Aggregating Life Tags for Opportunistic Crowdsensing with Mobile and Smartglasses Users

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ABSTRACT

We discuss in this work the opportunity of employing lifelogging devices, applications, and systems, such as systems that collect, process, and store video using mobile and wearable cameras, in order to run queries about objects and concepts of interest from everyday life. The outcome is an instance of "opportunistic mobile crowdsensing," which we implement with lifelogging technology, mobile video cameras, and camera glasses. We describe the implementation of our concept that builds on top of Life-Tags, a wearable system for abstracting life in the form of clouds of concepts automatically extracted from videos captured by lifeloggers. We show how Life-Tags can be extended with a mobile application and cloud-based services, the Firebase Realtime Database and Cloud Storage, toward integrated lifelogging and mobile crowdsensing, where the life tags of mobile and wearable users are queries for potential matches regarding specific objects and concepts of interest. We conclude with implications for the future integration of lifelogging technology, mobile and wearable computing, and crowdsensing.

CCS CONCEPTS

• **Human-centered computing** ~ **Human computer interaction (HCI)**; *Interactive systems and tools; Ubiquitous and mobile devices;* • **Software and its engineering.**

KEYWORDS

Smartglasses; Smart wearables; Mobile devices; Prototype; Mobile crowdsensing; Life-Tags; Participatory sensing.

1 INTRODUCTION

Lifelogging applications enable automatic and passive collection of personal data, *e.g.*, first-person images and video, GPS coordinates of journeys, and physiological measurements, among others, that are stored as memory aids to offer support for reliving past moments [1-4]. Several commercial products and applications are available for lifelogging in the form of clip-on wearable cameras [5-11], while recent research has explored new representations and visualizations for video and image-based lifelogs, such as clouds of tags automatically extracted from first-person, eye-level video [12]. In most cases where such systems are worn and active in public places, the information from the lifelogs they collect contains sensible information, such as regarding bystanders, which can generate complaints and opposition toward the wearers of such systems [13-15]. However, this information can equally be useful to the bystanders unwillingly caught on camera that could effectively use the lifelog collected by a third party for their own benefit.

Given that video lifelog processing can be automated in the cloud, having many mobile and wearable video camera users collecting data and acting as crowdsensing workers represents an opportunity for performing everyday visual search tasks more effectively, for example visual tasks that represent challenges for people with low vision [16]. Inspired by the practice of mobile crowdsensing [17-23], recent prototypes for camera-based smartglasses, such as LifeTags [12] and CueSee [16], designed to assist users by abstracting their life and improving the performance of visual search, respectively, we introduce in this paper the concept and opportunity of employing lifelogging applications, such as those running on mobile and wearable video camera devices, to enable queries about objects and concepts of interest. These queries could be answered effectively by means of opportunistic mobile crowdsensing. This way, the lifelog would be useful not just to the wearer of such technology, but also to the larger community, including remote users and bystanders. Our practical contributions are as follows:

1. We introduce the idea of using lifelogging applications to implement queries about objects of interest from everyday life that could be answered in real-time[2] by means of opportunistic crowdsensing implemented with video camera-based devices.
2. We describe an implementation of our concept by starting from the Life-Tags system of Aiordăchioae and Vatavu [12],

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[2] By "real-time," we mean a short interval of time in the order of seconds between the moment when the question is posed, *e.g., Where is the fruit section in this supermarket?* to the moment when results return from the cloud.

which we extend with cloud resources and services, *i.e.*, the Firebase Realtime Database [24], Firebase Cloud Storage [25], Google Cloud Vision [26], and a Node.js application. In our prototype, the tag clouds of many users are queried for potential matches of objects and concepts of interest.

3. We present preliminary results about our system and conclude with implications for future integration of lifelogging, mobile and wearable computing, and mobile crowdsensing.

2 RELATED WORK

We are witnessing a growth of mobile and wearable devices [27,28] that rely on embedded sensors for novel sensing applications. In this section, we discuss two instances of such applications represented by lifelogging and mobile crowdsensing.

