LifeSeeker 4.0: An Interactive Lifelog Search Engine for LSC'22

Thao-Nhu Nguyen*
Tu-Khiem Le*
Van-Tu Ninh*
Dublin City University
Ireland

Minh-Triet Tran
Nguyen Thanh Binh
University of Science
Vietnam National University
Ho Chi Minh city
Vietnam

Graham Healy
Sinéad Smyth
Annalina Caputo
Cathal Gurrin
Dublin City University
Ireland

ABSTRACT

In this paper, we introduce LifeSeeker 4.0 – an interactive lifelog retrieval system developed for the fifth annual Lifelog Search Challenge (LSC'22). In LifeSeeker 4.0, we focus on enhancing our previous system to allow users who have little to no knowledge of underlying system functioning and lifelog data to use it with ease by not only enhancing the text parser but also employing a Contrastive Language-Image Pre-training (CLIP) model as an extra search mechanism. Furthermore, we have exploited the music metadata to facilitate searches that may incorporate emotion. Event clustering is also improved in this version to increase user experience by reducing the occurrence of repeated images, and hence decreasing the search time.

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

Lifelogging can be referred to as a process of capturing the totality of an individual's life experiences using wearable sensing devices to form a complete digital record that can be stored permanently. The idea of lifelogging is originated from the vision of Vannevar Bush back in 1945 when proposing the Memex [2] as a means to externalise human memories. However, it was not until a few years ago that the idea of such a surrogate memory became feasible [7]. Many benchmarking datasets and challenges have been established to address different problems in lifelog data [4–6]. The largest of these is the Lifelog Search Challenge (LSC), which takes place annually to benchmark lifelog retrieval systems in an interactive retrieval setting since 2018. In this paper, we introduce new features, search mechanisms, and user interface upgrades to our existing interactive lifelog retrieval system, which was first introduced back in 2019 [11, 12, 17].

In this work, we introduce the fourth version of LifeSeeker that emphasises usage by users who have little to no knowledge about our system and lifelog data in general, which we refer to as novice users. Since the previous versions of LifeSeeker are concept-based retrieval systems, they depend heavily on the user's ability to formulate an appropriate information need using terms that match the indexed concepts. In order to allow a more natural query generation process, a query preprocessing technique is employed along with a new search mechanism utilising a pre-trained Contrastive Language-Image Pre-training (CLIP) model [18]. Moreover, to facilitate richer queries, we have incorporated emotion recognition which exploits the music metadata. To reduce the time needed to obtain correct results, LifeSeeker 4.0 is equipped with an enhanced event clustering technique to group similar images and show one representative image only for each cluster so that browsing can be done at speed.

2 RELATED RESEARCH

During the four years of the competition, Lifelog Search Challenge (LSC) has gained its reputation with an increasing number of participants from different organisations. Given a time-limited query, each team is requested to construct an interactive retrieval system having the ability to locate target images from a large collection that represents the lifelogger's life events. With several enhancements from the first version, MyScéal [23] in LSC'21 proved its potential as the top performing system with the highest overall score as well as the shortest query time. The authors implemented visual similarity alongside the query expansion with additional information from text and color. Vitrivr [8] developed a system adopted from the Video Browser Showdown (VBS) [21] that offers queries in multiple schemes ranging from sketches, and concepts to audio. In order to enhance the quality of daily-life egocentric images, they applied an image stabilisation module prior to the feature extraction. Meanwhile, Rossetto et al. [19] enriched the context of the textual query with the use of the knowledge graph representation. The graph was generated from the knowledge of both image's annotations and external information. Changes in query capabilities and result quality aimed to optimise the processing speed. Memento[1] participated with the aim to bridge the gap between textual and conceptional

*Three authors contributed equally to this research.

