Ranking Lifelogs for Memory Recall Support

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Abstract. Even though human memory is critical in our daily lives, it eventually becomes ambiguous and difficult to recall. In this research, we propose a text-based lifelog approach with attributes that capture useful features for memory recall as well as three lifelog ranking functions (an event ranking and two "remember" rankings) using features that can be calculated from a user's lifelog. We evaluated these ranking functions and developed a prototype system based on our approach. We found that a combination of the following is useful: event duration, place, person, social media post, and photo, especially place and photo.

Keywords: reminiscence · lifelog · memory support · place · photo

1 Introduction

Memory is undoubtedly essential for everyday survival. In addition, reminiscence is an important part of our daily lives that serves a variety of purposes, such as providing individuals with a sense of identity, the possibility to review their lives and accept their past, the vision to solve current issues and the chance to enhance relationships [1]. Furthermore, nostalgia, or memories over past events is an important resource for maintaining and promoting individual's physical and psychological health and the positive effect of nostalgia provides an effective way to improve subjective well-being [4]. However, since memories are generally vague, and the ability to recall them over time is often degraded, supporting their recall is vital.

In this research, we propose a text-based lifelog approach with attributes that can capture useful features for memory recall and lifelog ranking functions that support it. A lifelog contains 11 attributes, including a start date, a start time, an end date, an end time, a place, persons, a social networking service (SNS) post, and a number of photos. From these attributes, the following features are calculated: event duration, distance to the place, number of visits to it, number of times having met a particular person, and the number of days since the last meeting with him/her. Using these features, we developed and evaluated three ranking functions, *Event*, *Remember*1, and *Remember*2, and implemented a prototype system.

Below in Section 2 we explain an overview of our approach and three ranking functions in Sections 3 and 4. We describe experiments in Section 5 and an implemented prototype system in Section 6. We show related work in Section 7.

2 Approach

We propose a text-based lifelog approach with attributes that capture features useful for memory recall as well as lifelog ranking functions that support memory recall. A lifelog, which corresponds to an event, has 11 attributes: an ID, an event title, a start date, a start time, an end date, an end time, a place, persons, a tag, an SNS post, and a number of photos. From these attributes, the following features are calculated: event duration, distance to the place, number of visits to it, number of times having met this person, and number of days since the last meeting to the person.

We also propose three ranking functions (an event ranking and two "remember" rankings) using these features that can be calculated from user lifelogs.

3 Event Ranking

First we propose an event ranking function that lists events (i.e., lifelogs) by their order of importance. For such rankings, we use all the attributes except for IDs, event titles, and tags.

For $lifelog_i$, we define event ranking as follows:

$$Event_i = Duration_i + Place_i + avePerson_i + SNS_i + Photo_i. \tag{1}$$

Since there is only one element for each log (event) other than a person, although more than one person might be involved, $avgPerson_i$ is used in Eq. 1.

3.1 Event Duration

The longer an event's duration, the more important it is:

$$Duration_i = \frac{EventDuration_i - EventDuration_{\min}}{EventDuration_{\max} - EventDuration_{\min}}, \tag{2}$$

where $EventDuration_i$ is the time (in seconds) from the event's start time to its end time.

3.2 Place

Concerning place features, we believe that distant and infrequently visited places are important:

$$Place_i = Distance_i + SeldomVisit_i, \tag{3}$$

$$Distance_i = \frac{PlaceDistance_i - PlaceDistance_{\min}}{PlaceDistance_{\max} - PlaceDistance_{\min}}, \tag{4}$$

where $PlaceDistance_i$ is the distance (in km) from the user's location to the place:

$$SeldomVisit_i = 1 - \frac{TimesVisited_i - TimesVisited_{\min}}{TimesVisited_{\max} - TimesVisited_{\min}}, \tag{5}$$

where $TimesVisited_i$ is the number of times the user has visited the place.

