An innovative passive dietary monitoring system

Benny Lo, PhD
The Hamlyn Centre
Department of Surgery and Cancer
Dietary Assessment

- 24hr recall
- Food Frequency Questionnaire (FFQ)
- Weighed food record
- Urine biomarkers
- Blood biomarkers
- Doubly labelled water
An innovative passive dietary monitoring system

There is currently no accurate measurement of dietary intake. All current methodologies of assessing food intake have inaccuracy rates of 30-70%. Yet accurate assessment of nutritional intake is a prerequisite to define the nutritional status, nutritional needs of a population and to monitor the effectiveness of public health interventions to maintain nutritional health. To this end, it is necessary to develop tools that facilitate accurate assessment of nutritional intake in populations without affecting their normal routines. Existing dietary assessment methods are labour-intensive, expensive, and do not report nutritional intake accurately or social hierarchy of food intake. To address this gap in dietetics, the Bill and Melinda Gates Foundation funded project “An Innovative passive dietary monitoring system” aims to develop a passive dietary monitoring system for people living in Low-or-Middle Income Countries (LMICs) which does not rely on individual participation to record intake. This project focuses on both urban and rural areas in two African countries, Uganda and Ghana. To capture individual dietary intake, wearable camera technologies and fixed cameras are integrated into the system for capturing food preparation and eating activities in kitchens and dining areas. Extensive studies and field trials are being carried out in home settings in Uganda and Ghana.
Project overview

WP2 Hardware Design and Development
- Infant dietary intake
- Ear sensor
- Food preparation

WP4 Data repository

WP3 Food Recognition
- Automated food image recognition
- Video/image annotation
- Food volume estimation
- Detection of food intake
- Remove irrelevant images (not eating)

WP4 Quantify Dietary Intake
- Food composition analysis
- Analysis of mixed dishes and shared plates
- Nutritional content estimation by nutritionalists

WP5 Food preparation

WP4 Data repository
Nutrition intake estimate

Nutrient Estimate

- **Water (g)**: 146.92
- **Energy (kcal)**: 190
- **Protein (g)**: 3.44
- **Fat (g)**: 1.28
- **Carbohydrate (g)**: 46.5
- **Fiber (g)**: 3
- **Sugars (g)**: 38.16
- **Calcium (mg)**: 48
- **Iron (mg)**: 0.46
- **Magnesium (mg)**: 58
- **Phosphorus (mg)**: 42
- **Potassium (mg)**: 896
- **Sodium (mg)**: 4
- **Vitamin C (mg)**: 27.4

Jackfruit

USDA National Nutrient Database

Volume estimation

~200g
e-Button & e-Hat

Automatic Ingestion Monitor

AIM is a wearable device that:
- Fully passive, does not require user actions beyond wearing
- Objectively measures when, what, how much and how we eat

Jianing Qiu, Siyao Wang, Frank Lo, Yingnan Sun and Benny Lo, “Mining Discriminative Food Regions for Accurate Food Recognition,” in the Proceedings of BMVC2019
Food Datasets

The proposed approach was tested on two large-scale publicly available food datasets and one newly proposed fine-grained food dataset.

publicly available food datasets:
* Food-101 [1]: 101 common food categories and 101,000 food images in total;
* Vireo-172 [2]: 172 Chinese food categories and 110,241 food images in total.

food dataset proposed by this paper:
* Sushi-50: 50 different sushi categories and 3,963 images in total.

(a) One sample of each category in Sushi-50. (b) The number of images of each category in Sushi-50.
The proposed method achieves the current best accuracy on all three food datasets:

### Table 1: Comparison with other methods on the three food datasets chosen

<table>
<thead>
<tr>
<th>Method</th>
<th>Top-1 (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>RFDC [1]</td>
<td>50.76</td>
</tr>
<tr>
<td>DCNN-FOOD [3]</td>
<td>70.41</td>
</tr>
<tr>
<td>DeepFood [4]</td>
<td>77.4</td>
</tr>
<tr>
<td>Inception V3 [5]</td>
<td>88.28</td>
</tr>
<tr>
<td>DLA (CVPR2018) [6]</td>
<td>90.0</td>
</tr>
<tr>
<td>WISer (WACV2018) [7]</td>
<td>90.27</td>
</tr>
<tr>
<td>DSTL (CVPR2018) [8]</td>
<td>90.4</td>
</tr>
<tr>
<td>Ours</td>
<td>90.4</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Method</th>
<th>Top-1 (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>VGG [9]</td>
<td>80.41</td>
</tr>
<tr>
<td>Arch-D [2]</td>
<td>82.06</td>
</tr>
<tr>
<td><strong>Ours</strong></td>
<td><strong>90.2</strong></td>
</tr>
</tbody>
</table>