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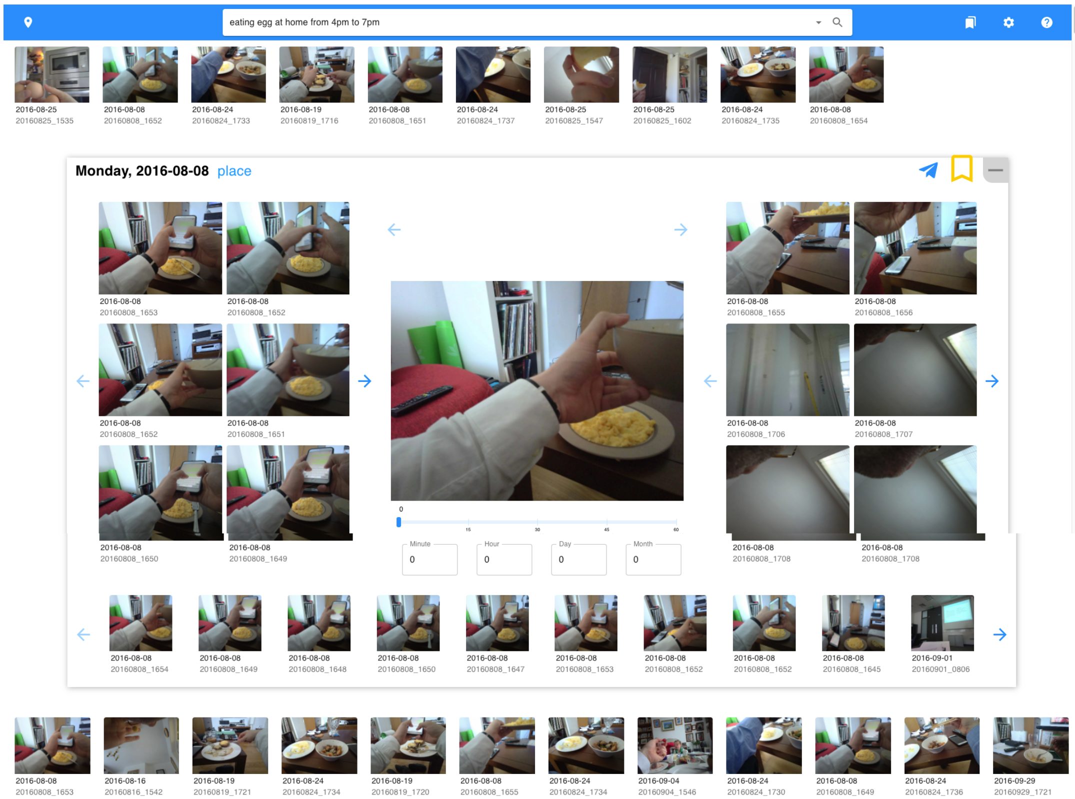

Figure 1: The User Interface of LifeSeeker 4.0

features by leveraging the CLIP model [18]. Instead of focusing on the concepts themselves, it took general image semantics into account by encoding images into high-dimensional representations. SomHunter [14] was initially introduced in LSC20 with a text-to-image search model named W2VV++ Li et al. [13] as their backbone. The new version for LSC'21 extended the search capabilities by providing different query types and re-ranking results from users' relevant feedback. As Memento, Lokoč et al. [14] also integrated a similar embedding model for browsing purposes.

The key idea behind our system's enhancement this year is to improve the user experience, especially for novice users, by providing four new functionalities. The first is the text parser which processes the input query before generating a ranked list. Event clustering is implemented as the second improvement in which groups of similar images are grouped using semantic visual features. Meanwhile, we also take into consideration the lifelogger's emotions obtained from music data. Lastly, we introduce a substitute search option built on top of the CLIP embedding model so as to exploit the image's semantic meaning, along with the conventional Elasticsearch approach.

3 OVERVIEW OF LIFESEEKER 4.0

While the system remains the same as the last year in terms of user interface (Figure 1), the architecture of the new semantic-based search mechanism is illustrated in Figure 2.