2.1 Lifelogging

Lifelogging is the process by which users record and store various aspects of their daily life [29], such as in the form of snapshots and videos captured by wearable cameras. Lifelogging systems are usually constituted of several components responsible for collecting, storing, analyzing, querying, presenting, and sharing data. Among the most relevant prototypes from the scientific literature, we note SenseCam [30], EyeTap [31], DejaView [32], and InSense [33]. Several commercial products are available for lifelogging enthusiasts including MeCam [6], Narrative Clip 2 [7], SnapCam [8], and Google Clips [9]. Unlike clip-on video cameras, smartglasses can record video from the first-person and eye-level perspective [10,11].

Preliminary work on lifelogging applications has focused on monitoring various aspects of life, such as food-logging [34], computer usage [1], sleep patterns [35], wordometer systems [36], vehicular lifelogging [37,38], thing-logging for the Internet-of-Things [39], and applications that collect data for the purpose of evaluating the quality of life [40]. For example Zini *et al.* [40] proposed a system to monitor four distinct aspects of life quality, such as activities, sleep, fatigue, and mood. For people with severe memory problems, lifelogging applications provide memory support, referred as "memory prosthesis," by enabling users to relive recent experiences with the help of the lifelog [2-4].

2.2 Mobile crowdsensing

Ganti *et al.* [17] introduced the term "mobile crowdsensing" (MCS) to denote a general paradigm for mobile phone-based sensing in the context of crowdsourcing. Systems that build on this approach utilize sensors and communications interfaces embedded in mobile devices, *e.g.*, cameras, microphones, GPS and inertial measurement units. However, in order to operate effectively and attain the goal for which they were designed, MCS systems require the participation of a large number of users. Practical applications for mobile crowdsensing are useful for communities to collectively acquire data from which to extract information to analyze, estimate, and predict events of interest. For example, such systems have frequently addressed smart cities [18-20]. The Leelou Private Eye [20] is a crowd-sourced scanning network based on smartglasses that locates missing persons and warns about people with a criminal history. Jigsaw [19] is a floor plan reconstruction system that leverages crowdsensed data.

Mobile crowdsensing systems have practical applications for people with visual impairments to help identifying objects with the support of remote assistants [21] or computer vision analysis [22,23]. For example, VizWiz [21] is a mobile application that enables people who are blind to solve visual problems in near real-time with the participation of human workers; TapTapSee [22] is an application designed for people with visual impairments that employs computer vision [41] to identify objects; and VizMap [23] employs computer vision and crowdsourcing to collect visual information about the environment (posters, signs, exit doors, etc.) from videos taken on-site by volunteers. These videos are then employed to build a 3D point cloud representation of the environment for localization and navigation.

2.3 Summary and contribution

In this work, we demonstrate the opportunity of a new concept by combining two existing technologies: lifelogging and mobile crowdsourcing. The outcome is an instance of opportunistic mobile crowdsensing, where data collected by mobile and wearable camera devices is used to perform queries regarding everyday objects and concepts of interest. Our approach is to start from an existing prototype [12], originally designed for single-user operation, and show how it can be extended with cloud services toward multi-user opportunistic crowdsensing. We demonstrate the concept with a functional prototype, for which we present engineering details and preliminary evaluation results, while we leave in-depth evaluation for future work.

3 LIFE-TAGS

Life-Tags [12] is a wearable prototype designed to automatically capture snapshots using a camera glasses and to summarize life with word clouds. Life-Tags focuses on the concept of abstracting life by providing users with executive summaries of what their visual experiences were like, as recorded from the first-person, eye-level perspective of the smartglasses rather than with a list of snapshots and videos as in conventional lifelogging applications.

