LifeSeeker 3.0: An Interactive Lifelog Search Engine for LSC’21

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ABSTRACT
In this paper, we present the interactive lifelog retrieval engine developed for the LSC’21 comparative benchmarking challenge. The LifeSeeker 3.0 interactive lifelog retrieval engine is an enhanced version of our previous system participating in LSC’20 - LifeSeeker 2.0. The system is developed by both Dublin City University and the Ho Chi Minh City University of Science. The implementation of LifeSeeker 3.0 focuses on searching and filtering by text query using a weighted Bag-of-Words model with visual concept augmentation and three weighted vocabularies. The visual similarity search is improved using a bag of local convolutional features; while improving the previous version’s performance, enhancing query processing time, result displaying, and browsing support.

CCS CONCEPTS
• Information systems → Multimedia databases; Users and interactive retrieval; Search interfaces; Human-centered computing → Interactive systems and tools.

KEYWORDS
lifelog, interactive retrieval, information system

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1 INTRODUCTION
With the rapid development of sensor technology, commercial wearable devices are being widely used to capture many aspects of one’s life, and serve many purposes, such as health analysis [34], sport performance analysis [2], or self-quantifying physical and mental health prediction [30]. Due to the growing popularity of using sensors and wearable devices for self-quantifying/self-tracking, passive image capturing and video recording, the vision of “The Memex Concept” originating by Bush in 1945 [4], which aims to create “an archive of a personal lifetime experience and knowledge storage for later usage and sharing”, is being gradually implemented. Lifelogging, which began to develop since the capability of implementing “The Memex Concept” had become possible, has not been an active research topic until the seminal MyLifeBits [8] lifelog database in 2006 and the release of the upgraded MyLifeBits multifaceted retrieval system in the same year [8].

In recent years, many research challenges have been organized to introduce new problems in the lifelog domain to the research community: ImageCLEF [5–7, 29], NTCIR [9–11], and the Lifelog Search Challenge (LSC) [13]. Among the newly introduced problems, the Lifelog Moment Retrieval Task (LMRT) is an important one that has been attracting much attention from the lifelogging research community, with its vision to develop a lifelog-based memory prothetic, as well as providing a deep insight into an individual’s habits and activities. Among many lifelogging research challenges, the Lifelog Search Challenge (LSC) is the most competitive one, which aims to become an international competitive benchmarking activity to support the fair and accurate comparison of different approaches to interactive retrieval from lifelog datasets [14].

In this paper, we analyze LifeSeeker 2.0’s performance during last year’s challenge and introduce the LifeSeeker 3.0 - an enhanced version of this retrieval system. The new features developed in LifeSeeker 3.0 are as follows:

• Metadata Enhancement: We refine the semantic location from the provided metadata and manually cluster them into 32 categories. The city and country labels of the semantic locations are also added based on the given GPS data. In addition, more visual concepts are extracted automatically using the ResNet-101 model trained on the Visual Genome dataset [20] and Microsoft Vision API.

• Image Visual Similarity Matching: We construct a Bag-of-Features representation using Local Convolutional Features (LCF) for visual similarity search, which has been competitive on the Oxford and Paris buildings benchmark [26].

• Weighted Bag-of-Words for Free-text Search: We weight the terms in the L2-norm Bag-of-Words query vector during the cosine similarity computation to re-rank the retrieval results for the free-text search features. The weights (w) are based on the importance of terms in three predefined vocabularies: time, location (loc), and visual concepts (vc) (with wtime > wloc > wvc). Thereby, the multifaceted filter panel is also attached to the free-text search features and
time/location information can be used to retrieve the desired moments precisely.

2 RELATED RESEARCH

Image retrieval [17] has seen a significant increase in research interest over the past decade. At the early stages, retrieval techniques were based on textual features, which first annotate images with text and then search by using text-based methodologies [16, 27]. Since manual annotation of large modern datasets is time-consuming and labor-intensive, the emergence of other worthwhile approaches which utilize the visual properties of images, i.e. content-based image retrieval (CBIR) [18, 28, 33], became necessary. Especially, CBIR extracts visual concepts such as objects, colors, texts, and so forth in order to create metadata represented by a set of multi-dimensional vectors. The system converts different forms of user queries into vectors in the multi-dimensional space, where similarities are computed regarding the searching process. We rely extensively on such visual analytics.