3.1 Metadata Enhancement

Lifelog dataset. Newly released this year, the LSC'22 dataset [1] is a novel multimodal data collection of one lifelogger over the period of 18 months in 2019 and 2020. This dataset contains over 725K egocentric photos in which identifiable faces are redacted and sensitive texts removed to protect personal privacy. Along with those images, visual and textual annotations were extracted by utilising Microsoft Computer Vision API and Google Cloud Vision API respectively. The organisers also provide various metadata, including location, time, biometrics, and music listening history to provide some contextual evidence for the egocentric images.

With the use of the new dataset this year, we re-define some additional metadata following the similar data enhancement process in Lifeseeker 3.0. From the given GPS coordinates, we initiate some supplemental labels that include address, city, and country before clustering those geographic points into 32 primary categories. Moreover, we revise any incorrect conversions from UTC to the local time of the places where the lifelogger was. We also construct three different vocabularies in terms of concept, location, and time, used as a filter to refine the search results.

3.2 Text Parser Enhancement

Lifeseeker 3.0 generated a ranked list of images based on a collection of syntaxes, including visual concepts, time, date, location,

[1] http://lsc.dcu.ie/lsc_data/

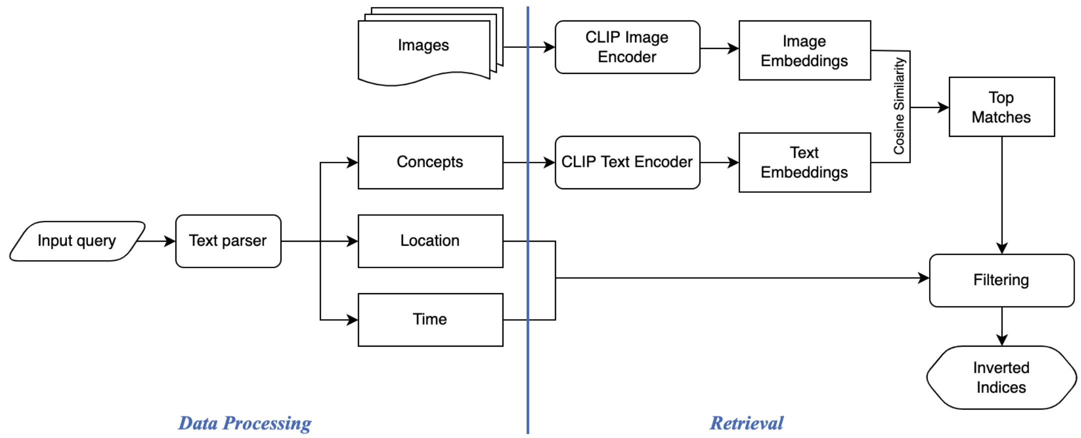

Figure 2: The extra semantic search architecture and the workflow of LifeSeeker 4.0

and activity. Users formed queries by inputting a combination of keywords and facet features. While this approach can work well for expert users, system developers, or those who have a knowledge of both dataset and how the systems work, novice users, having no clue about any visual concepts indexed, might struggle to interact with the system. Therefore, this optimised version, LifeSeeker 4.0, integrates an enhanced text parser to facilitate the searching process for newcomers. This new functionality splits the original query into three main parts corresponding to concepts, time, and location. SUtime [3] extracts the temporal information from the initial query. Meanwhile, place details are pulled out by matching with the location name collection. Keywords that are not matched to the two fields of time and location are otherwise listed as concepts.

