantly impact cosmetics purchases [3-5].

However, finding a suitable makeup video among the over 65 million available online using conventional text-based searches is challenging. Additionally, since makeup involves many processes (refer to Table 1 in section 3) and many people have unique methods of makeup [6], it's easier to adopt new methods from videos that resemble their process rather than entirely different ones. Despite many studies recommending cosmetics or techniques based on users' facial and cosmetic attributes [7-9], none focus on process similarities, forcing users to sift through numerous videos manually. Such a recommendation method using process information can also be used for the previously proposed support methods for makeup techniques [10, 11] and for increasing the variation of makeup [12, 13]. Creating a makeup video recommendation service demands a system that calculates the similarities between a user's routine and the process shown in video content.

Makeup involves applying many products to different face parts. For example, the same item may be applied to different parts or layered with different textures. Flowcharts visualize complex processes and are used in various fields beyond programming, such as culinary arts, medicine, and educational research [14-16]. However, makeup application varies significantly based on time, place, occasion, and individual preferences. Creating a standardized makeup flowchart with general services is problematic due to the diverse techniques and preferences.

This paper proposes a Make-up FLOW system that represents the makeup process using a flowchart format. We also developed a prototype system and created flowcharts from makeup tutorials by beauty YouTubers. To explore the feasibility of a video recommendation service based on flowchart similarities, we evaluate the effectiveness of recommendations based on the process similarities.

The contributions of our paper are as follows:

- We proposed the Make-up FLOW system, which stores and visualizes the user's makeup process using a flowchart and defined an appropriate format.
- We created a makeup flowchart dataset based on 103 makeup tutorial videos by 53 beauty YouTubers and the makeup processes of 34 female college students.
- We proposed a method to calculate makeup process similarities among users by representing these processes as strings of characters.

2 Make-up FLOW

2.1 Basic survey on the makeup process

Before implementing Make-up FLOW, we conducted a foundational study to determine suitable flowchart formats for the makeup process.

First, we collected makeup flowcharts using draw.io [17], an existing flowcharting service. We recruited 20 female university students to independently create a flowchart of their typical makeup process. The participants used three nodes: a start/end node, a makeup node (indicating a process always performed), and a makeup branch node (indicating a process sometimes not performed). Considering that an individual's motivation level can influence their routine, we introduced a motivation branch node.

Analysis of the flowcharts showed variations in process division and notation among participants. For instance, one participant broke down the eyebrow makeup process into separate steps for each texture, while another consolidated it into one step. We also observed differences in terminology (e.g., face powder vs. powder) and the level of detail provided. These discrepancies pose challenges for analyzing flowcharts and offering makeup support. Predefining process names that users can select in the system would ensure consistency in notation. In some cases, participants applied the same item to various face parts or used items with different textures on the same part. To address this, makeup nodes must explicitly include the item name, application area, and texture.

Next, we conducted a questionnaire survey about makeup routines to choose the type of branch node. From the survey, we selected the presence or absence of motivation, time spent on makeup, length of time out of the house, and seasonal differences as the branches of a Make-up FLOW flowchart.

2.2 Implementation of the prototype system

We implemented a prototype system of Make-up FLOW. Fig. 1 shows a screenshot of the system, with each area delimited by a light blue border and numbered.

The makeup node displays an icon of the facial part where makeup is applied, the item's name, and the texture name in brackets if the item has multiple textures. The system generates a makeup node automatically when the user selects elements from the pull-down menu in the area (3). Users can choose 30 items listed in a category from a well-known cosmetics information website. The branch node includes four conditions: motivation level, makeup time, outdoor time, and seasonal changes. An illustrative face (Fig. 2), shown in area (2), helps users visualize their daily makeup routine by updating with each new process added. Users create a makeup flowchart by dragging and dropping nodes from area (4) to (5) and connecting them.

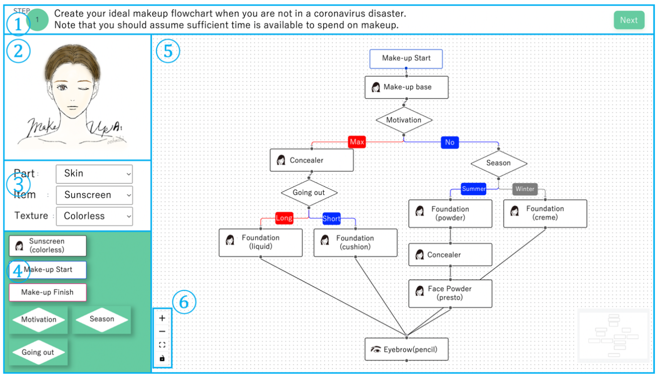

Fig 1. Make-up FLOW system

Fig 2. Changes in facial illustration with the addition of the make-up process

3 Dataset

At first, we recruited 34 female university students to use the Make-up FLOW system. Then, our system collected over 150 makeup flowcharts from them. Fig. 3 shows three examples from the collected flowcharts, demonstrating that the complexity of the flowchart, including the number of processes and branches, varies from user to user.