The Lifelog Search Challenge (LSC), an annual image retrieval competition in the ACM International Conference on Multimedia Retrieval (ICMR), has been organized since 2018. In order to compete in the challenge, each team is required to build a real-time interactive tool that can complete both known-item and ad-hoc tasks over a large multimodal lifelog dataset. Among 14 teams partaking last year, we highlight three teams whose systems performed the best. For the very first time, Mysceal [32], the most effective system presented at LSC’20, introduced an efficient engine through the combination of Elastic Search and automatic query expansion. Besides developing a TFIDF-based similarity search procedure, Tran et al. exploited the use of the map as not only a filter but also a movement visualization [32]. This engine outperformed all other competitors as the one with the lowest searching time and the highest number of occurrences of top-3 correct submissions. With very close results, SOMHunter [25], an adaptive video retrieval system developed for the Video Browser Showdown (VBS) [31] re-purposed for the LSC’20 task, ranked second place. SOMHunter enabled users to flexibly query by presenting the users with three different visualizations of the search results: (1) original ranked results, (2) re-scoring by user’s relevance feedback, and (3) ranking using temporal features. Kovalčík et al. [19] proposed the VBS-inherited-system named VIRET [19], which was among the top-performing architectures also in the LSC’20 competition. Their query mechanism is considerably updated; users can search either traditionally by a textual query, visually by drawing a color, or semantically by sketching.

Like most traditional retrieval systems, LifeSeeker 3.0 is a search engine based on textual and visual features. The most remarkable contribution of the LifeSeeker 3.0 this year is to improve the free-text query by using a weighted Bag-of-Words model with visual concept augmentation and three different vocabularies in terms of time, location, and visual concepts. Besides, the image visual similarity matching also plays a vital part in the system implementation performance.

3 LIFEOLOG DATA FOR THE EXPERIMENT

The LSC’21 organizers used a slightly reduced version of the dataset employed for LSC’20 and generated a new set of information needs. The dataset is a multimodal dataset that combines data of a single lifelogger from the three previous LMRT challenges, NTICR 2015, 2016, and 2018 [14]. It contains 114-day multimodal lifelog data captured and synchronized from both smartphone and multiple sensors recording continuously for several years. The lifelog images are fully anonymized to prevent any personal information leaking, which could be used to trace back the identity of both the lifelogger and other people appearing in the images. The metadata provided by the organizers is enriched to provide descriptive and temporal information for each moment. This includes the automatic extraction of location attributes, location categories, and objects in the images using computer-vision neural networks including Places365CNN [36] and Mask-RCNN [15, 35] pre-trained on the COCO dataset [23] respectively.

4 LIFESEEKER 2.0 IN LSC’20

4.1 Overview of LifeSeeker 2.0

We developed LifeSeeker 2.0 [22] for LSC’20, which was an enhanced version of its first implementation in 2019 [21]. The system was designed to maintain an innovative user interface and optimize the search time by minimizing redundant interactions (e.g. animations, selection boxes, filtering sliders, menu bar) while maximizing the amount of information displayed to the users. LifeSeeker 2.0 introduced a number of enhancements over the first version. Firstly, image thumbnail size was reduced to accommodate more images on screen, which facilitated a more efficient relevance judgement process by enabling the user to quickly skim through the retrieval results without having to scroll too much. Secondly, additional metadata was made available for each image (e.g. date, time, imagery details that match query description), which were displayed in a pop-up window as illustrated in Figure 1. The image’s details and its temporal linkages and visual similarity relationships with other images were efficiently encapsulated within the pop-up window. Finally, the temporal linkage was one of our main contributions to LifeSeeker 2.0, which we named Elastic Sequencing, and which displayed the moments before and after the current image respectively. This allows users to adjust how far in time should the moment be shown. This was accomplished by setting a delta time (time difference between images) to adjust the sequence of temporal images to be displayed. The Elastic Sequencing allows for a quicker check of chronological events, which is particularly useful for certain queries that involve events and times.

Along with the improvements in the user interface, the core indexing and retrieving system of LifeSeeker 2.0 was also upgraded. In addition to the automatically generated visual concepts provided by the organizers (as described in Section 3), we further tagged the images with the concepts from the Visual Genome dataset [20] using the Bottom-Up Attention model [1], and extracted any text visible in the images using CRAFT [3]. Moreover, the GPS readings were synthesized into human-readable addresses to be used as part of the indexing process. For retrieval, the LifeSeeker 2.0 relied
Figure 1: The interface of the system when searching for the query "Four red figures, maybe they are aliens. It looked like a painting of aliens. There were walking on the desert. There was a big red wall behind the painting". The details window shows the image’s preview in the center, the left and right sections display the temporal linkage controlled by the Elastic Sequencing, the bottom are images that are visually similar to the current image.

mainly on two search techniques: the Elastic Search and Bag-of-Words models. The users were able to use these interchangeably during their search.