3.3 Semantic Search Mechanism

Contrastive Language-Image Pre-training (CLIP) [18], developed by OpenAI team, is an embedding model that learns the relation between visual and semantic concepts of the scene. With the zero-shot transferability, CLIP has been widely used for different tasks ranging from self-supervised learning [16], action recognition [9] to image captioning [15]. In the lifelog area, there have been several teams [1, 14] who applied CLIP as part of their search mechanism yielding good results at LSC’21. Therefore, we deploy CLIP as an extra search mode to our retrieval system in this year’s challenge to evaluate its performance against our search technique in LifeSeeker 3.0. As can be seen from Figure 2, the pre-trained image embedding model converts lifelog images into high-dimensional feature vectors. By doing so, we leverage the contextual meaning of the general image rather than using some keywords to describe the scene only. Afterward, the input text query is embedded into the same latent space via the CLIP pre-trained text encoder. The text-and-image relation is measured by the cosine similarity. Noticeably, the location and time information are still exploited as filters, as we previously did.

3.4 Music Emotion Recognition

Although the lifelog music data was introduced in LSC’18[2] and LSC’19[3], this type of data was rarely exploited in lifelog search system as well as in the description of the queries. From our point of view, the lifelog music data has potential to be very useful as it can provide useful insights into the mood and emotion of the lifelogger at any point when music was played. The emotion of the music could be related to the emotion of the lifelogger at that point in time, reflected in the biometrics values such as skin response, heart rate [22], or potentially future data sources, such as electroencephalography or event-related brain potentials [20]. It is known that emotional response to an event is one of the essential factors affecting the recalling process of a person [10], hence we consider it to be a potentially valuable part of the search process.

The music emotion recognition is conducted based on the arousal and valence detection of a song using the OpenAPI provided by Spotify. The music is represented by two dimensions: arousal and valence, whose value of each one ranges from $[-1, 1]$. Considering these two dimensions are the axes of the $2D$-coordinate, then high and low values of these two dimensions, which is a point on the $2D$-coordinate, can be classified into four classes corresponding to four directions on two axes of a planar representation. Precisely, a high valence value indicates a happy song while a low valence one implies a sad song. Similarly, an energetic (awakening) song has a high arousal value while a quiet/relaxed song has a low arousal value. More details on the implementation and description of the music emotion recognition algorithm can be found on https://github.com/nhstaple/feelskunaman.

3.5 Event Clustering

This functionality is designed as a post-processing technique aiming to cluster consecutive images of a single event into a sequence in which the main or the middle image of the group is the representative image. By doing so, we optimise the use of screen real-estate and avoid showing duplicate images while keeping other nearby moments accessible via temporal features in the user interface.

[2]http://lsc.dcu.ie/2018/
[3]http://lsc.dcu.ie/2019/

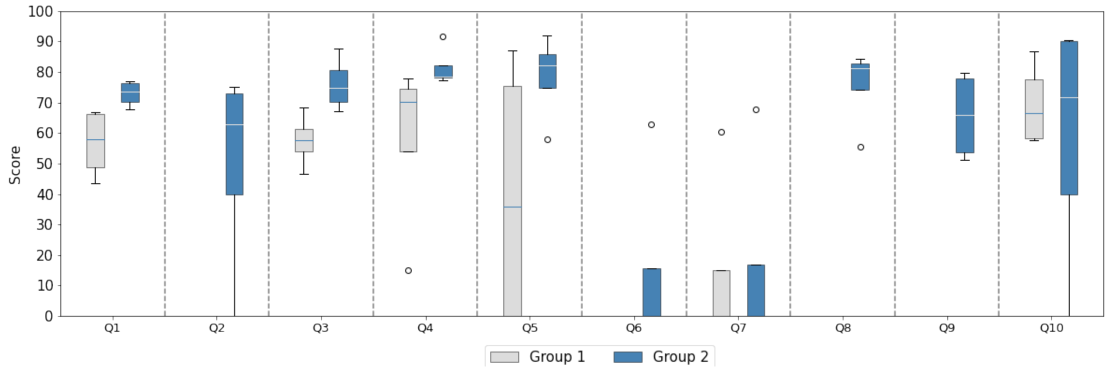

Figure 3: Score of 2 novice user groups divided by query. Group 1 and Group 2 are denoted for participants using concept-based system and semantic-based system, respectively.