Using Life-Tags, life experiences are stored for future consultation. Users can also choose to select synthetic parts of the lifelog, *e.g.*, a cloud of concepts, to share data on social networks, or other systems for rendering ambient media [42,43], without affecting the privacy of bystanders. Life-Tags was demonstrated with a camera-based glasses featuring a full-HD micro video camera, Wi-Fi operation, and a 90˚ field of view [44]. Snapshots are captured using an Android application on a smartphone and, are periodically offloaded to a desktop PC, from where they are sent to Clarifai [45], a third-party service for the automatic description of images; see Figure 1 for a JSON-formatted response for a photograph captured in a park on a cloudy day. The Life-Tags visualization application presents users with snapshots and video montages corresponding to the identified tags [46]; see Figure 2, left for examples of snapshots captured by Life-Tags during a walk in the park and the corresponding tag clouds. The

```json
{
  "concepts": [
    {"id": "ai_rsX6XWc2", "name": "building", "value": 0.9812162, "app_id": "main"},
    {"id": "ai_9Dcdh0PK", "name": "house", "value": 0.9801461, "app_id": "main"},
    {"id": "ai_TjbmxC6B", "name": "tree", "value": 0.9799994, "app_id": "main"},
    {"id": "ai_PBTpj0kl", "name": "park", "value": 0.9797851, "app_id": "main"},
    {"id": "ai_FWCjC8jZ", "name": "architecture", "value": 0.97643596, "app_id": "main"},
    {"id": "ai_x3vjxJsW", "name": "home", "value": 0.9688132, "app_id": "main"},
    {"id": "ai_G8PC3qNc", "name": "university", "value": 0.9670366, "app_id": "main"},
    {"id": "ai_GjVpxXrs", "name": "street", "value": 0.9653459, "app_id": "main"},
    {"id": "ai_WBQfVV0p", "name": "city", "value": 0.9586494, "app_id": "main"}
  ]
}
```


Figure 1. Example of a JSON message used by Life-Tags [12] containing concepts detected during a walk in the park.

work that introduced Life-Tags [12] focused on single-user applications and on practical aspects regarding the storage and the optimal frequency at which to record data. In this work, we employ Life-Tags as the starting point for our multi-user mobile and wearable opportunistic crowdsensing system. The next section presents the technical details of our implementation.

4 TOWARD AN EXTENSION OF LIFE-TAGS FOR CROWDSENSING

To extend the functionality of Life-Tags and implement our concept, we designed a mobile crowdsensing system to foster community queries about objects of interest. Our system falls into the category of opportunistic mobile systems because lifelogs are captured passively. Figure 3 shows snapshots from two scenarios, an university campus and a supermarket. The software architecture of our system consists of a server, a backend component, and a user interface. On the client side, we employed standard web technology, such as HTML, CSS, Javascript, the Google Maps library [48], the Firebase Realtime Database [24] and the Firebase Cloud Storage [25]. The Firebase Realtime

Figure 2: Examples of snapshots captured by Life-Tags [12] in the park (left) and supermarket (right). The images at the bottom show two tag clouds generated by Life-Tags.

Database is used to share query-related information, *e.g.*, user "X" is looking for object "Y," between many crowdsensing workers in real-time. We used the Firebase Cloud Storage to implement high-scalability storage for the images automatically captured by the crowdsensing devices when the specified objects were identified. The Google Maps SDK [48] was employed to display the location where a specific object was found via the navigator.geolocation functionality available in modern web browsers. The client runs in

