Overview of NTCIR-13 Lifelog-2 Task

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ABSTRACT

In this paper we review the NTCIR13-Lifelog core task, which ran at NTCIR-13. We outline the test collection employed, along with the tasks, the submissions and the findings from this pilot task. We finish by suggesting future plans for the task.

Keywords

lifelog, test collection, information retrieval, multimodal, evaluation

1. INTRODUCTION

Lifelogging is defined as *"a form of pervasive computing, consisting of a unified digital record of the totality of an individual's experiences, captured multi-modally through digital sensors and stored permanently as a personal multimedia archive"* [4]. Lifelogging has been gaining increasing attention in the research community in recent years due to the increasing prevalence of lifelogging devices in the marketplace and the challenges posed by organising the associated lifelog data [7]. Lifelogging typically generates multimedia archives of life-experience data in an enormous (potentially multi-decade) lifelog.

In this paper we describe the NTCIR13-Lifelog task, one of the core tasks at NTCIR-13, which is a continuation of the pilot task [6] from NTCIR-12. Lifelogging, as a task is receiving increasing levels of attention from the research community and this NTCIR activity is operating in parallel to the ImageCLEF2017 lifelog task [2]. Additionally, we note the LTA (Lifelogging Tools and Applications workshop series which has been running since 2016.

We begin this paper with a description of the lifelog test collection, followed by a description of the four sub-tasks. Finally we outline the submissions received and the plans for the next edition of the Lifelog task at NTCIR.

2. TASK OVERVIEW

The lifelog-2 task explored a number of approaches to information access and retrieval from personal lifelog data, each of which addressed a different challenge for lifelog data organization and retrieval. The four sub-tasks, each of which could have been participated in independently, are as follows:

- Lifelog Semantic Access sub-Task (LSAT) to explore search and retrieval from lifelogs.
- Lifelog Event Segmentation sub-Task (LEST) to explore knowledge mining and visualisation of lifelogs.
- Lifelog Annotation sub-Task (LAT) to explore search and retrieval from lifelogs.
- Lifelog Insight sub-Task (LIT) to explore knowledge mining and visualisation of lifelogs.

2.1 LSAT SubTask

The LSAT subtask was a known-item search task applied over lifelog data. In this subtask, the participants had to retrieve a number of specific moments in a lifelogger's life in response to a query topic. We consider moments to be semantic events, or activities that happened at least once in the dataset. The task can best be compared to a known-item search task with one (or more) relevant items per topic. Participants were allowed to undertake the LAST task in an interactive or automatic manner. For interactive submissions, a maximum of five minutes of search time was allowed per topic. The LSAT task included 24 search tasks, generated by the lifeloggers and guided by Kahneman's lifestyle activities [8].

2.2 LEST SubTask

The LEST subtask tackled a persistent problem for lifelog researchers, that of how to segment the continuous lifelog data into indexable document units called events. As of yet there is no standard approach to event segmentation for lifelog data, so this task aimed to explore alternative approaches to event segmentation.

2.3 LAT SubTask

The LAT subtask was a subtask aimed at computer vision researchers to develop approaches for annotation of the multimodal lifelog data with a fixed set of fifteen high-level labels chosen from a larger ontology of lifelogging activities. Each image was to be labeled with the concepts from the analogy. These concepts are based on both the activities (facets of daily life) of the individual and the environmental settings (contexts) of the individual.

2.4 LIT SubTask

The LIT subtask was exploratory in nature and the aim of this subtask was to gain insights into the lifelogger's daily life activities. It followed the idea of the Quantified Self movement [10] that focuses on the visualization of knowledge mined from self-tracking data to provide "self-knowledge through numbers". Participants were requested to provide insights about the lifelog data that support the lifelogger in reflecting upon the data, facilitate filtering and provide for efficient/effective means of visualisation of the data. The LIT task included five information needs. We did not have an explicit evaluation for this task, rather we expected all participants to present their demonstrations or reflective outputs at the NTCIR conference.

3. DESCRIPTION OF THE LIFELOG TEST COLLECTION

In design and construction of lifelog dataset, there are significant technical challenges to be solved, arising from the gathering, semantic enrichment, and pervasive accessing of these vast personal data archives. To overcome these challenges, we addressed the issues and proposed principles as well as processes to collect such kind of data, presented in [3]. In summary, we had defined a number of requirements for the collection, which were based on the requirements employed for the NTCIR-12 lifelog pilot task [6]:

- To be large enough to support a number of different retrieval tasks, but not so large as to discourage participation and use.
- To include appropriate and real-world lifelog data gathered in a conventional lifelogging situation.
- To lower barriers-to-participation by including sufficient metadata and a baseline search engine, so that researchers interested in a broad range of applications, with a range of expertise, can utilise the test collection.
- To consider the principles of privacy-by-design [1] when creating the test collection, because personal sensor data (especially camera or audio data) carries privacy concerns.
- To include realistic topics representing real-world information needs of varying degrees of difficulty.
- To include a set of relevance judgments for each task that can be utilised both as a source of data for comparative evaluation as well as being later utilised as a source of training data for future experimentation.