Taking advantage of the semantic features extracted in 3.3, images having the shortest distance will be grouped together in the interface.

4 EVALUATION WITH NOVICE USERS

In order to examine the performance between the previous concept-based system and the newly introduced semantic-based system (LifeSeeker 4.0) for novice users, we conducted an experimental study whose format was adapted from the LSC competition (i.e., seeking target lifelog moments in a limited time, given a description of the moment). The participants in the experiment were divided into two groups, in which one group performed the search tasks using the concept-based system (Group 1), while the other used the semantic-based system (Group 2). There were a total of $N = 8$ participants recruited for this study (3 undergraduate students, 3 postgraduate students and 2 researchers), and hence, each group has 4 people ($N_{Group\_1} = N_{Group\_2} = 4$). There were no specific criteria regarding technical experience for the recruitment process. Participants who do not have either the knowledge about lifelogging and lifelog dataset or experience in how LifeSeeker 4.0 operates, were eligible. In terms of search tasks, a total of 10 queries were randomly sampled from the LSC'21 query collection (full descriptions can be found in Appendix 7.1). Each query contains one initial description and 5 following-up hints. Hints were set to display continuously after every 30 seconds, making a 3-minute duration at most to address one query. The study lasted for about 1 hour, including task introduction and breaks.

Regarding the evaluation of the performance of the participants, we employed a similar scoring scheme used in LSC. In particular, for each query, a participant who submits a correct result at time-step t will receive a score S as given in the following the formula:

$$S = \max\left(0, M + \frac{D - t}{D}(100 - M) - W * 10\right)$$

where M is the minimum score that one could earn, D represents the maximum time duration for each query and W is denoted the number of wrong submissions. In this case, M and D are 50 and 180, respectively. In other words, if the users are not able to locate the target, the score will be zero. Otherwise, it is linearly reduced from 100 to 50 over 180 seconds with a penalty of 10 points for each wrong submission.

The score of two teams divided by query is drawn in Figure 3. In general, people using the CLIP-embedding-model-based search engine (group 2) outperformed people using the keyword-based search engine (group 1). While volunteers from group 2 have solved almost all queries, twice earning more than 90 points, those from group 1 struggle and can not find the answer for Q2, Q6, Q8 and Q9. It is worth noting that the highest score of all queries belongs to group 2's participants leading to their total score being nearly doubled group 1's score (see the score detail in Table 1).

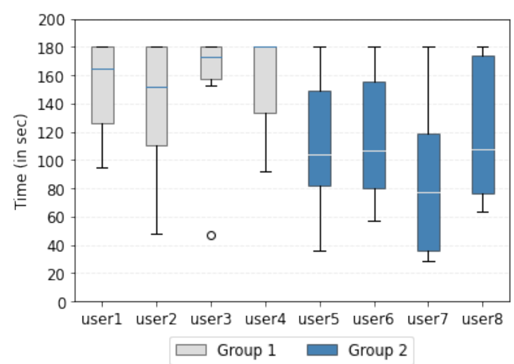

Figure 4: Distribution of solving time of all novice users. Group 1 and Group 2 are denoted for participants using the concept-based system and semantic-based system, respectively.

Solving time is also a key feature in highlighting how efficiently a system supports accurate retrieval. Hence, we investigated the distribution of search time of all volunteers during 10 queries, as shown in Figure 4. Overall, newcomers from group 2 need a shorter time to find the target compared to those from Group 1. Precisely, half of the queries have been solved by group 2 in less than 110s compared to more than 150s of the other team.

Table 1: Total score of all users over 10 queries.