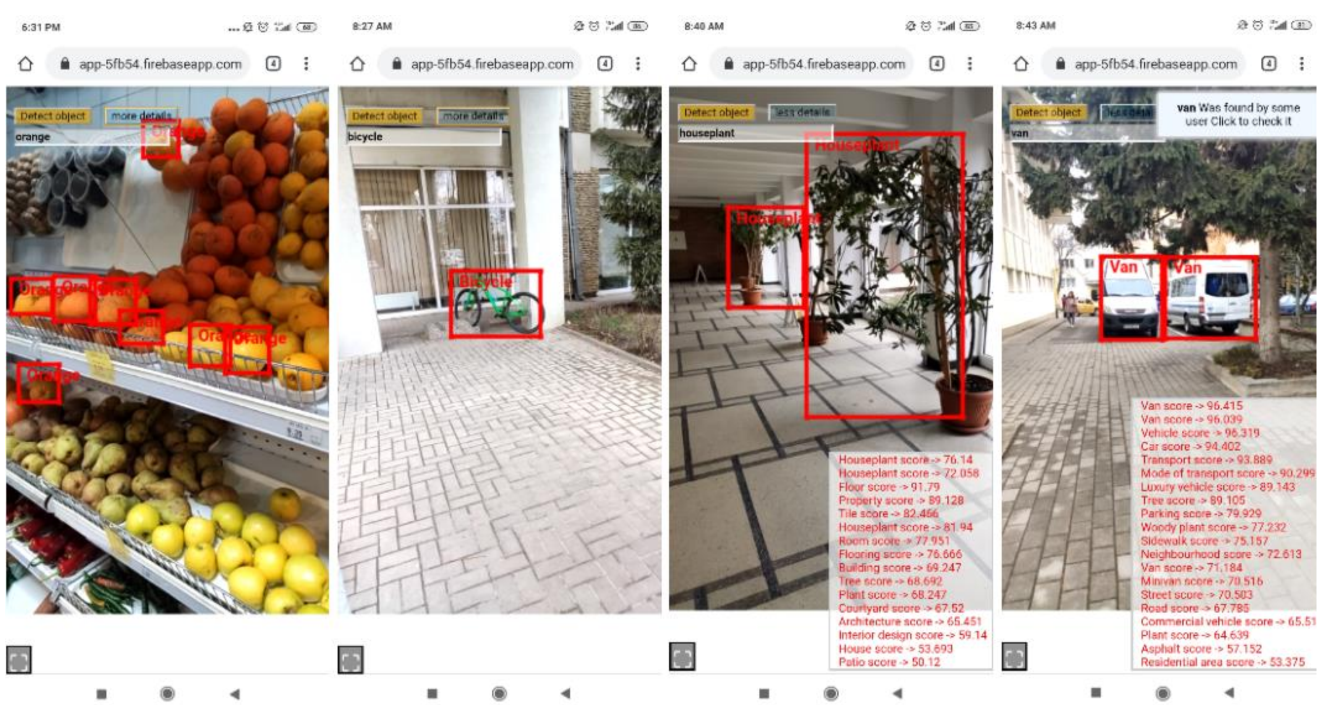


Figure 3: Examples of snapshots captured by our mobile and wearable crowdsensing system.