In addition, to verify the effectiveness of recommending makeup videos based on process similarities, we created a beauty YouTubers flowchart dataset from tutorial videos of Japanese beauty YouTubers with over 50,000 subscribers. To ensure various makeup processes, we included anyone regularly posting beauty videos as a beauty YouTuber, regardless of their primary occupation.

We recruited four participants with over six months of experience using our system. We asked them to create flowcharts while watching the videos using our system. We instructed them to make flowcharts for two genres of makeup videos posted in the past year. Examples of keywords for videos in each genre are as follows.

- Everyday makeup: Everyday, Time reduction.
- Special makeup: Enhance, Look good, Popular, Live concert, and Party.

We obtained 103 makeup flowcharts from 53 YouTubers, averaging 706,000 subscribers. Three YouTubers had not posted any special makeup videos in the past year, resulting in 53 everyday makeup' and 50 special makeup' flowcharts.

Table 1 shows the statistics of the maximum number of process routes in the flowcharts of 53 YouTubers and 34 female university students created during the same period. This indicates that YouTubers had more processes than general female university students.

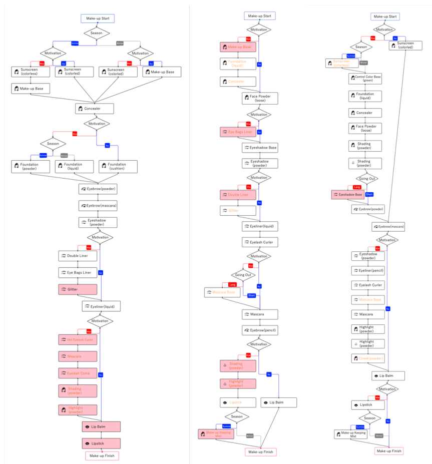

Fig 3. Example of make-up flowcharts by 3 female university students

Table 1. Statistics on the maximum number of process routes for each category

	Min	Max	Average	Std. Dev.
Female university students	5	29	16.0	5.7
Beauty YouTubers	9	42	19.5	6.5

4 Experiment with recommending makeup videos

We conducted an experiment that analyzed the similarities between the makeup process of participants and beauty YouTubers and recommended videos based on these similarities. Participants were told to create a makeup flowchart in advance. We then calculated the similarities between participants and YouTubers using the Levenshtein distance and the cosine similarity based on N-gram frequency. Based on the classification described in section 4.1, we selected two videos with high and slightly low similarities for each calculation method. Each participant watched eight different videos. After viewing each video, participants completed a questionnaire evaluating aspects such as the video's helpfulness. We recruited five female university students.

4.1 Calculating the process similarities between participants and YouTubers

Using the dataset constructed in section 3, we calculated the process similarities between participants and beauty YouTubers. We used string similarity calculation methods, specifically the standardized Levenshtein distance and cosine similarity based on N-gram frequency. Each makeup route in the flowchart was represented as a string, and process similarities were calculated based on these strings.

1. We encoded the makeup node's part, item, and texture information with alphabet characters, symbols, and numbers (e.g., "A$2" for A: skin, $: foundation, and 2: liquid). This method is referred to as compound notation. Alternatively, converting the three characters representing a makeup node into a single unique character is called substitution notation.
2. We arranged and concatenated strings of makeup nodes in the sequence of the makeup process. This order reflects the sequence of application in the makeup route.

For the part, a total of five types (e.g., skin and eyebrows) are indicated by A to E. For the item, 30 types (e.g., foundations and eye shadows) are indicated by symbols such as "$" and "%." For the texture, up to seven types (e.g., liquid and powder) are represented by 0 to 6. Fig. 4 shows an example of a makeup route converted into a string of characters in compound notation. We focused on the most detailed makeup routes—those with the maximum number of processes—as these are most beneficial for users. The median similarity was 1.20 using the Levenshtein distance and 0.05 for the N-gram frequency. Based on previous research, the part-only distance and the

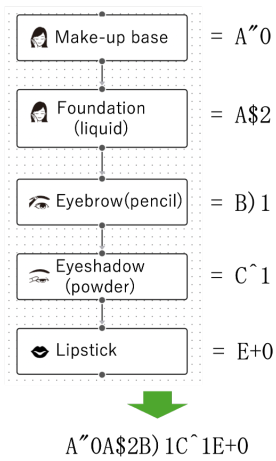

Fig 4. Example of replacing a makeup root with a string in compound notation

item-and-texture distance were summed to calculate the Levenshtein distance, resulting in a maximum value of 2.00. Consequently, any value less than half of that maximum was considered short. Distances longer than the median were considered slightly long. For cosine similarity, where the maximum value is 0.50, values above 0.20 were considered high similarities, while those below 0.06 were considered slightly low.