Group	**Group 1**				**Group 2**			
User name	User 1	User 2	User 3	User 4	User 5	User 6	User 7	User 8
Q1	66.94	65.83	43.61	50.28	70.83	76.11	**76.94**	67.78
Q2	0.00	0.00	0.00	0.00	0.00	53.33	**75.00**	72.22
Q3	58.89	56.39	46.67	68.33	71.39	67.22	**87.78**	78.33
Q4	73.61	77.78	15.00	66.94	77.22	78.33	**91.67**	78.89
Q5	71.67	0.00	86.94	0.00	83.61	58.06	**91.94**	80.56
Q6	0.00	0.00	0.00	0.00	0.00	**62.78**	0.00	0.00
Q7	0.00	60.28	0.00	0.00	**67.78**	0.00	0.00	0.00
Q8	0.00	0.00	0.00	0.00	55.56	84.17	80.28	**82.22**
Q9	0.00	0.00	0.00	0.00	77.22	**79.72**	54.44	51.11
Q10	58.61	86.67	57.50	74.44	90.00	0.00	**90.56**	53.33
Total score	329.72	346.94	249.72	260.00	593.61	559.72	**648.61**	564.44

5 CONCLUSION

In this paper, we introduce three main enhancements to the LifeSeeker 4.0 search engine to support interactive search made by novice users, which include developing a text parser, attaching the CLIP model to the searching mechanism, and event clustering. While the semantic search mechanism employs the CLIP model as the core engine of the search system, the concept-based search mechanism uses the same Bag-of-Words approach as in previous versions of LifeSeeker. Both of them employ the enhanced text parser and event clustering function as the preprocessing approach and the postprocessing approach, respectively. Additionally, the experiment we conducted for novice users has demonstrated that the semantic-based search engine is more friendly to the user and more efficient in terms of search accuracy and time. Apart from these two enhancements, we also revise the metadata provided by the organisers to extract supplemental labels including music emotion and address, as well as adjust incorrect local time information.

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7 APPENDIX

7.1 Queries used in the experiments

Ten queries used in the experiments are defined as follows:

- **Q1** Planning a thesis/dissertation on a whiteboard with my PhD student, who was wearing a blue and black stripey top… in my office in 2016. We were using blue, black and green pens. After this I went back to work at my computer. It was on the 27th September.
- **Q2** I was organizing technology devices (phones, ipads, etc) on the wooden floor at home in an attempt to show a lifeloggers toolkit. There was a phone, an ipad, an ipad mini, a book, and other devices on a Sunday evening in 2016.
- **Q3** I was taking a photo of a lake with a DSLR camera. It was my Sony camera. I was driving outside of Sheffield before and after stopping at the lake. It was in 2015 on a Saturday.
- **Q4** I was taking a photo of grandfather clocks while shopping in the UK. It was a Saturday in an antiques store in March 2015. I had driven a rental car to the store.
- **Q5** I was going into Northside Shopping Centre. I was there to get new keys. I drove to the shopping centre from work and then I drove home. It was in 2015 in the morning time.
- **Q6** Drinking a bottle of Budweiser beer at home. This was during a BBQ in the evening in summer 2018. I had driven back home in someone else’s car before putting on the BBQ and getting the beer on a dull evening.
- **Q7** I was lost and looking for directions on a street, close to an asian restaurant called Maple Leaf. It was in the late afternoon or evening and it was in Wexford. I had driven there in 2015.
- **Q8** Colleague in my office; she was carrying a large paper envelope full of documents. The envelope looked very heavy. She was wearing red trousers, a white shirt and a polkadot top. I remember my office door was open. It was in September in 2016. On the 27th I think, in the afternoon.
- **Q9** Eating a large plate of scrambled egg at home, alone in the late afternoon. I was in my living room, with the TV on and using my phone. I was sitting on my red chair with a green exercise mat visible. It was in 2016.
- **Q10** Birds in a cage, a yellow one on the lower left. There was also one box with a small, GREEN old car (Beetle-like). No, the car was BLUE! It was in 2018 in May. I think it was a sunday.

