Chapter 4
FoodLog: Multimedia Food Recording Tools for Diverse Applications

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Abstract Our daily food is an emerging target for multimedia research community. Health care field is paying considerable attention on dietary control, which requires that individuals record what they eat. We developed and made publicly available multimedia applications, that are, FoodLog, multimedia food recording tools that allow users to take photos of their meals and to produce food records. We developed two kinds of tools: One is FoodLog Web and the other is FoodLog app used by smartphones. In both systems, image processing techniques are incorporated. For example, in case of FoodLog app, unlike conventional smartphone-based food recording tools, it allows users to employ meal photos to help them to input textual descriptions based on image retrieval. We summarize the outline of FoodLog, its deployment in diverse applications including health care, and analysis of data captured by a year-long operation of FoodLog app.

Keywords Food log · Food record · Dietary assessment · Image processing · Multimedia

4.1 Importance of Food Recording

Food is an emerging issue for multimedia technology. It is indispensable in our daily life. It is also deeply related to many different matters such as healthcare, nutrition, diet, cooking, recipes, restaurants, social interaction, food marketing, food production, agriculture and culture etc. In this project, we investigated capture, processing and utilization of multimedia data of our daily food, with the objective of improving the health and quality of our life in a practical way. Our technology can be related to various applications as well. In our project, which was supported by the JST CREST project (from October 2011 to March 2015), we created "FoodLog: a multimedia

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T. Nishida (ed.), *Human-Harmonized Information Technology, Volume 1*,
DOI 10.1007/978-4-431-55867-5_4

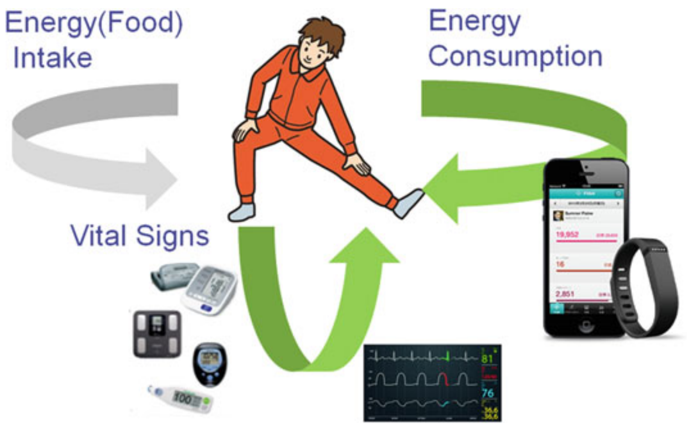

Fig. 4.1 Progress of healthcare technology. Food intake is the one which most needs IT innovation

food recording tool", which is a novel method to record our daily food intake primarily for healthcare purposes. In addition to healthcare, it has diverse applications. As far as we know, FoodLog is the only food recording service available for the public that makes use of image processing techniques.

Food recording is an important issue for healthcare. Healthcare requires the monitoring of three factors as shown in Fig. 4.1: energy consumption (i.e. activity), vital signs (i.e. blood pressure etc.), and energy intake (i.e. food). Energy consumption monitoring is easy by using the widely available wearable activity meters. Vital signs can be also measured by household instruments which are also available. However, recording food intake in most cases follows the traditional method, which depends on human memory, and manually complete forms to remember what was eaten. Manually recording detailed information about meals is a tedious task, and it is difficult for people to adhere to the process for a long time. Thus, there is a strong demand for information technology to help people record their food intake [1].

In this chapter, we would like to present FoodLog: multimedia food recording tools primarily for healthcare applications. Differing from conventional food recording tools, FoodLog tools make full use of images of foods. There are two types: FoodLog Web [2] and FoodLog app [3]. The former is the one we made earlier before smartphones have become widely available, and the latter is our later outcome. Both are made open to public use. We will describe the outline of each of them and some applications. FoodLog was initially created in our university research project. Later, in parallel to our project, a startup company foo.log Inc. takes care of its management and contributes to developing new services, while we, in the university, continue to work on various research issues of data analysis and new possibilities related to FoodLog.

4.2 Related Works: "Food" Is an Emerging Issue for Information Technology

Food is merging as the object of works in information processing as shown in the multiple workshops. For example, meetings such as "Workshop on Multimedia for Cooking and Eating Activities", "Computer Cooking Contest (in the field of AI)", and "Workshop on Multimedia Assisted Dietary Management" are open in 2015 [4]. In addition, giant IT companies such as IBM and Google recently announced their efforts in food-related developments.