3.3 Person

The people we meet often and those we have met recently are important for a person feature. As described above, since the user can interact with more than one person at an event, we use $avgPerson$:

$$avgPerson_i = \ average\, of\ Person_k, \tag{6}$$

where k is a person met by the user in $lifelog_i$:

$$Person_k = FreqMet_k + RecentMet_k, \tag{7}$$

$$FreqMet_k = \frac{TimesMet_k - TimesMet_{\min}}{TimesMet_{\max} - TimesMet_{\min}}, \tag{8}$$

where $TimesMet_k$ is the number of times the user met $person_k$:

$$RecentMet_k = 1 - \frac{DaysSinceLastMet_k - DaysSinceLastMet_{\min}}{DaysSinceLastMet_{\max} - DaysSinceLastMet_{\min}}, \tag{9}$$

where $DaysSinceLastMet_k$ is the number of days since the user last met $person_k$.

3.4 SNS Post

Events posted on SNSs are important:

$$SNS_i = \begin{cases} 1 & \text{if}\, posted, \\ 0 & \text{otherwise.} \end{cases} \tag{10}$$

3.5 Photo

The events at which many photos were taken are also significant:

$$Photo_i = \frac{NumPhotos_i - NumPhotos_{\min}}{NumPhotos_{\max} - NumPhotos_{\min}}, \tag{11}$$

where $NumPhotos_i$ is the number of photos taken in connection with an event.

3.6 Example

Here is an example calculation for $lifelog_{104}$ in a user's one-month lifelog: picnic with D and E at Daisen Park (Fig. 1):

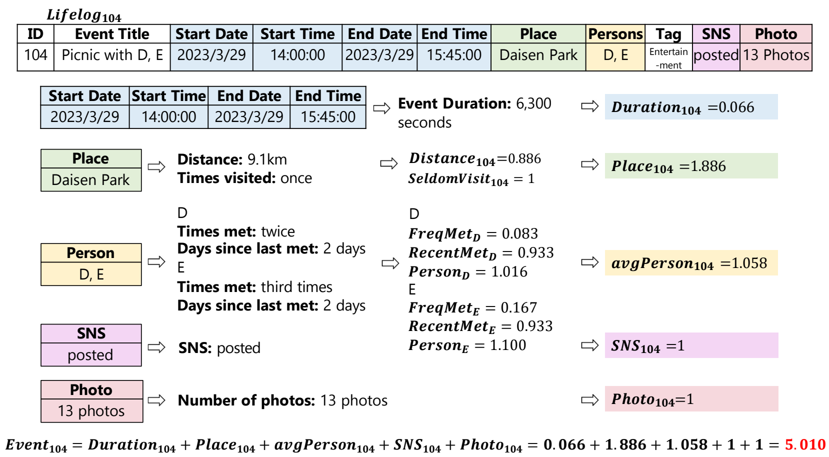

Fig. 1. Example calculation of event ranking

With an event duration of 6,300 seconds, $Duration_{104}$ becomes 0.066. Based on the distance from home to Daisen Park, $Distance_{104}$ becomes 0.886. Since Daisen Park was visited only once, $SeldomVisit_{104}$ is 1. Then $Place_{104}$ becomes 0.886+1=1.886. The user met D twice and E three times in this period. $FreqMet_D$ is 0.083, and $RecentMet_D$ is 0.933, resulting in a score of 1.016 for $Person_D$. Similarly, $Person_E$ is 1.100 and the $avgPerson_{104}$ becomes 1.058. The user posted about this event and SNS_{104} is 1. 13 photos were taken at it, and since this is the maximum value, $Photo_{104}$ is 1. In summary, the $lifeLog_{104}$ score is 0.066+1.886+1.058+1+1= 5.010.

4 Ranking Using Correlation Analysis

Our proposed event ranking function requires many features and attributes. However, since completely describing the attributes is rather labor intensive, we reduced their number by examining the ranking functions useful for event recall using Kendall's correlation analysis. We performed a correlation analysis between the features and the values a user wants to remember (see Experiment in Section 5) and extracted some of the former.