These requirements guided the test collection generation process.

3.1 Data Gathering Process

The data was gathered by two lifeloggers who wore the lifelogging devices and gathered basic medical data for most (or all) of the waking hours in the day. One lifelogger gathered one month of data and one lifelogger gathered two months of data, giving a total of 90 days of data for the test collection. The lifeloggers wore a Narrative Clip wearable camera clipped to clothing or worn on a lanyard around the neck which captured the daily activities of the wearer (from the wearer's viewpoint) and operated for 10-12 hours on a battery charge gathering in the region of 1,250 - 1,500 images per day. This camera takes photos passively (i.e. without explicit user intervention) at about two images per minute. Additionally the lifeloggers included data from the Moves lifelogging app (locations and physical movements) and a record of music listened to captured from `Last.fm` accounts. The Moves app is a smartphone app that automatically records user activity in terms of semantic locations and physical activities (e.g. waking, cycling, running, transport) by running in the background on a smartphone. Finally, the dataset included health and wellness data from continual heart-rate monitors, daily blood glucose monitors with additional weekly cholesterol and uric-acid readings, along with manual annotations of food and drink consumption.

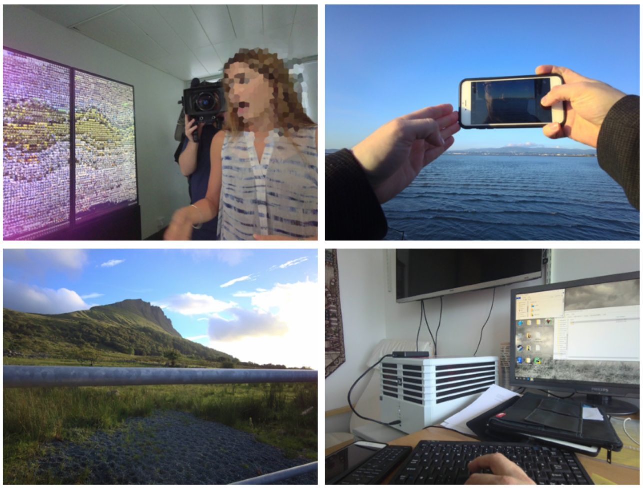

Figure 1: Examples of Wearable Camera Images from the Test Collection

Following the data gathering process, there were a number of steps that were taken to ensure that test collection was both as realistic as possible, and took into account sensitivities associated with personal data:

- Temporal Alignment. All data was temporally aligned to UTC time where possible.
- Data Filtering. Given the personal nature of lifelog data, it was necessary to allow the lifeloggers to remove any lifelog data that they may be unwilling to share. Additionally all lifelog data was reviewed by a trusted organiser who ensured that no personally sensitive data was released with the collection.
- Privacy Protection. Privacy-by-design [1] was one of the requirements for the test collection. Consequently, two steps were taken to ensure privacy of both the lifeloggers and any recognisable individuals captured in the lifelog data. Each recognisable face and device screen in every image was blurred in a manual process that took a number of weeks to accomplish. In addition, every image was also resized down to 1024×768 resolution which had the additional effect of rendering any on-screen content illegible. The Moves app naturally protects privacy of our lifeloggers by converting all locations from absolute locations to semantic locations, which resulted in sensitive absolute addresses being labeled as 'home' or 'work'.

3.2 Details of the Dataset

The data consists of a large collection of multimodal lifelog data over 90 days by two lifeloggers. In most cases the activities of the lifeloggers were separate and they did not meet. However on a small number of occasions the lifeloggers appeared in each other's data. The data consists of:

Table 1: Statistics of NTCIR-12 Lifelog Data

Number of Lifeloggers	2
Number of Days	90 days
Size of the Collection	26.6 GB
Number of Images	114,547 images
Number of Locations	138 locations
Number of LSAT Topics	24 topics
Number of LEST Event Types	15 event types
Number of LAT Concepts	15 concepts
Number of LIT Topics	5 topics