Most of the previous work on the image processing of food images has focused mainly on recognition of meals or food items. Joutou and Yanai [5] investigated recognition of the meal associated with a food image from among 50 selected meals. They estimated the meal with an accuracy of up to 61.30 %. Their approach involved a bag-of-features (BoF) model, color histograms and Gabor texture features as the image features and multiple kernel learning as the machine-learning method. Zhu et al. [6] estimated the amount of food that a person had eaten. They used photographs of the food and the plates both before and after the meal. When taking the photographs, they used a white dish on a black and white checkerboard. They identified 19 food items in a small dataset of 63 images and the accuracy was between 84.5 and 95.8 %, depending on the amount of training data used within the dataset. Wu and Yang [7] estimated the calorie content of a limited set of fast-food menus. They used the matching of SIFT features and Web-based calorie data for fast food. The estimation accuracy was between 40 and 73 %. Yang et al. [8] proposed a method for identifying fast-food items. They used pairs of pixels and their local features. The accuracy was up to 28 %. Bosch et al. [9] evaluated various global and local image features for food classification. The number of images in the dataset was limited to 179 images in total, and they found color features contributed most and local features such as SIFT were also efficient. Kawano developed FoodCam, a smartphone implementation of food image recognition composed of GrabCut segmentation and linear SVM. They built a dataset of food images, that is EUC-Food 101 which consists of 101 food classes with app. 100 images per class, to evaluate the recognition performance, and obtained 79 % classification rate for top 5 category candidates [10]. Bossard et al. applied a random forest algorithm to mine descriminative superpixels of food images and applied SVM for classification [11]. For the evaluation, they built a food image dataset, Food-101 containing 101 classes of foods with 1000 images per class collected from a social media. Very recently, following the significant advance of Deep Learning, CNNs have been applied to food images as well. Bossard reported CNN showed better performance compared to their proposal [11]. Kagaya et al. investigated the parameters of CNN, compared them against existing techniques based on SVM, and showed CNN outperform them [12].

Apart from recognition of food images, Kitamura et al. [13] presented our previous system for detecting food images and estimating food balance [14] i.e., the categorization of food into grains, vegetables, meat/fish/beans, fruit and milk products. The system extracted image features such as colors, circles and scale-invariant feature transform (SIFT) features from each image, and analyzed them using either support vector machines (SVMs) or AdaBoost. The performance with respect to food-image detection was 92 % and food-balance estimation had an average error of 0.69 SVs in each category per image. Miyazaki et al. [15] presented calorie content estimation based on visual similarity, in which the food photograph is visually searched using low-level features in a food-photograph dataset with calorie values and the higher-ranked candidates are used in a regression to produce the estimation. The average estimation error of their method was 140 kcal per image. In general, previous works all used general datasets and did not consider any statistical bias that depends on a specific person. Aizawa et al. [16] presented that the estimation was made more accurate by personalization by making use of personal dietary tendencies in image analysis. Ogawa et al. [17] and Aizawa et al. [18] developed a smartphone based food recording tool that assists users by visual search of a food domain interactively specified on the touch screen.

From application system point of view, a few systems were proposed which can be potentially applied to food recording. For example, in TADA project, a mobile based system was proposed, which includes food image recognition function mentioned above [6]. A crowd sourcing, Platemate [19], was designed for food recording using food images in such a way that tasks for food region segmentation, labeling food region and nutrition value counting were separated. However, none of those systems have been utilized in real situation. On the other hand, our FoodLog tools have been used by general public users. FoodLog web has been open since 2009, and FoodLog app since 2013.

In the following, we would like to summarize our works in making practical food recording tools, FoodLog: FoodLog web and FoodLog app. We made both tools available to general public. FoodLog app, a smartphone based tool has been accepted by a number of people, and the number of food records exceeds one million after one year operation. We found the data acquired by users are largely diverse and the number of food classes surprisingly huge. We also describe our work investigating the diverse nature of the data.

4.3 FoodLog Web with Image Processing for Food-Balance Estimation

To make it easy to keep a record of one's meals using photos, we first developed the FoodLog web-based system [13, 16]. In this system users create a food log simply by taking a photo of what they eat, using their mobile phone or smartphone, and uploading the photo to the server. In addition to displaying the uploaded photos, FoodLog performs image processing analyses on the photos to generate food-balance information. FoodLog is the world's only website open to the public that offers these features. Food-balance is a simple way to assess a meal by classifying food into five categories, namely staple foods (e.g.: grains), main dishes (e.g.: meat/fish/beans), side dishes (e.g.: vegetables), dairy products, or fruits.

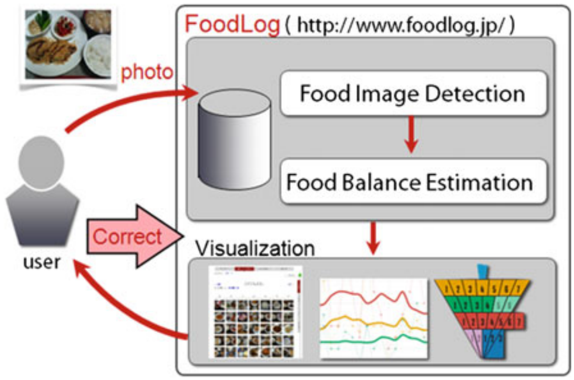

Fig. 4.2 FoodLog web: the user uploads his/her photos, the images are analyzed and they are arranged into food diary with estimation of food balance

The following is an overview of the six main functions currently offered by the FoodLog website (see Fig. 4.2).