In LSC’21, we continue improving this system by introducing a third version of LifeSeeker, which inherits the core functionalities of the 2.0 version, with minor fixes discussed in Section 4.2. LifeSeeker 3.0 is further enhanced with additional metadata and improved retrieval algorithms.

4.2 System Performance Analysis from LSC’20 Results
In the LSC’20 challenge, 24 queries were employed to evaluate 14 participating retrieval systems. Of these, 17 could be classified as descriptive topics and 7 classified as temporal topics. The descriptive topics describe the scenes and moments in great detail with visual clues; while the temporal topics emphasize the time sequences of activities. Figure 2, shows a summarised performance comparison of participating systems in LSC’20 by displaying the number of correct submissions of all teams, categorized by query type. LifeSeeker 2.0
achieved the overall score of 1,053 at the challenge and came mid-range among 14 participating systems ($\mu = 1,038, \sigma = 398$). The winning system achieved the highest score of 1,635. The overall score is calculated based on the search time and the number of incorrect submissions. A detailed description of how the score is calculated could be found in the LSC’18 overview paper [12]. The system was able to solve only 15 out of 24 topics (12 descriptive and 1 temporal queries, which resulted in a precision of 0.54). With respect to the top-5 performing systems in the challenge (Table 1), LifeSeeker was competitive in terms of descriptive topics, but performed poorly on the temporal ones.

Table 1: Performance comparison with top-performing teams in LSC’20 challenge

<table>
<thead>
<tr>
<th>Team</th>
<th>All Topics</th>
<th>Descriptive</th>
<th>Temporal</th>
</tr>
</thead>
<tbody>
<tr>
<td>MySceal</td>
<td>0.79</td>
<td>0.76</td>
<td>0.85</td>
</tr>
<tr>
<td>SOM Hunter</td>
<td>0.83</td>
<td>0.82</td>
<td>0.85</td>
</tr>
<tr>
<td>VIRET</td>
<td>0.75</td>
<td>0.82</td>
<td>0.57</td>
</tr>
<tr>
<td>lifeXplore</td>
<td>0.75</td>
<td>0.76</td>
<td>0.71</td>
</tr>
<tr>
<td>vitivr</td>
<td>0.70</td>
<td>0.64</td>
<td>0.85</td>
</tr>
<tr>
<td>LifeSeeker (Ours)</td>
<td>0.54</td>
<td>0.70</td>
<td>0.14</td>
</tr>
</tbody>
</table>

From Table 1, it is clear that the precision of our system is negatively impacted by temporal topics. The significant difference between the scores for descriptive and temporal topics was caused by an error in the source code that affected the accuracy of temporal sequencing presented to the user. This issue also slightly influences LifeSeeker’s performance on descriptive topics, as most of these include a temporal clue in the last expansion of the query. For example, the query: “I see Steve Wozniac on a wall of portraits. The wall was a brick wall with a door and large heater. I was speaking to an audience before seeing the photos. I left by driving back to work. It was in 2015 in March on a Wednesday”, contains an indication of time (Wednesday in March 2015), which helps to narrow down the search space and to identify the correct answer. Failing to deal with the temporal descriptions made LifeSeeker unable to retrieve the desired images.

5 OVERVIEW OF LIFESEEKER 3.0

In general, the user interface and interactive mechanism of LifeSeeker 3.0 are not extensively different from version 2.0, except that more details of a selected moment are shown. As illustrated in Figure 3, LifeSeeker 3.0 consists of three main parts: the indexed database, the interactive user interface of the search engine (client), and the server running retrieval algorithms which provides Application Programming Interfaces (APIs) for communications between the client and the server.

The indexed database consists of three weighted vocabularies (time, location, and visual-concepts); an inverted index; a listing of the top-50 visually similar search results of each lifelog image; and the pre-processed metadata in json format. The interactive user interface is kept the same as its previous version as illustrated in Figure 1; it has a free-text search bar with a list view of images showing the retrieval results. LifeSeeker 3.0 users have two options to search for the desired moment via server’s APIs: Elastic Search or weighted Bag-of-Words; these can be toggled in the settings icon in the user interface. The weighted Bag-of-Words utilizes a conventional inverted index over the three pre-processed vocabularies extracted from the provided metadata. Elastic Search only requires a single json-format file containing all the pre-processed metadata.