- Multimedia Content. Wearable camera images were gathered using a Narrative Clip 2 wearable camera capturing about two images per minute and worn from breakfast to sleep. Accompanying this image data is a timestamped record of music listening activities sourced from Last.FM.
- Biometrics Data. Using the Basis smartwatch, the lifeloggers gathered 24×7 heart rate, galvanic skin response, calorie burn and steps. In addition, daily blood pressure and blood glucose levels were recorded every morning before breakfast and weekly cholesterol and uric acid levels were recorded.
- Human Activity Data. The daily activities of the lifeloggers were captured in terms of the semantic locations visited, physical activities (e.g. walking, running, standing) along with a timestamped diet-log of all food consumed drinks taken.
- Enhancements to the data. The wearable camera images were annotated with the outputs of a semantic concept detector from Microsoft accessible via their computer vision API. In addition, to support participants in their software development, a baseline search engine was developed to support basic queries to the system. Queries were submitted that generate ranked lists based on faceted queries, by userID, location visual concept and/or physical activity.

3.3 Topics

The LSAT task includes 24 topics with full relevance judgments, though only 20 of these were used in the final calculating of performance. These LSAT topics were evaluated in terms of traditional Information Retrieval effectiveness measurements such as Precision, Recall and NDCG. An example of an LSAT topic is included as Figure 3. For a full list of the topics see Table 2. In this table, the number of groundtruth relevant events are shown for each topic is shown.

These 24 topics were labeled as being either difficult or easy, based on the complexity of the query topic in terms of the number of components to the query. For example, a topic 'at the seaside' would be considered to be easy, whereas a topic 'taking a photo at the seaside' would be complex, due to the fact that there are two components to this query (seaside and taking a photo).

For the LEST Event Segmentation subtask, there were fifteen types of events defined. These were defined in order to make it easier for participants to develop event segmentation algorithms for the very subjective human event segmentation tasks. The fifteen types of event are:

- travel: travelling (car, bus, boat, airplane, etc)

TITLE: Gardening
DESCRIPTION: Find moments when I was gardening in my home.
NARRATIVE: Relevant moments should show the user in the garden and interacting with vegetation in some way, such as trimming bushes or cutting grass. The gardening activity must take place in the user's home and not any other location.

Figure 2: LSAT Topic Example

TITLE: Preparing Meals
DESCRIPTION: Annotate all moments when the user is preparing meals.
NARRATIVE: Preparing meals involves the preparation of food items that occurs before the user, or bystanders eat the meal. In order to be considered correct, the food preparation process must be visible. The location where the food is prepared does not matter.

Figure 3: LAT Topic Example

- f2f: face-to-face interaction with people (excluding social interactions)
- computer: using desktop computer / laptop / tablet / smartphone
- meals: preparing meals (include making tea or coffee)
- eating: eating meals in any location
- children: taking care of children / playing with children
- home: working in the home (e.g. cleaning, gardening)
- relax: relaxing at home (e.g. TV, having a drink)
- paper: reading paper
- social: socialising outside the home or office
- pray: praying / worshipping / meditating
- shop: shopping in a physical shop (not online)
- gaming: playing computer games
- physical: physical activities / sports (walking, playing sports, cycling, rowing, etc)
- creative: creative endeavours (writing, art, music)
- other: any other activity not represented by the fourteen labels above.

The LAT task aimed to annotate the visual lifelog data with fifteen labels taken from a larger ontology of common daily activities that were developed by the organisers, but based on Kahenmann's most enjoyable lifestyle activities.

These fifteen lifestyle activity labels were listed in Figure 4.

Additionally, there were five LIT insight topics representing the challenge of supporting *Reflection* from memories. These were called LIT (Lifelog Insight) Topics and are not evaluated in a traditional sense. Participants were encouraged to prepare insights and demonstrate them directly at the NTCIR-13 Conference.

Table 2: LSAT topics for NTCIR-13 Lifelog-2 subtask

Topic Title	Topic Title	Topic Title
Eating Lunch	Fruit or Vegetable Juice	Working Late
Gardening	Photo of the Sea	Exercises
Castle at Night	Having Beers in a Bar	On the Computer
Coffee	Greek Amphitheatre	Benbulbin Mountain
Sunset	Television Recording	Cooking
Graveyard	Working in a Coffee Shop	Hiking
Presenting / Lecturing	Painting Walls	Flying
Grocery Shopping	Eating Pasta	Turtles

Commuting	Travelling	Preparing Meals
Eating / Drinking	Socialising	Reading
Watching TV	Walking	Exercise
Writing	In a Kitchen	In a restaurant
At a tourist site	On the street	A passenger in a car

Figure 4: The fifteen lifestyle activity labels.