(1) FoodLog makes recording meals as simple as possible.
A user takes a photo of a meal with a digital camera, mobile phone, or smartphone and uploads the photo. Users can upload photos directly to FoodLog or using a photo-sharing website such as Flickr. After linking the accounts, if necessary, FoodLog imports the photos and creates the food log.
(2) An image processing engine analyzes the content of the meals.
The image processing engine determines whether the picture is a food image. If so, it processes the image to determine what food types appear in the picture and how they fit into the dietary balance. It then estimates the dietary balance values. Dietary balance is a simple way to assess a meal by classifying food into one of five categories, namely staple foods (e.g., grains), main dishes (e.g., meat/fish/beans), side dishes (e.g., vegetables), dairy products, or fruit. Figure 4.3 (top) shows the monthly calendar view of the food photos and an example of a result of details of the estimation of food balance (bottom).
(3) FoodLog displays the photos and presents an analysis of the results in visual form.
The system displays the information recorded in various formats. Users can view their food log in calendar format, as a list of meal times or as photos of meals appearing on a map if the photos provide location data. They can also view the results of a dietary balance analysis in graphical form.
(4) Users can interactively correct data.
Because the analysis offered by the image-processing function may not be 100 % accurate, the software lets users correct the results as necessary.
(5) Users can label tags for search.
A user can add a description of a meal (such as the name of the dish) and then later conduct a search using these keywords.
(6) Users can share their logs.
Users can view pictures of meals from other users if permission has been given.

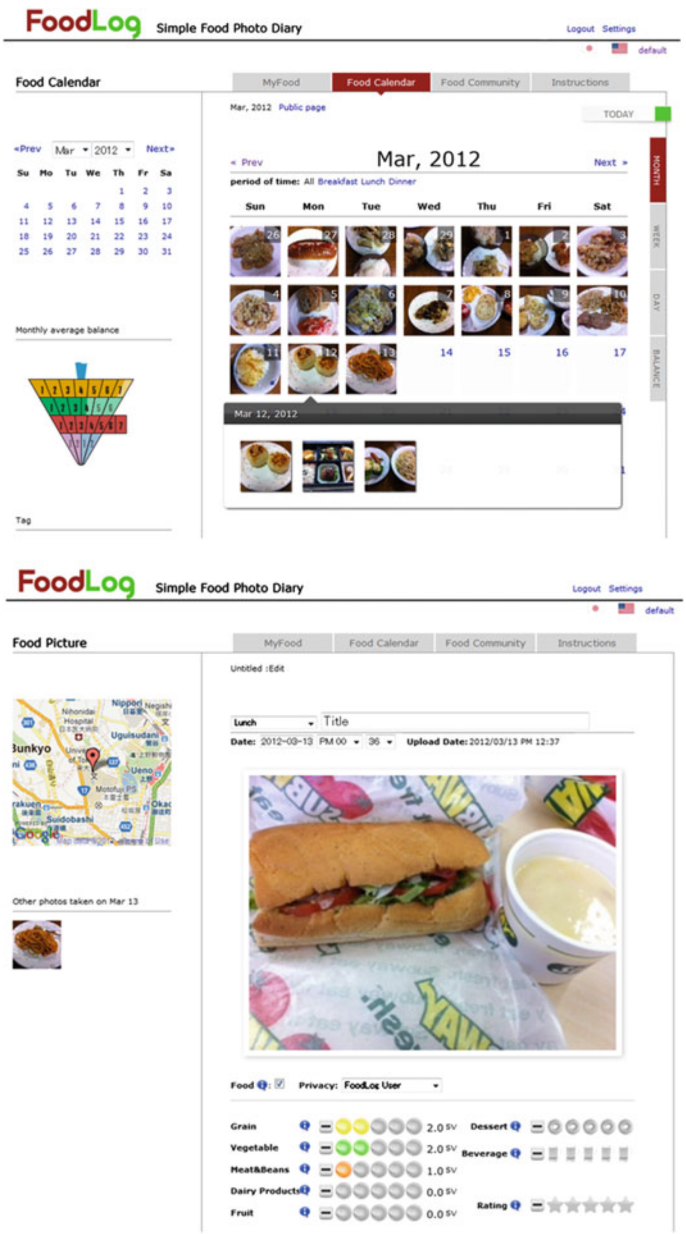

Fig. 4.3 FoodLog web. Calendar view (*top*) and the result of food balance estimation for the food (*bottom*)

Food images largely vary between users because of not only the food content itself, but also the imaging environment (camera and illumination). The food image content is very distinct among people. Accordingly, the processing of food log images has to be personalized. The personalization is an important nature of multimedia food data processing [16].