5.1 Metadata Processing and Enhancement

Gaining insights from data is a key factor in every retrieval system and for the purpose of LSC’21, we mainly concentrate on revising the incorrectly located points, which consequently led to the identification of distant places having no connection with the correct answer. To be more precise, we refine the geographic coordinates of the given semantic locations and group them into 32 separate classes manually. Additionally, tagging cities and countries - especially for locations outside Ireland - could expedite the search process; while using elevation with a threshold could indicate whether the lifelogger is on a plane or not. On top of that, the Microsoft Vision API is used as an automatic feature extractor for lifelog images in order to expand the variety of visual concept annotations.

5.2 Visual Similarity Search using Local Convolutional Features

We derive this idea from the work of Mohedano et al., which uses the activation of the last convolutional layer of VGG16 network structure, pre-trained on ImageNet dataset, as the local features [26] for Bag-of-Features encoding instead of using SIFT features [24]. The dimension of the output of the activation function after going through the last convolutional layer is $N \times M \times D$. This means that it has $D$ different $N \times M$ feature maps which can be considered as $N \times M$ local CNN features (descriptors) in dimension $D$. The procedure of using Bag-of-Features is the same as described in [22].

The visual similarity search employs the global search approach with global query expansion as described in [26]. In detail, the Bag-of-Visual-Words (BoVW) vector is built with all the local CNN features extracted from the queried image and is compared with other BoVW vectors using cosine distance to find the top seven most visually similar images in the corpus. These top-seven image BoVW vectors are then averaged with the original query image vector to generate a new vector representation. Finally, this vector is used to compute the similarity with all the images and generate the final list of the 50 top-ranked images.

5.3 Weighted Bag-of-Words for Free-text Search

Besides using Elastic Search for retrieval, we also implement a customized Bag-of-Words algorithm for both free-text search and filtering. In detail, we construct three vocabularies from the pre-processed metadata which include time, location, and visual concepts.

- **Time vocabulary:** contains the information of month (from January to December), weekday (from Monday to Sunday), part of the day (early morning, late morning, afternoon, etc.).
- **Location vocabulary:** contains the refined semantic location names, countries, cities, and place categories outputted from Places365CNN.
• **Visual-concept vocabulary**: contains the object labels (MS-COCO and Visual Genomes dataset) detected automatically from the lifelog images using ResNet-101 model.

The vocabularies are refined so that there are no overlapping terms between the three vocabularies. In addition, we also manually filter the vocabularies to remove meaningless terms. The weight \( w \) for each vocabulary is also different. We select the weight based on the importance of the vocabularies. In this case, the weight of the terms in time vocabulary \( \text{time} \) is higher than the location one \( \text{loc} \). The location vocabulary is considered more important than the visual-concept one \( \text{vc} \), as it would be easier to navigate to the desired moment if the location is given in the query. These weights are combined into a vector, then it is multiplied into the L2-norm term frequency vector of the query. Thereby, the weights can amplify the time and location when computing cosine similarity between the query vector and the L2-norm term-frequency vector extracted from the annotation of the lifelog image \( i \) in the dataset respectively. The term weighting of three vocabularies (time, location, and visual concepts) is represented by a vector \( w \). The score computed from our re-defined cosine similarity follows the formula:

\[
\text{score} = \frac{(w \odot tf_q) \cdot tf_i}{\|tf_q\| \|tf_i\|}
\]

**6 CONCLUSION**

In this paper, we present LifeSeeker 3.0 - a new interactive retrieval system for the LSC challenge that improves previous systems of the same name.

We briefly analyzed LifeSeeker 2.0’s performance in LSC’20 based on the results provided by the organizers to identify potential opportunities for improvement.

While the user interface of LifeSeeker 3.0 has not changed, the underlying searching mechanism is improved with weighted Bags-of-Word for free-text search and visual similarity search using local convolutional features. With more concepts extracted from Microsoft Vision API, refined GPS data, and semantic location names, both the variety of visual-concept labels and the accuracy of filtering results using semantic location increases.

As a plan for future improvements, we are investigating approaches to build a semi-automatic label recommendation system that could propose unknown objects in lifelog images for annotation. Thereby, the lifelog images can have better tags, which will boost the search engine’s performance. Moreover, we plan to conduct a user study to test the efficiency of our new searching algorithms in LifeSeeker 3.0 to identify further improvements that could be added to the system.