- Diet: Provide insights into the diet and blood sugar levels of the lifeloggers. For example, how does diet impact on the blood sugar levels of the lifeloggers?
- Exercise: Describe the exercise, sleep and physical activities of both lifeloggers
- Social: Socialisation levels are a good indicator of the health of individuals. Provide a themed social diary for each individual.
- Where: Provide insights onto the location and movement patterns of the lifeloggers (e.g. are they ever in the same place?)
- Compare: Comparison between two individuals across multiple dimensions (where the dimension is up to you).

3.4 Relevance Judgments

Manual (non-pooled) relevance judgments were generated manually for all 24 LSAT topics, all fifteen LAT topics/labels and a manual event segmentation was performed for the LEST task.

3.5 Baseline Search Engine

Together with the collection and topics, a baseline search engine was also provided. This baseline search engine can be used to retrieve lifelog moments based on four criteria: user, location, concept, and activity. By given this engine, we expected that it can be exploited to solve LAT and LSAT tasks. The tool can be accessed at: `http://search-lifelog.computing.dcu.ie/`. For more details of this baseline search engine, please refer to [14].

4. PARTICIPANTS AND SUBMISSIONS

In total nineteen participants signed up to the Lifelog task at NTCIR-13, however only five participants managed to submit to any of the sub-tasks of the Lifelog task. This was a disappointing rate of submission and provided little ability to engage in any form of comparative evaluation. We will now summarise the effort of the participating groups in the sub-tasks that they submitted to.

4.1 LSAT Sub-task

Three participating groups took part in the LSAT sub-task, all in an automated manner. The *DCU group* took part with their baseline search engine [5]. Details of this have been provided earlier in this paper. There were two runs submitted, one that automatically generated a query from the words in the topic, and a second run that employed a human-in-the-loop to translate the topic into a faceted query for the baseline search engine. The baseline search engine got an AP score of 0.098 for the automatic query generation approach and 0.329 for the manual query-generation run.

VCI2R (Singapore) proposed a general framework to bridge the semantic gap between lifelog data and the event-based LSAT topics [9]. The key components of this approach were the use of CNNs to translate lifelog images into object and scene features, concepts and event-adapted feature weights and temporal smoothing across content within an event. In this technique, lifelog images, locations and timestamps were represented by a series of feature vectors representing a number of object-centric pre-trained classifiers. For each type of feature, concepts with high response to an event were considered as 'relevant' concepts to that event. Feature importances were learned with a Conditional Random Field (CRF) model to weight the contricutiotions of gestures for specific events. Finally, temporal smoothing is employed with the assumption that adjacent images are semantically coherent. This approach proved the most successful at 0.576 AP.

The PGB group (NTT, Japan) focused on the image and location data when developing their approach to LSAT search, due to a belief that these are likely to be the most important points for understanding user activities and context [13]. For object recognition from the visual data, two deep neural network models were created using GoogLeNet and AlexNet, while for scee recognition four DNN models were emploted using GoogLeNet, AlexNet, VGG and ResNet. Additionally, using HOG feature vectors, the number of people in each image were detected. This resulted in a 3,463 dimension visual feature for each image. Locations were indexed using point-stay detection using the D-Star algorithm and important location detection using the DBSCAN algorithm. In order to perform retrieval over the user topics, a text retrieval method was employed, which labeled every image ID with both the provided labels and the labels calculated using the image and location detection approaches just described. The queries were then processed using a standard approach to text retrieval. Finally, a temporal filter was applied to optimise results for time-specific queries. This approach aimed an AP score of 0.278.

4.2 LEST Task

The PGB group (NTT, Japan) took part in the LEST task and developed an approach to event segmentation that identified the end-image of every event and from that, automatically found the starting (next) image of the following event [13]. There were our different approaches developed spanning a range of alternative techniques. The first approach is a similarity-based approach that used GoogleNet's ImageNet score to identify the similarity between sequences of images and where the similarity was under a threshold, there was an event-end declared. The second approach was based on identifying the stay-regions of the user as an indication of the likelihood of an event-boundary. A third approach used LDA to reduce the dimensions of the images to a number of latent topics and following that, Welch's t-test was employed to detect unnatural image groups using a sliding window. Thresholding was then employed to detect the end-of-event image. The final approach was the Gated CNN approach which used features from several pieces of time-step data (images and GPS sequences). Cosine similarity was employed in detecting the end of a segment using sliding windows. Although some approaches performed better in terms of either precision or recall, the second approach based on the D-Star location ranking seemed to score highest in terms of F1 score. The official score of PGB group for this task is 0.579.