Although FoodLog was designed as a self-monitoring tool, it can also enable third parties such as dietitians, nurses, and doctors to monitor their clients. A health insurance organization uses FoodLog to monitor and instruct a group of its clients. For such usage, the browser is customized so that the dietitian can give comment feedback to the patient.

4.4 Image Analysis of FoodLog Web

4.4.1 Overview of Existing System

Both food-image detection and food-balance estimation were performed via image analysis. Supervised learning based on multiple image features was used.

The food-image detection uses SVM with the common image features except block features described below. Using the image features, SVM is applied to classify the image into the binary classes, namely, "food" or "nonfood".

In the estimation of the food balance, the quantities of five dietary components, based on the Japanese Food Balance Guide [14] (Fig. 4.4), are estimated. It classifies food into five categories, namely grains, vegetables, meat/fish/beans, fruit and dairy

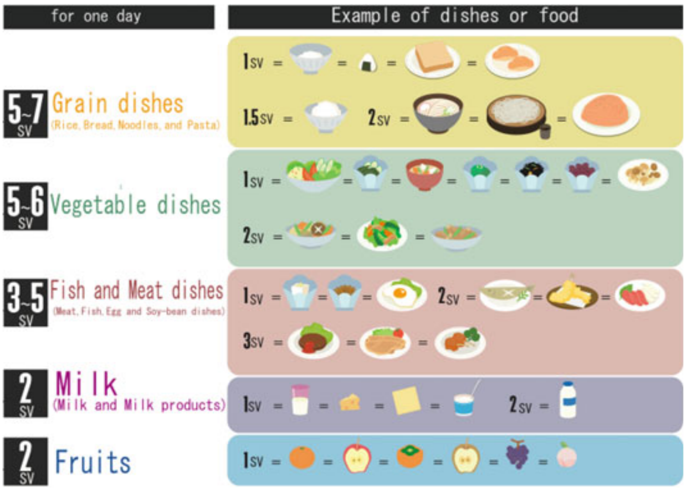

Fig. 4.4 Japanese food-balance guide [14]

products. It assesses a meal by the value of SVs in each category. The SV unit enables ordinary people to assess their food intake easily, giving a reasonable description of the volume of each food category. For example, as shown in Fig. 4.4, food balance is used in general as a discrete value for simplicity. The value varies by the volume and content of the food. For example, if the food image contains a cup of rice, a dish of salad, a dish of baked fish, it is evaluated as 1 SV in grain, 1 SV in vegetable, and 2 SVs in meat/fish/beans categories. The specification has guidelines on how many SVs in each category should be consumed per day. An ordinary person is recommended to take in a day 5–7 SVs in grain, 5–6 SVs in vegetable, 3–5 SVs in meat/fish/beans, 2 SVs in milk/dairy and 2 SVs in fruit categories. FoodLog users can compare their daily consumption with these guidelines to keep track of and improve their dietary balance. Because each category in general has several or a few levels of SVs, the estimation of food balance can be considered a classification problem. The level will be called a "class" below. Unlike the general classification problem, we evaluate the results by average distance between classes of the actual and the estimated SVs, which corresponds to the mean errors of the estimation.

The food-balance estimation has two major components. The first component is an analysis of blocks of the image using image features, that is, assigning each block into one of the six labels including the five categories and "nonfood". The second component is the analysis of the whole image using image features and the histogram of the labels (block features) made by the block-wise analysis. The image is standardized into 320×240 pixels during preprocessing, the size of each block is 16×16, and as a result, there are 300 blocks in the image.

Image features such as colors and BoF of local features were chosen. These features are widely used. Colors and textures are considered important for food images. Bosch et al. [9] also showed that colors and local features are most effective in food recognition. In addition, we also used a circle feature, which possibly reflects round objects such as plates in the images.

All of the above features were finally merged into a 552-dimensional feature vector. Different AdaBoost classifiers were formed for each food category. Finally, SVs of each food category of the image were estimated by classifying the vector into one of several or a few classes by AdaBoost. Regarding the performance of the current deterministic approach, the accuracy of food-image detection is over 90 %, and the average error in food-balance estimation is 0.69 SVs. The error of food-balance estimation is measured by the average absolute difference between the classes; for example, the estimation error would be 1 SV if the image of 2 SVs of grain would be estimated as 1 SV.

The automatic estimation is not always correct, and the user can adjust the estimation if needed.