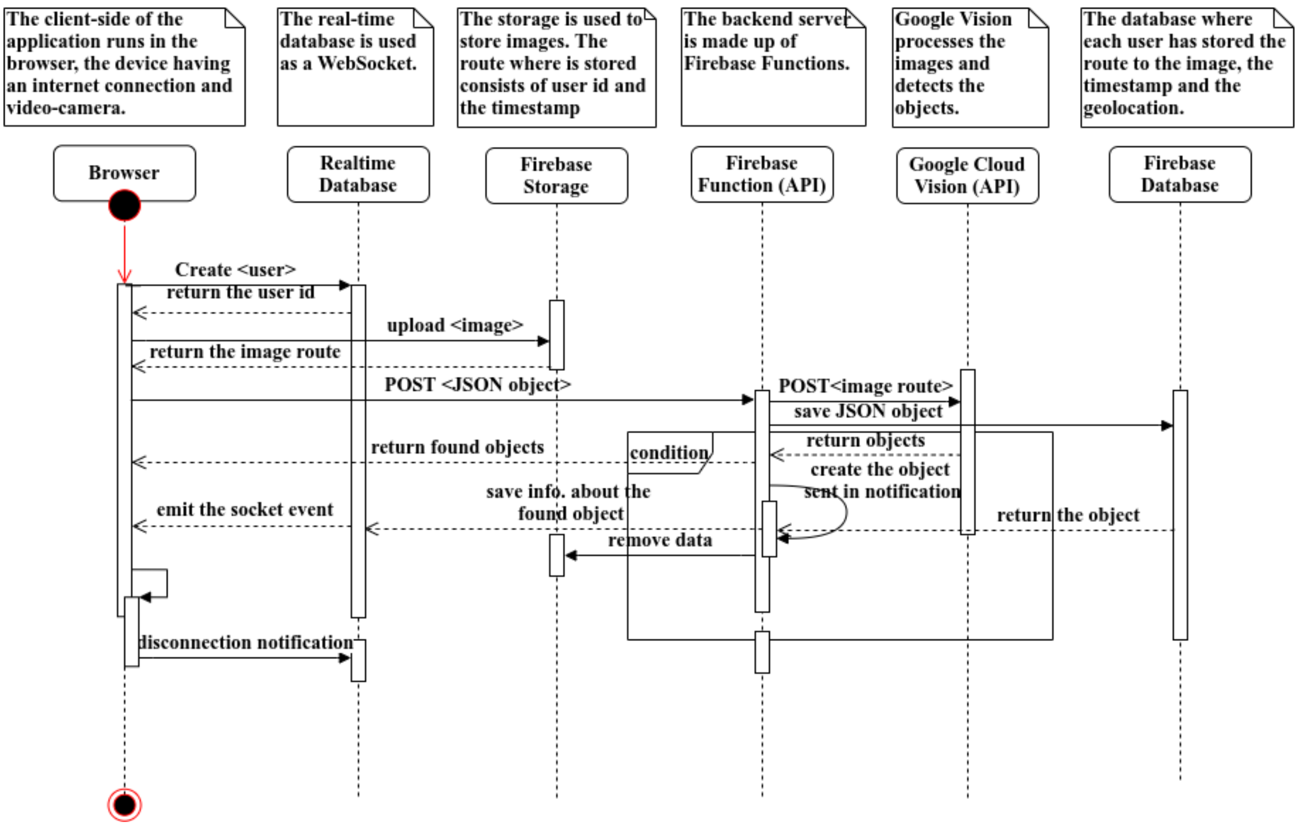
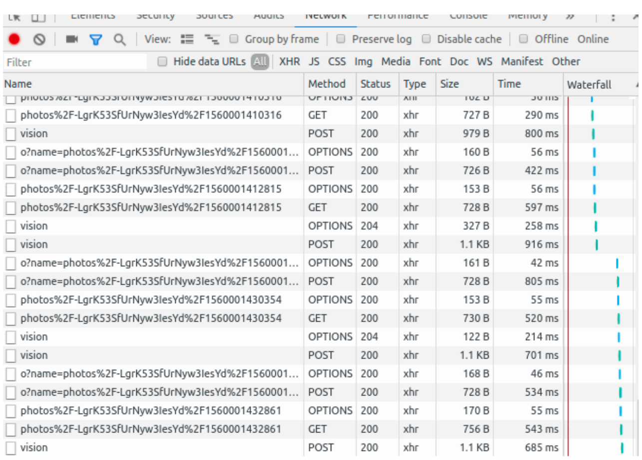


Figure 4. Block sequence diagram for our opportunistic mobile and wearable crowdsensing system.