4.1 Remember Ranking 1

By observing the correlation analysis results of the 11 subjects' individual March evaluation values and nine features, we selected $Place$, $avgPerson$, and $Photo$ to determine remember ranking 1:

$$Remember1_i = Place_i + avgPerson_i + Photo_i. \tag{12}$$

4.2 Remember Ranking 2

As a result of the correlation analysis between the March and June evaluation values of all subjects and nine features (Table 1), $Photo$ (0.304), $Place$ (0.260), $SeldomVisit$ (0.250), SNS (0.204), and $Distance$ (0.202) were higher than 0.2. Since $SeldomVisit$ and $Distance$ are included in $Place$, we selected $Photo$, $Place$, and SNS to determine remember ranking 2:

$$Remember2_i = Place_i + SNS_i + Photo_i. \tag{13}$$

$Place$ and $Photo$ are common for remember rankings 1 and 2. $avgPerson$ and SNS are different.

Table 1 shows the correlation analysis results between the March and June evaluation values of all the subjects and nine features and three ranking functions. After defining the remember rankings using correlation analysis between the values and nine features, the correlation analysis between the values and the three ranking functions was performed. Among the latter, remember ranking 2 correlated best with the subjects' ratings.

Table 1. Results of correlation analysis

Method	Correl
Remember2	**0.305** **
Photo	0.304 **
Place	0.260 **
Remember1	0.259 **
Event	0.254 **
SeldomVisit	0.250 **
SNS	0.204 **
Distance	0.202 **
FreqMet	0.159 **
avgPerson	0.144 **
RecentMet	0.114 **
Duration	-0.113

**: $p < .01$

5 Experiment

To evaluate the effectiveness of our proposed lifelog approach and three ranking functions, we conducted an experiment with 11 subjects (five men and six women) in their 20s.

5.1 Method

Subjects completed lifelogs for March and June 2023 and rated on a 5-point scale how much they wanted to recall them (5: very much; 1: not at all).

26 methods (12 methods, a timeline order, and the reverse order of each) were evaluated. The timeline order and its reverse order were used as a baseline. As evaluation metrics, we employed Normalized Discounted Cumulative Gain (NDCG) (in this research, the top 10 results: NDCG@10) and Average Precision (AP), both of which are commonly used to evaluate information retrieval. We used the users' 5-point ratings as is for NDCG, and for AP, 4 and 5 were considered as relevant.

5.2 Results and Analysis

The experiment results, sorted in descending order of NDCG, are shown in Table 2.

The proposed methods, $Event$, $Remember2$, and $Remember1$ were ranked high in the NDCG@10, confirming its effectiveness in presenting a lifelog that users want to remember. Next, $Place$, $Distance$, and $SeldomVisit$ are all location-related methods, confirming the importance of place/location in events that users want to recall. The number of photos and SNS posts were also effective. The features related to people exceeded the baseline for $RecentMet$ and $FreqMet$.

As for AP, the first and second places were identical for $Event$ and $Remember2$, followed in third place by $FreqMet$. We believe individual and situational differences can be found in the person features.

6 Prototype System

We developed a prototype system, as shown in Fig. 2. A user sorted her one-month lifelogs using the event ranking function. $Lifelog_{104}$ is displayed at the top of the list (See Section 3.6 for the calculation). In her case, the top ten lifelogs are tagged as entertainment and events with her friends.

The user can sort her lifelogs by such other ranking functions as timeline, timeline reverse, and remember rankings 1 and 2. She can also sort them by selecting a person or a place.