4.4.2 *Improving Estimation by Using Personal Dietary Tendencies*

Estimation relying on photograph-only seems unnecessarily limited because we know that dietary habits are richly diverse. We can imagine that food images of each individual reflect personal dietary tendencies to some extent because of individual preferences. For example, Fig. 4.5 shows sets of images uploaded by three FoodLog users labeled A, B and C. There are significant visual differences for these different users. Therefore, we decided to improve the accuracy of food-balance estimation by making use of personal dietary tendencies that differ from the estimation made by the global model.

We introduce a Bayesian framework in place of the deterministic approach in order to make use of personal dietary tendencies improve the estimation. The Bayesian framework facilitates incrementally updating the estimator using the correction. Specifically, likelihood, prior distribution and mealtime categories are taken into account.

The extension of this Bayesian approach to food-balance estimation involves the following equation.

$$P(\theta_i|\boldsymbol{F}^N, c_j) = \frac{P(\boldsymbol{F}^N|\theta_i, c_j)P(\theta_i|c_j)}{P(\boldsymbol{F}^N|c_j)} \tag{4.1}$$

Here, each c_j indicates one of the five categories of food balance (grains, vegetables, meat/fish/beans, fruit and dairy products), $\boldsymbol{F}^N$ is the N-dimensional feature vector extracted from the image and θ_i indicates the class corresponding to the SV being estimated. Grain, meat/fish/beans and vegetables have four classes each, with fruit and dairy products having two classes each. $P(\boldsymbol{F}^N|\theta_i, c_j)$ is called the likelihood, and $P(\theta_i|c_j)$ is the prior probability. Mealtime, such as breakfast, lunch and dinner, is also taken into account by defining five categories for each meal time. Expression (4.2) can be used for Bayesian estimation because the right-side denominator $P(\boldsymbol{F}^N|c_j)$ of expression (4.1) is invariant with respect to the class θ_i.

$$P(\theta_i|\boldsymbol{F}^N, c_j) \propto P(\boldsymbol{F}^N|\theta_i, c_j)P(\theta_i|c_j) \tag{4.2}$$

Fig. 4.5 Differences between user images

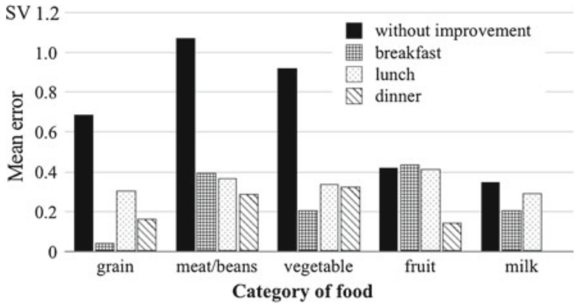

Fig. 4.6 Mean absolute errors when using all three factors: personal trends, prior probabilities and mealtime categories. The average error for the five food groups is significantly improved from 0.69 to 0.28 SVs

The prior probability can be calculated simply by using statistical information, whereas the likelihood requires an approximation because it is not easy to evaluate directly. A global Bayesian estimation model is created using the data from many users. To adapt the global model to a specific user, the Bayesian estimation model should be updated by corrections made by the user. Please see the details in [16].

In the experiment to investigate food-balance estimation, we used the 616 food images from 79 users of FoodLog to create the general model, and 497 images for the test from two users (215 from user A, and 282 from user B). The results shown in this section are the average of results for the two users, there being no significant

By incorporating likelihoods, prior probabilities and mealtime categories together to the food-balance estimation, the average error was found to improve significantly, from 0.69 SVs to 0.28 SVs, as shown in Fig. 4.6. In the figure, the results for three major categories, namely grains, meat/beans and vegetables, are greatly improved by using the three factors.

4.5 FoodLog App: Assistance of Food Recording by Image Retrieval

In the second phase of our project, we built a FoodLog app that runs on smartphones with connection to cloud storage [17, 18]. Differing from FoodLog Web, which only contains images and food balance evaluation, we aimed at including more detailed description (meal name and volume) of food in a similar way to the traditional food recording methodology. Using a food nutrition database, the meal name and volume of food are sufficient to compute the nutritional content such as energy (calorie). Although the description result follows the traditional method, we make use of multimedia technology to assist users. Screen shots are shown in Fig. 4.7.

FoodLog app allows users to use photos of meals to help them input textual descriptions based on image retrieval. It has two modes for the input of names for food items: a text-based mode and an image-assisted mode as shown in Fig. 4.8.

The text mode is the baseline method in the system and the image mode assists users to input textual descriptions via image retrieval. In the text-based mode, the

Fig. 4.7 Screen shots of FoodLog app. Calender views (*top*) and detailed views (*bottom*). In the calender view, the food domains cut out from the images are shown. In the detailed view, the textual descriptions are shown for the image, and tags of calories displayed for food domains

food name and portion size are required inputs. Part of the name is sufficient as an input because partial match searching is enabled. A default common database is searched when part of the name of the dish is entered as text. A personal database based on the user's history is also searched simultaneously. Both of the search results are displayed as a list. The user can select from the list and select the portion size. Free text input is also available if no items are found in the databases.