Vireo-172

<table>
<thead>
<tr>
<th>Method</th>
<th>Top-1 (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ResNet-101 [10]</td>
<td>90.0</td>
</tr>
<tr>
<td><strong>Ours</strong></td>
<td><strong>92.0</strong></td>
</tr>
</tbody>
</table>

Food-101                     Sushi-50
Results

Jianing Qiu, Siyao Wang, Frank Lo, Yingnan Sun and Benny Lo, “Mining Discriminative Food Regions for Accurate Food Recognition,” in the Proceedings of BMVC2019
Portion size estimate
Volume Estimation - deep learning view synthesis

Po Wen Lo, Yingnan Sun, Jianing Qiu, Benny Lo, "Food Volume Estimation based on Deep Learning View Synthesis from a Single Depth Map", Nutrients 2018, 10(12), 2005;

USDA National Nutrient Database
1. Water (140.62g)
2. Energy (600kcal)
3. Protein (3.44g)
4. Fat (1.28g)
5. Carbohydrate (46.5g)
6. Fibre (3g)
7. Sugar (38.16g)
8. Calcium (48mg)
9. Iron (0.46mg)
10. Magnesium (58mg)
11. Phosphorus (42mg)
12. Potassium (896mg)
13. Sodium (4mg)
14. Vitamin C (27.4mg)
Volume Estimation

Detailed information

• A stereo or depth sensor is required to capture an image from any convenient viewing angle and position.

• Each food item is segmented out through a segmentation method.

• The depth image is converted from image coordinate to camera coordinate so that the partial point cloud of each food item

• Point completion network is applied.

Po Wen Lo, Yingnan Sun, Jianing Qiu, Benny Lo, "Food Volume Estimation based on Deep Learning View Synthesis from a Single Depth Map", Nutrients 2018, 10(12), 2005;
A Vision-based Dietary Assessment Approach using View Synthesis

Po Wen Lo, Yingnan Sun, Jianing Qiu, Benny Lo, "Food Volume Estimation based on Deep Learning View Synthesis from a Single Depth Map", Nutrients 2018, 10(12), 2005;
Volume Estimation in Real World Scenarios

Po Wen Lo, Yingnan Sun, Jianing Qiu, Benny Lo, "Food Volume Estimation based on Deep Learning View Synthesis from a Single Depth Map", Nutrients 2018, 10(12), 2005;
Communal eating/
Shared plate
Communal eating/Shared plate
Communal eating/Shared plate
Studies
Studies

- Study 1: Laboratory validation of food intake estimation devices
- Study 2: Acceptability and feasibility in the field
  - Phase 1: Household food behavior
  - Phase 2: Pre-field test data gathering prior to the preliminary field test:
    - Acceptability of the devices
    - Preliminary field test for acceptability, reliability and performance of recording devices
- Study 3: Field validation studies in Uganda and Ghana
  - Phase 1: Preliminary field data (~4 households at each site (~16 in total) lasting one day)
  - Phase 2: System validation in target populations (in ~22 households at each site (~88 in total) lasting three consecutive days)
Study 1: Laboratory validation of food intake estimation devices

Food images captured by eButton

Food images captured by Glass-worn device
Study 2: Acceptability and feasibility in the field in households in Ghana

- Identify and solve field related challenges to assess the feasibility, acceptability and general performance of devices
- Completeness of data collection
  - Clarity of food related images
Phase 2 of Study 2

• Feasibility of passive devices in dietary assessment
  • Consent and device demonstration
  • Day 1 - Introduction and demonstration of devices to households
  • Day 2 - Devices worn and installed for data collection
  • Day 3 - Independent field assistant conducted device assessment
    • 24-hour dietary recall
  • Day 4 - Repeat of Day 2 activities
    • 24-hour dietary recall
    • Weighed food intake
Study 2: Data collected in Ghana

• Examples of eButton images (containing foods)
Study 2:

(Sample Images captured by) AIM
Blowing a Balloon!
Hanging out with friends!
Watching TV
Working
Shopping
Reading
Shopping
Reading
Challenges

• Ethics
• Device issues
• Wearability
• Image and lighting
• User compliance
• Vast amount of data
• COVID-19