Table 2. Experiment ranking results

Method	NDCG@10		AP	
Event	**0.899**	[1]	**0.679**	[1]
Remember2	0.897	[2]	0.662	[2]
Remember1	0.881	[3]	0.632	[4]
Place	0.881	[4]	0.548	[7]
Distance	0.872	[5]	0.593	[6]
Photo	0.848	[6]	0.513	[9]
SeldomVisit	0.845	[7]	0.629	[5]
SNS	0.790	[8]	0.506	[11]
RecentMet	0.749	[9]	0.512	[10]
FreqMet	0.742	[10]	0.639	[3]
Timeline Reverse (baseline)	0.739	[11]	0.482	[12]
avgPerson	0.729	[12]	0.514	[8]
Duration	0.727	[13]	0.475	[13]
SNS Reverse	0.695	[14]	0.391	[19]
Photo Reverse	0.677	[15]	0.413	[17]
Timeline (baseline)	0.668	[16]	0.402	[18]
FreqMet Reverse	0.660	[17]	0.369	[22]
RecentMet Reverse	0.643	[18]	0.442	[15]
Duration Reverse	0.642	[19]	0.376	[20]
Distance Reverse	0.641	[20]	0.373	[21]
avgPerson Reverse	0.632	[21]	0.444	[14]
Place Reverse	0.614	[22]	0.424	[16]
SeldomVisit Reverse	0.611	[23]	0.365	[25]
Event Reverse	0.609	[24]	0.365	[23]
Remember1 Reverse	0.608	[25]	0.365	[24]
Remember2 Reverse	0.601	[26]	0.363	[26]

[] means rank

7 Related Work

Takahashi et al. [12] proposed a memory recall support system based on active acquisition and the accumulation of memory fragments. Their work is related to ours in terms of presenting a framework for accumulating lifelogs, but they did not sort lifelogs in the order desired by the user to remember.

Since the 1990s our work has developed many systems for supporting everyday memory in the artifical intelligence community (e.g. [5, 8, 10, 6, 9, 7]). Matsumoto et al. [6, 9] and Murakami and Murakami [7] developed a system that supports memory recall using a calendar, SNS posts, and the number of photos, based on the idea that days on which users post on SNS and take many photos are memorable. This study developed lifelog ranking functions using such features as places and people in addition to SNS posts and the number of photos.

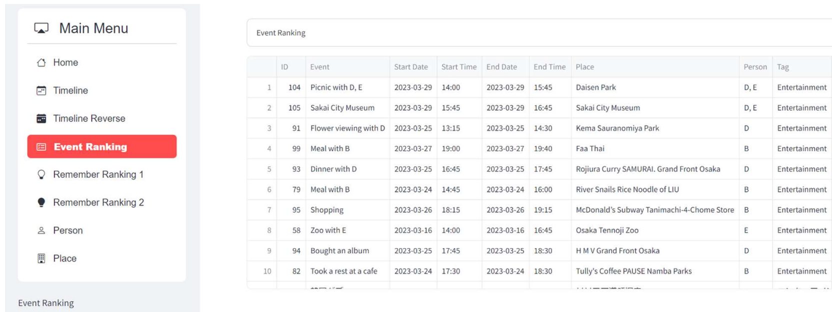

Fig. 2. Prototye system

There is growing attention in the HCI community on how technology could be designed to support experiences of reminiscence on past life experiences [14]. Existing studies have investigated the use of personal digital data and interactive technologies to support reminiscence [3]. Pensieve [11] is one such system that supports everyday reminiscence by emailing memory triggers to people that contain either social media content they previously created on third-party websites or text prompts about common life experiences. We presented a text-based lifelog architecture and developed ranking functions using various features, including places, persons, and other media usages.

In recent years, lifelogging has become a research focus in multimedia and multimodal contexts in the information retrieval community [15, 2]. NTCIR Lifelog task aims to advance the state-of-the-art research in lifelog analytics and retrieval as an application of information retrieval [15]. The Lifelog Search Challenge (LSC) goal is to comparatively evaluate system capabilities to access large multimodal lifelogs comprising hundreds of thousands of records [2]. Much work has described methods of ranking images based on user's input [13]. This study is positioned as a text-based lifelog study, and text lifelogs are ranked using various features including number of photo images related to the lifelogs.

8 Conclusions

We proposed a text-based lifelog approach with attributes that can capture features useful for memory recall and calculated three lifelog ranking functions (an event ranking and two "remember" rankings) using features from user lifelogs. We evaluated these ranking functions and developed a prototype system based on our approach and found that a combination of event duration, place, person, SNS post, and photo, especially place and photo, are useful.

Future work includes the following. First, to accommodate individual differences, we will adjust the weight of the score depending on the individual. We should also consider using tags that were not employed in the calculation.

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