We developed the image-assisted mode to make these interactions simpler and more intuitive using an image retrieval technique. The system is operated as follows.

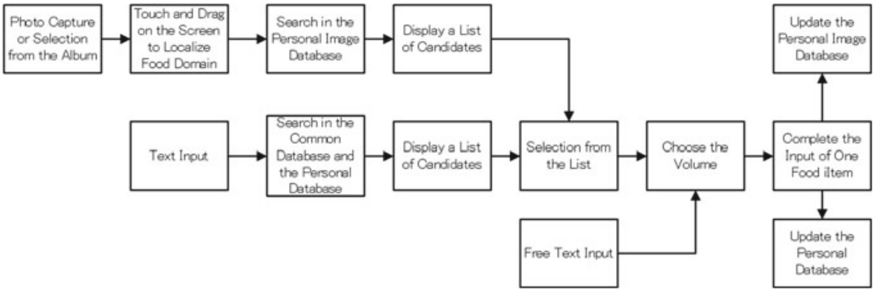

Fig. 4.8 Flowchart of food recording with FoodLog

Fig. 4.9 Image assisted mode of FoodLog app. A user takes a photo and specifies a food domain (*left*), and visual search in a personal database results in top 20 candidates

(1) Take a photo of a meal.
(2) Specify the food domain by touching the screen and adjust the size. of the domain (Fig. 4.9 left). A visual similarity search in the personal image database is performed by the smartphone, and the top 20 results are shown as a list (Fig. 4.9 right).
(3) Choose the appropriate food from the list and adjust its portion size. The specified food domain is then registered in the personal image database for the next search. The visual search process was sufficiently fast because the time required to search was much less than 1 second. Since FoodLog makes use of a user's personal database, the precision of top 20 candidates is sufficiently high.

Provided that the food can be identified in the candidate list, the user operations are simply touch, adjust, and select. However, if the target food is completely new or the visual search results do not contain the appropriate food, the user employs the text-based mode to specify the food domain.

4.6 FoodLog App: Accuracy of Food Image Retrieval

Regarding the visual search of the image retrieval, FoodLog app currently makes use of food image data only in his/her personal use history (personal database). Then, at the beginning of the use, FoodLog app functions as a text based baseline system. As the user uses FoodLog app, he/she grows the amount of food images in the personal database. Since eating is habitual, it is often we have the same food again in a short interval. The next time the user has the same meal as the one already recorded, FoodLog can likely assist the user by image retrieval. The current visual search makes use of color-based image feature, that is, a spatial pyramid of color feature. Food contents are very diverse among users and the imaging conditions such as lighting are diverse as well. The use of personal data helps keeping accuracy higher in the retrieval.

Figure 4.10 shows evaluations of its precision of the personalized visual search. The precision of the retrieval is sufficiently high. We made a dataset of three different users' food records which were obtained from their three month long use. 1/4 of the data were chosen for the test, and the evaluation was repeated 5 times. The number of unique food items was different among the three. User A, User B and User C had 461, 165 and 501 different food items, respectively. Figure 4.10 shows top 5, top 10 and top 20 precision for the three users. Top 20 precision was higher than 80 % for all the three: For User B, it was higher than 94 %.

As described above, the cold start, that is, the user has to start with a text only system, is one of the limitations of the current system. In order to improve the cold start problem, the use of huge number of images uploaded by many different users would be beneficial. Considering the state of the art of image recognition, making

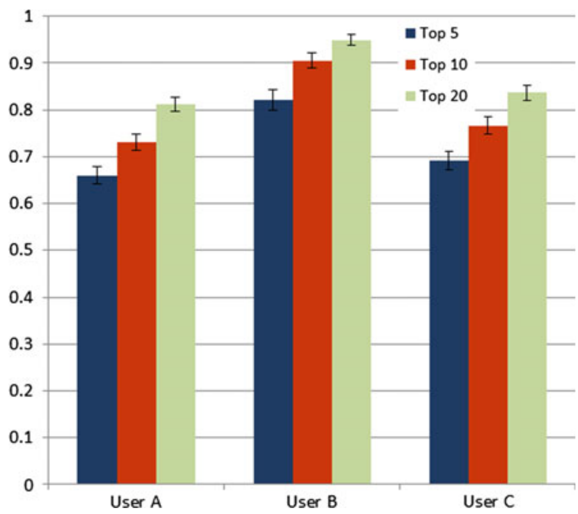

Fig. 4.10 Precision of image retrieval for a dataset of three different users of their three month long use

use of deep features would make visual search accurate [12]. However, there are a lot of problems in making use of the huge data from many users before applying the new methodology. We are currently in the process of these improvements.