REFERENCES

[1] Naushad Alam, Yvette Graham, and Cathal Gurrin. 2021. Memento: A Prototype Lifelog Search Engine for LSC’21. In *Proceedings of the 4th Annual on Lifelog Search Challenge* (Taipei, Taiwan) *(LSC ’21)*. Association for Computing Machinery, New York, NY, USA, 53–58. https://doi.org/10.1145/3463948.3469069

[2] Vannevar Bush. 1945. As We May Think. *Atlantic Monthly* 176, 1, 641–649. https://doi.org/10.1145/227181.227186

[3] Angel X. Chang and Christopher D. Manning. 2012. SUTime: A library for recognizing and normalizing time expressions. In *LREC*.

[4] Duc-Tien Dang-Nguyen, Luca Piras, Michael Riegler, Minh-Triet Tran, Liting Zhou, Mathias Lux, Tu-Khiem Le, Van-Tu Ninh, and Cathal Gurrin. 2019.

Overview of ImageCLEFlifelog 2019: Solve my life puzzle and Lifelog Moment Retrieval. In *CLEF2019 Working Notes (CEUR Workshop Proceedings)*. CEUR-WS.org <http://ceur-ws.org>, Lugano, Switzerland.

[5] Cathal Gurrin, H. Joho, Frank Hopfgartner, Liting Zhou, Tu Ninh, Tu-Khiem Le, Rami Albatal, D.-T Dang-Nguyen, and Graham Healy. 2019. Overview of the NTCIR-14 Lifelog-3 task.

[6] Cathal Gurrin, Björn Þór Jónsson, Klaus Schöffmann, Duc-Tien Dang-Nguyen, Jakub Lokoč, Minh-Triet Tran, Wolfgang Hürst, Luca Rossetto, and Graham Healy. 2021. Introduction to the Fourth Annual Lifelog Search Challenge, LSC'21. In *Proceedings of the 2021 International Conference on Multimedia Retrieval* (Taipei, Taiwan) *(ICMR '21)*. Association for Computing Machinery, New York, NY, USA, 690–691. https://doi.org/10.1145/3460426.3470945

[7] Cathal Gurrin, Alan F. Smeaton, and Aiden R. Doherty. 2014. LifeLogging: Personal Big Data. *Found. Trends Inf. Retr.* 8, 1 (jun 2014), 1–125. https://doi.org/10.1561/1500000033

[8] Silvan Heller, Ralph Gasser, Mahnaz Parian-Scherb, Sanja Popovic, Luca Rossetto, Loris Sauter, Florian Spiess, and Heiko Schuldt. 2021. Interactive Multimodal Lifelog Retrieval with Vitrivr at LSC 2021. In *Proceedings of the 4th Annual on Lifelog Search Challenge* (Taipei, Taiwan) *(LSC '21)*. Association for Computing Machinery, New York, NY, USA, 35–39. https://doi.org/10.1145/3463948.3469062

[9] Evgeny Izutov. 2021. LIGAR: Lightweight General-purpose Action Recognition. *ArXiv* abs/2108.13153 (2021).

[10] Elizabeth A Kensinger. 2009. Remembering the details: Effects of emotion. *Emotion review* 1, 2 (2009), 99–113.

[11] Tu-Khiem Le, Van-Tu Ninh, Duc-Tien Dang-Nguyen, Minh-Triet Tran, Liting Zhou, Pablo Redondo, Sinead Smyth, and Cathal Gurrin. 2019. LifeSeeker: Interactive Lifelog Search Engine at LSC 2019. In *Proceedings of the ACM Workshop on Lifelog Search Challenge* (Ottawa ON, Canada) *(LSC '19)*. Association for Computing Machinery, New York, NY, USA, 37–40. https://doi.org/10.1145/3326460.3329162