4.2 Results

To determine which similarity calculation method better recommends videos, we analyzed the relationship between each method's similarity scores and the video ratings from the questionnaire. We calculated each participant's similarities to beauty YouTuber videos and ranked them according to their similarity scores. We then calculated Spearman's correlation coefficients (ρ).

The analysis used three evaluation criteria from the questionnaire: the helpfulness of the videos, the willingness to adopt the techniques introduced, and the subjective similarity of the process between the participants and the video. Although the participants' flowcharts contained branch nodes and the YouTubers' flowcharts contained only one route, participants judged the similarity level by considering only their main makeup route. The effect of this difference on the subjective similarity was considered small. We first calculated ρ for each evaluation criterion. The results showed no correlation for all evaluation criteria (correlation range: -0.11~0.27).

Next, we calculated a weighted average of the evaluation criteria that maximized the ρ and ranked the videos from 1 to 8. The results showed that the Levenshtein distance had a weak correlation (0.26) when assigning a weight of 0.1 to helpfulness, 0.4 to willingness to adopt techniques, and 0.5 to perceived similarity. N-gram frequencies were uncorrelated (0.08) when assigning a weight of 0.0, 0.5, 0.5.

The first half of the makeup process involves essential elements like base makeup, while the second half creates eye and lip makeup moods. Therefore, we calculated similarities based on the first or second-half processes and determined the weights that maximized the ρ. Table 2 shows the results of each calculation method. The numbers in brackets indicate the weighting of the evaluation criteria (helpfulness: willingness to adopt techniques: perceived similarity). This reveals a weak correlation when the first half is used to calculate the Levenshtein distance. These weight values were intuitive since the most critical factor was whether the video was helpful to the user. However, the N-gram frequencies consistently showed no correlation. Table 3 presents the ρ for each participant and indicates that some participants strongly correlate with the Levenshtein distance. When we asked Participant C why she rated the video with high similarities low, she explained, "I did not gain any new knowledge; the beauty of her true face was remarkable."

Table 2. ρ for each similarity calculation method

	Leven's ρ	N-gram's ρ
First half of process	0.38 (0.6 : 0.2 : 0.2)	0.08 (0.0 : 0.1 : 0.9)
Second half of process	0.21 (0.1 : 0.7 : 0.2)	0.14 (0.5 : 0.3 : 0.2)

Table 3. ρ for each similarity calculation method per participant

	A	B	C	D	E
Leven's ρ	0.32	0.64	-0.07	0.12	0.88
N-gram's ρ	0.28	0.40	-0.37	-0.48	0.22

5 Discussion & Conclusion

We found that the highest correlation was obtained using the Levenshtein distance in the first half of the process. However, the overall correlations were low. The cosine similarity based on the N-gram frequency consistently showed no correlation, indicating that it was unsuitable for recommending makeup videos.

Participants' comments for low-rated videos included, "She discussed the topics I already knew, or that were unsuitable for me." and "My usual process is quite similar, so I felt I was not learning any new techniques." Conversely, comments for high-rated videos included, "She described items I had never used before." and "Though the process was different, she explained tips for effective makeup application in great detail." Trust in beauty Influencers is essential when watching their videos; Ding et al. [5] found that trust in beauty YouTubers was related to their expertise in makeup and appearance. Rasmussen [4] noted that popular beauty YouTubers used professional lighting and sound. Therefore, factors beyond process probably influenced the videos' evaluation, weakening the overall correlation when recommendations were based solely on process similarities.

We initially believed that recommending makeup videos based on the similarities in the process would be effective. However, considering other factors, such as the items used, explanation quality, and video composition, may be essential. In such cases, if it is possible to automatically recognize YouTube videos, it would be better to automatically calculate the similarities to the flowchart created by the user and display recommendations for videos with high similarity on Make-up FLOW. Another application of the process similarities is in sort functionality. For example, allowing users to perform a keyword search on YouTube, analyze the process of the top videos, and then sort them based on their similarities can help users find videos that are easy to follow and practice. In the future, we plan to clarify the factors in evaluating makeup videos and investigate support methods that effectively utilize process information. Based on our findings, we aim to develop a new system that recommends and searches for makeup flowcharts and beauty YouTubers' videos. This system would help users improve and diversify their makeup routines.

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