4.7 User Studies of FoodLog App: Is the Image Assistance Beneficial?

We investigated if the novel function of FoodLog app (image-assisted mode) benefits users. We compared two food recording tools: One is FoodLog app with image assistance, and the other is a food recording tool with text input only, which was the baseline of FoodLog app [18]. Hereafter, FoodLog app, and FoodLog with text input only are abbreviated as FL-I and FL-T, respectively. Eighteen university students were recruited for the one month long experiments. The students were not familiar with the FoodLog application. They used the tools in their daily lives. They were divided into two groups, one group started using FL-I, and the other FL-T. After two weeks, the FL-I group started using FL-T for another two weeks. At the same time, the FL-T group switched to the FL-I system for another two weeks. In total, each group used the Foodlog systems for one month.

Figure 4.11 shows the result of their subjective evaluation in terms of ease of use (A1), fun (A2), frequency of browsing (A3), and intention to continue using the system (A4). The subjective evaluation showed significant differences in the responses to questions (A2), (A3), and (A4) for FL-I and FL-T. The remarkable difference in question (A2) indicated that all of the participants had fun when using FL-I. The responses to question (A3) showed that the participants browsed their food records more frequently with FL-I than FL-T. The responses to question (A4) showed that the participants were more positive about their intention to continue using FL-I than FL-T. The difference in ease of use (A1) was not significant. Regarding (A1),

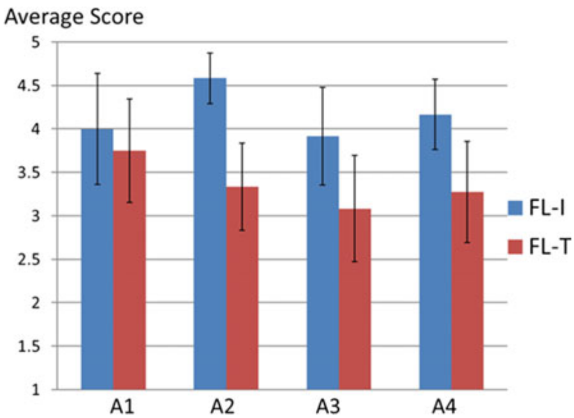

Fig. 4.11 Subjective evaluation results, showing the average scores for: ease of use (*A1*), fun (*A2*), frequency of browsing (*A3*), and intention to continue use (*A4*)

according to the comments written in the questionnaires, a few participants who scored text input higher reported that they felt unpleasant when they missed taking meal photos, and they might have needed more time to get used to it.

In summary, the image assistance is beneficial for the user to keep food records. At the same time, there is a need to improve the user interface. This result is very encouraging for further improvements.

4.8 Analysis of FoodLog Data

FoodLog app was launched in July 2013 in the Apple's AppStore and in October of the same year in Google's Play Store. Since then, food recording data has been continuously accumulated. At the end of the first year's operation (July 2014), the number of food records (textual description) exceeded one million. We started the investigation of the food records using the one year long data. What was surprising to us was that within one million food names, we found approximately 70,000 unique food names. Our default food database has approximately 2,000 names. There were so many new food names, registered or customized, that we found it overwhelmingly difficult to calculate even simple statistics because of the variation of the food names.

Because of this fact, we summarized food names to represent food categories [20]. In order to create such food category representatives, each food name was decomposed into words, which were then grouped with similar group of names of entire FoodLog data. A word graph was made for the group and the minimum path found was used as the representative. The abstract level of the representatives is controlled by changing the size of the group. Figure 4.12 shows the frequency of the representatives when the number of them is approximately 15,000. As it is possible to see, the frequency follows a very steep power law. Only 500 representatives (indicated by the dotted line) are enough to cover 80 % of the entire data.