[12] Tu-Khiem Le, Van-Tu Ninh, Minh-Triet Tran, Thanh-An Nguyen, Hai-Dang Nguyen, Liting Zhou, Graham Healy, and Cathal Gurrin. 2020. *LifeSeeker 2.0: Interactive Lifelog Search Engine at LSC 2020*. Association for Computing Machinery, New York, NY, USA, 57–62. https://doi.org/10.1145/3379172.3391724

[13] Xirong Li, Chaoxi Xu, Gang Yang, Zhineng Chen, and Jianfeng Dong. 2019. W2VV++: Fully Deep Learning for Ad-Hoc Video Search. In *Proceedings of the 27th ACM International Conference on Multimedia* (Nice, France) *(MM '19)*. Association for Computing Machinery, New York, NY, USA, 1786–1794. https://doi.org/10.1145/3343031.3350906

[14] Jakub Lokoč, František Mejzlik, Patrik Veselý, and Tomáš Souček. 2021. Enhanced SOMHunter for Known-Item Search in Lifelog Data. In *Proceedings of the 4th Annual on Lifelog Search Challenge* (Taipei, Taiwan) *(LSC '21)*. Association for Computing Machinery, New York, NY, USA, 71–73. https://doi.org/10.1145/3463948.3469074

[15] Ron Mokady, Amir Hertz, and Amit H. Bermano. 2021. ClipCap: CLIP Prefix for Image Captioning. *ArXiv* abs/2111.09734 (2021).

[16] Norman Mu, Alexander Kirillov, David A. Wagner, and Saining Xie. 2021. SLIP: Self-supervision meets Language-Image Pre-training. *ArXiv* abs/2112.12750 (2021).

[17] Thao-Nhu Nguyen, Tu-Khiem Le, Van-Tu Ninh, Minh-Triet Tran, Nguyen Thanh Binh, Graham Healy, Annalina Caputo, and Cathal Gurrin. 2021. LifeSeeker 3.0: An Interactive Lifelog Search Engine for LSC'21. In *Proceedings of the 4th Annual on Lifelog Search Challenge* (Taipei, Taiwan) *(LSC '21)*. Association for Computing Machinery, New York, NY, USA, 41–46. https://doi.org/10.1145/3463948.3469065

[18] Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, Gretchen Krueger, and Ilya Sutskever. 2021. Learning Transferable Visual Models From Natural Language Supervision. *CoRR* abs/2103.00020 (2021). arXiv:2103.00020 https://arxiv.org/abs/2103.00020

[19] Luca Rossetto, Matthias Baumgartner, Ralph Gasser, Lucien Heitz, Ruijie Wang, and Abraham Bernstein. 2021. Exploring Graph-Querying Approaches in LifeGraph. In *Proceedings of the 4th Annual on Lifelog Search Challenge* (Taipei, Taiwan) *(LSC '21)*. Association for Computing Machinery, New York, NY, USA, 7–10. https://doi.org/10.1145/3463948.3469068

[20] Hans-Eckhardt Schaefer. 2017. Music-Evoked Emotions—Current Studies. *Frontiers in Neuroscience* 11 (2017).

[21] Klaus Schoeffmann. 2019. Video Browser Showdown 2012-2019: A Review. In *2019 International Conference on Content-Based Multimedia Indexing (CBMI)*. 1–4. https://doi.org/10.1109/CBMI.2019.8877397

[22] Alan F. Smeaton and Sandra Rothwell. 2009. Biometric Responses to Music-Rich Segments in Films: The CDVPlex. *2009 Seventh International Workshop on Content-Based Multimedia Indexing* (2009), 162–168.

[23] Ly-Duyen Tran, Manh-Duy Nguyen, Nguyen Thanh Binh, Hyowon Lee, and Cathal Gurrin. 2021. Myscéal 2.0: A Revised Experimental Interactive Lifelog Retrieval System for LSC'21. *Proceedings of the 4th Annual on Lifelog Search Challenge* (2021).