4.3 LIT Sub-task

For the LIT task, there were no submissions to be evaluated in the traditional manner; rather the LIT task was an exploratory task to explore a wide-range of options for generating insights from the lifelog data. Five suggested topics were given, but the participants were free to choose any topics of interest. Three groups took part in the LIT task:

Tsinghua University (China) The group from Tsinghua University used the lifelog-2 dataset to give insights into the big-five personality traits, moods, music moods, style detection and sleep-quality prediction [11]. The team augmented the lifelog-2 dataset with lifelog data gathered by other volunteers. The team found that their approaches achieved objective results with a high degree of accuracy, and note the implications for improving traditional psychological research by employing lffelog data.

Institute for Infocomm Research (Singapore) The group from I2R presented a method for finding insights from the lfielog data by creating a minute-by-minute annotation of the user's activities with respect to the five identified topics [12]. This was achieved by applying deep-learning approaches for image analytics and then fusing the multimodal sensor data. Insights were then generated in terms of activity occurrence, temporal and spatial patterns, associations among activities, etc. A prototype mobile app was developed to visualize the extensive insights generated.

DCU, Ireland. The submission from Dublin City University introduced an interactive lifelog interrogation system which was implemented for access in a Virtual Reality Environment [5]. The system was designed to allow a user to explore visual lifelog data in an interactive and highly visual manner. Three of the five LIT topics were implemented in the VR lifelog tool where each topic (social, diet and exercise) could be selected by a user using a virtual-reality equivalent of an artists easel, which converted the three topics (manually mapped) into a set of visual concepts which were used to highlight related visual content from the lifelog data. The topic-related lifelog data was then displayed in the VR environment for the user to view and interact with.

4.4 LAT Sub-task

The PGB group (NTT, Japan) took part in the LIT task to automatically label the lifelog images with fifteen concept labels [13]. A DNN model was employed with a fusion layer of thi-modal data (image, location and biometric). The visual and location indexing process is described above. The biometric features were encoded by a fully-connected neural network to one feature representation, the outer layer of which estimates the lifelog labels via fifteen sigmoid functions. There was an element of group suggest tat visual and biometric features can enhance the automatic annotation process, yet location reduces reduce it.

5. LEARNINGS & FUTURE PLANS

This was the second collaborative benchmarking exercise for lifelog data at NTCIR. It attracted five active participants, three for the automatic LSAT search task, three for the LIT task, and one each for the LEST and LAT tasks. We can summarise the learnings from this task as follows:

- We were disappointed by the number of submissions received. We are endeavouring to ascertain if the task was too complex or demanded too much effort from participants. We note that the baseline search engine did not appear to be used by participants.
- After the NTCIR-12 lifelog pilot task, we noted that there was still no standardised approach to retrieval of lifelog data; this position has not changed.
- The dataset should contain more semantically rich data to support mare groups to take part.
- For future datasets, a stricter protocol for data gathering needs to be designed and enforced to ensure that both automatically and manually generated metadata is fully accurate and time-aligned.
- The LSAT task is a valuable task, though effort should be made to encourage more participants. In future years, we intend to make Japanese and Chinese versions of the data available.
- The LAT and LEST tasks did not attract sufficient participants so it is our assumption that these tasks are likely not of interest to the research community at NTCIR in the near future. We intend to focus these tasks in the ImageClef community in 2018 and focus our NTCIR-14 sub-tasks on the information retrieval challenges, such as LSAT and LIT sub-tasks.

5.1 Future Plans for the Test Collection

The test collection just described will be released for wider public use in a reduced form. The test collection to be released will be the same as the original dataset, though with the following two exceptions:

- Only User 1 will be included, with a subset of the 60 days of data.
- There will be additional data included on the information creation and consumption data from computer usage, including keystrokes, URLs and application usage. Initially

this was planned to be included in the NTCIR-13 Lifelog-2 dataset, but it was not included.

- Accompanying the dataset will be a set of manually captured smart-phone photos.

6. CONCLUSION

In this paper, we described the data and the activities from the lifelog-2 core-task at NTCIR-13. There were four sub-tasks prepared for this year. Although it is difficult to draw many conclusions from these findings, we do note that there is still a lot of research that needs to be done to develop annotation and search tools for lifelog archives. In future years, we hope to continue this lifelog task (e.g NTCIR-14 Lifelog-3), but we will reduce both the size of the collections and the number of sub-tasks that are on offer and focus effort on the tasks that are most likely to attract interest from NTCIR participants.

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