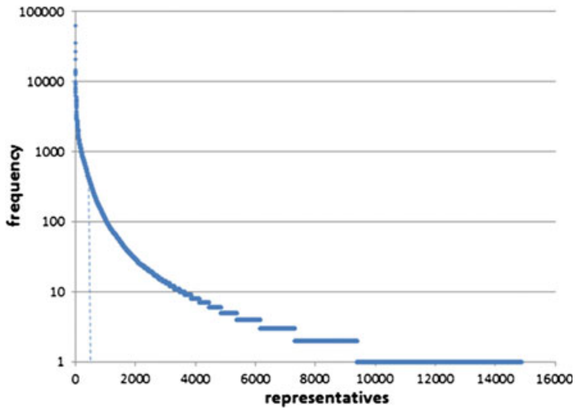

Fig. 4.12 Frequency versus food category representatives

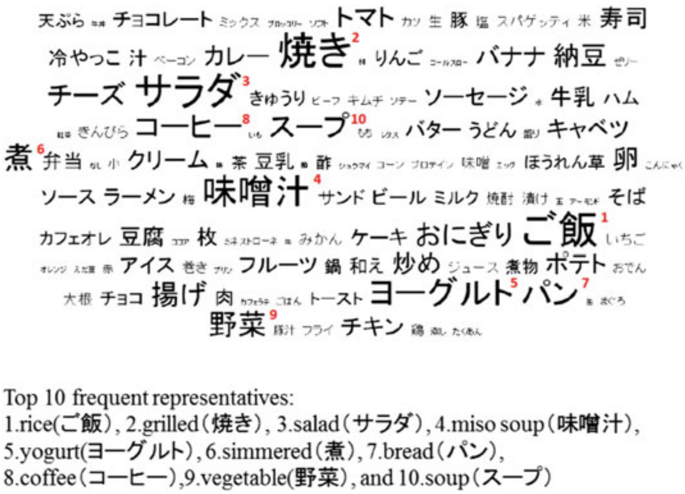

Fig. 4.13 The top 100 frequent representatives of FoodLog data: the larger the font size, the higher the frequency. The top 10 frequent representatives are shown at the *bottom*

Figure 4.13 shows top 100 food category representatives extracted from the entire FoodLog data. In the figure, the top 10 frequent representatives are numbered. They are rice, grilled, salad, miso soup, yogurt, simmered, bread, coffee, vegetable, and soup. See the bottom of Fig. 4.13 for their correspondence to Japanese words. Note that “grilled” and “simmered” are familiar words related to cooking methodsthey appeared because of the decomposition of the food names.

4.9 Development and Applications

FoodLog Web and FoodLog app share their database, and the data uploaded by FoodLog app can be seen in FoodLog Web interface, too. The database plays the role of platform for various extended applications as shown in Fig. 4.14.

Currently, Web API is provided to 29 organizations and 14 of them are in use of either real services or limited experiments. For example, we have a collaboration with the hospital of the University of Tokyo, where they focus on self-management of health for diabetic patients. Three factors are used by them: vital signs, exercises, and food intake [21]. Vital sign and exercises are recorded by home instruments and wearable devices, and the data is uploaded to their servers. FoodLog included in their interface works for food recording. Proper comments are informed to the patients based on these records. The system is being evaluated in the hospital.

Donation associated with food logging [22] is another interesting example of its application which creates new value for FoodLog through a joint project with a nonprofit organization called Table for Two (TFT). TFT provides a unique program

Fig. 4.14 Development of FoodLog. FoodLog platform is applied to various applications

called "calorie transfer" to support school lunches for children in five African countries. TFT partners with hundreds of corporate cafeterias, university dining halls, and restaurants, and offers a healthy, set of TFT menu items. Whenever a diner orders one of these items, 20 yen of his/her payment is donated to TFT, where one school lunch costs 20 yen. In developed countries, where overeating and obesity are serious problems, the TFT program offers healthy menus and it encourages people to make healthy choices. As a result, eating more healthily helps children in need in underdeveloped countries. The system we developed through joint efforts by FoodLog and TFT is now available free of charge as an iPhone app (called the TFT app) based on the FoodLog platform [23]. The concept of the system is drawn in Fig. 4.15. Its main features are as follows.

(1) The TFT app runs on a smartphone. The user can simply take a photo and upload it via the smartphone.
(2) As one of its basic functions, the app creates a food log similar to that created by FoodLog, enabling users to keep a meal diary to help manage their dietary balance. In addition to supporting dietary balance, it provides an estimation of the calorific content of the food [15].
(3) Each time a user uploads a meal photo, he/she clarify whether the meal is healthy or not.
(4) Each time a user declares a healthy meal and uploads the photo to FoodLog, this single upload generates a donation of one yen. Uploading 20 photos of healthy meals pays for one school lunch. At the end, the screen shows a photo of African children and a "Thank you" message.

The only thing users need to do is to upload photos of the healthy meals they eat. The actual donation money comes from contributions that companies make to TFT, not from the users themselves. Users can find value in accumulating meal photos by helping not only themselves, but also other people and society as a whole.

Fig. 4.15 An application of FoodLog for reducing international imbalances in food intake, with photos of healthy food being transformed into donations

The donations are more than simple cash donations because they are generated by people's decisions to eat healthy meals. The system of donations therefore works both ways. In what might sound like an overstatement, the system encourages people who might overeat to become healthier while providing meals for children in impoverished countries. The contributions of the companies that make donations are also twofold: they not only support food for the children overseas, but also promote healthy eating at home.

4.10 Conclusion

In this chapter, we summarized our research project on multimedia FoodLog. FoodLog is a specific application, but it is possible to generate new applications from the existing logs. For user of FoodLog tools, the value lies in personal enjoyment, in managing their health, or in making a social contribution, depending on how they choose to use it. Being able to generate such additional applications may be a key factor in encouraging users to change their lifestyles.

There are still a lot of topics untouched. The huge accumulating food data is excellent source for data analysis. Finding knowledge in the data will leads to far wider applications of food related services. Food is so essential in our daily life.

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