Name	Method	Status	Type	Size	Time	Waterfall
photos%2F-LgrK53SfUrNyw3IesYd%2F1560001410316	GET	200	xhr	727 B	290 ms	
vision	POST	200	xhr	979 B	800 ms	
o?name=photos%2F-LgrK53SfUrNyw3IesYd%2F1560001…	OPTIONS	200	xhr	160 B	56 ms	
o?name=photos%2F-LgrK53SfUrNyw3IesYd%2F1560001…	POST	200	xhr	726 B	422 ms	
photos%2F-LgrK53SfUrNyw3IesYd%2F1560001412815	OPTIONS	200	xhr	153 B	56 ms	
photos%2F-LgrK53SfUrNyw3IesYd%2F1560001412815	GET	200	xhr	728 B	597 ms	
vision	OPTIONS	204	xhr	327 B	258 ms	
vision	POST	200	xhr	1.1 KB	916 ms	
o?name=photos%2F-LgrK53SfUrNyw3IesYd%2F1560001…	OPTIONS	200	xhr	161 B	42 ms	
o?name=photos%2F-LgrK53SfUrNyw3IesYd%2F1560001…	POST	200	xhr	728 B	805 ms	
photos%2F-LgrK53SfUrNyw3IesYd%2F1560001430354	OPTIONS	200	xhr	153 B	55 ms	
photos%2F-LgrK53SfUrNyw3IesYd%2F1560001430354	GET	200	xhr	730 B	520 ms	
vision	OPTIONS	204	xhr	122 B	214 ms	
vision	POST	200	xhr	1.1 KB	701 ms	
o?name=photos%2F-LgrK53SfUrNyw3IesYd%2F1560001…	OPTIONS	200	xhr	168 B	46 ms	
o?name=photos%2F-LgrK53SfUrNyw3IesYd%2F1560001…	POST	200	xhr	728 B	534 ms	
photos%2F-LgrK53SfUrNyw3IesYd%2F1560001432861	OPTIONS	200	xhr	170 B	55 ms	
photos%2F-LgrK53SfUrNyw3IesYd%2F1560001432861	GET	200	xhr	756 B	543 ms	
vision	POST	200	xhr	1.1 KB	685 ms	

Figure 5. Examples of request-response times for our technical implementation.

a web browser, captures images and stores them into the Firebase Cloud Storage, from where they are processed by the Google Cloud Vision API and the response is saved in the Firebase Database as a list of objects with corresponding GPS coordinates. On the server side, a Node.js application running on Cloud Functions for Firebase is responsible for the management of the queries, sending video frames from crowdsensing workers to the Google Cloud Vision API [26], parsing the results, and returning matches to the client that generated the request; see Figure 4.

We performed a preliminary evaluation of our system using the DevTools panel in Google Chrome. Figure 5 shows results regarding the upload time of images to the Firebase Storage (less than one second), while receiving results from the Google Cloud Vision API takes less than one second as well. Of course, request-response times are influenced by the speed of the Internet connection, the available bandwidth, and the size of the data that is transmitted. We monitored the performance with up to twenty users simulated in the web browser to see how the application responds. Our preliminary results showed that the average request-response time did not exceed one second.

5 CONCLUSION AND FUTURE WORK

In this work, we contributed the idea of abstracting everyday life for a community of users in the form of concepts automatically extracted from video captured by the cameras embedded in mobile and wearable devices. We showed how a mobile crowdsensing system could be implemented as the evolution of a life abstracting system, Life-Tags [12], toward crowdsourcing queries and identification of objects and concepts of interest inside a community, and addressing practical aspects from scaling single-user applications [12] to multi-user systems.

It is interesting to look at the implications of the concept that we demonstrated. On one hand, we present an alternative use for lifelog data, converting it from a private resource to a public one for the benefit of the community. This perspective enables bystanders, which are regularly impacted negatively by video recording cameras in public places [13-15], to benefit from data collected by users of mobile and wearable camera devices. On the other hand, we showed how mobile crowdsensing can employ large amounts of data collected by lifelogging enthusiasts for the purpose of increasing the performance of crowdworkers. We believe that further investigation of the connections and mutual benefits resulting from integrated lifelogging and mobile and wearable crowdsensing technology will reveal new opportunities for new applications. For example, interesting future work will focus on using crowdsourcing similarity criteria [49], integration with smart environment software architecture [50,51] and with systems designed for mass-computer interaction [52], and on deploying the system in real-world scenarios to understand technical performance and social acceptability [53]. Applications for people with low vision to improve visual search are another direction for further examination and exploitation of our concept.

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