Deep Learning-Based Food Calorie Estimation Method in Dietary Assessment

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Abstract

Obesity treatment requires obese patients to record all food intakes per day. Computer vision has been introduced to estimate calories from food images. In order to increase accuracy of detection and reduce the error of volume estimation in food calorie estimation, we present our calorie estimation method in this paper. To estimate calorie of food, a top view and side view is needed. Faster R-CNN is used to detect the food and calibration object. GrabCut algorithm is used to get each food's contour. Then the volume is estimated with the food and corresponding object. Finally we estimate each food's calorie. And the experiment results show our estimation method is effective.

Keywords: computer vision, calorie estimation, deep learning

1. Introduction

Obesity is a medical condition in which excess body fat has accumulated to the extent that it may have a negative effect on health. People are generally considered obese when their Body Mass Index (BMI) is over 30 kg/m^2. High BMI is associated with the increased risk of diseases, such as heart disease, type two diabetes, etc[1]. Unfortunately, more and more people will meet criteria for obesity. The main cause of obesity is the imbalance between the amount
of food intake and energy consumed by the individuals. Conventional dietary assessment methods include food diary, 24-hour recall, and food frequency questionnaire (FFQ)\(^2\), which requires obese patients to record all food intakes per day. In most of the cases, patients do have troubles in estimating the amount of food intake because of unwillingness to record, lack of related nutritional information or other reasons. While computer vision-based measurement methods were introduced to estimate calories from images directly according to the calibration object and foods information, obese patients have benefited a lot from these methods.

In recent years, there are a lot of methods based on computer vision proposed to estimate calories\(^3\)[4, 5, 6]. Among these methods, the accuracy of estimation result is determined by two main factors: object detection algorithm and volume estimation method. In the aspect of object detection, classification algorithms like Support Vector Machine (SVM)\(^7\) are used to recognize foods type in general conditions. In the aspect of volume estimation, the calibration of food and the volume calculation are two key issues. For example, when using a circle plate\(^3\) as a calibration object, it is detected by ellipse detection; and the volume of food is estimated by applying corresponding shape model. Another example is using peoples thumb as the calibration object, the thumb is detected by color space conversion\(^8\), and the volume is estimated by simply treating the food as a column. However, thumbs skin is not stable and it is not guaranteed that each persons thumb can be detected. The involvement of human’s assistance\(^4\) can improve the accuracy of estimation but consumes more time, which is less useful for obesity treatment. After getting foods volume, food’s calorie is calculated by searching its density in food density table\(^9\) and energy in nutrition table\(^1\). Although these methods mentioned above have been used to estimate calories, the accuracy of detection and volume estimation still needs to be improved.

In this paper, we propose our calorie estimation method. This method takes
two images as its inputs: a top view and a side view of the food; each image includes a calibration object which is used to estimate images scale factor. Food(s) and calibration object are detected by object detection method called Faster R-CNN and each foods counter is obtained by applying GrabCut algorithm. After that, we estimate each food’s volume and calorie.

2. Material and Methods

2.1. Caloric Estimation Method Based On Deep Learning

Figure 1 shows the flowchart of the proposed method. Our method includes 5 steps: image acquisition, object detection, image segmentation volume estimation and calorie estimation. To estimate calories, it requires the user to take a top view and a side view of the food before eating with his/her smart phone. Each images used to estimate must include a calibration object; in our experiments, we use One Yuan coin as a reference. In order to get better results, we choose to use Faster Region-based Convolutional Neural Networks (Faster R-CNN)[10] to detect objects and GrabCut [11] as segmentation algorithms.

2.2. Deep Learning based Objection detection

We do not use semantic segmentation method such as Fully Convolutional Networks (FCN)[12] but choose to use Faster R-CNN. Faster R-CNN is a framework based on deep convolutional networks. It includes a Region Proposal Network (RPN) and an Object Detection Network[10]. When we put an image with RGB channels as input, we will get a series of bounding boxes. For each bounding box created by Faster R-CNN, its class is judged.

After the detection of the top view, we get a series of bounding boxes $box_1^T, box_2^T, ..., box_m^T$. For $i$th rectangular area $box_i^T$, its food type is $type_i^T$. Besides these food areas, we regard the bounding box $c_T$ which is judged as the calibration object with the highest score to calculate scale factor of the top view. In the same way, after the detection of the top view, we get a series of bounding boxes $box_1^S, box_2^S, ..., box_n^S$. For $i$th ($i \in 1, 2, ..., m$) rectangular area $box_i^S$, its food
type is $type_2$. Besides these food areas, we regard the bounding box $c_S$ which is judged as the calibration object with the highest score to calculate scale factor of the side view.

### 2.3. Image Segmentation

Before estimating volume, we choose to segment each bounding box first. GrabCut is an image processing approach based on optimization by graph cuts[11]. Practicing GrabCut needs user to draw a bounding box around the
object; and such boxes can be provided by Faster R-CNN. Although asking user
to label the foreground/background color can get better result, we refuse it so
that our system can finish calorie estimation without users assistance. For each
bounding box, we get precious contour after applying GrabCut algorithm. After
segmentation, we get a series of food images $P_{T_1}, P_{T_2}, \ldots, P_{T_m}$ and
$P_{S_1}, P_{S_2}, \ldots, P_{S_n}$. The size of $P_{T_i}$ is the same as the size of $box_{T_i}$ ($i \in 1, 2, \ldots, m$), but the values
of background pixels are replaced with zeros, which means that only the fore-
ground pixels are left. The calibration object boxes $c_T$ and $c_S$ are not applied
by GrabCut. After image segmentation, we can estimate every foods volume and
calorie.

2.4. Volume Estimation

In order to estimate volume of a single food, we need to calculate scale
factors based on the calibration objects first. When we use the One Yuan coin
as the reference, according to the coin’s real diameter (2.50 cm), we calculate the
side view’s scale factor $p_B (cm)$ with Equation \(1\)

\[
\alpha_S = \frac{2.5}{(W_S + H_S)/2}
\]  (1)

Where $W_S$ is the width of the bounding box $c_S$ and $H_S$ is the height of the
bounding box $c_S$.

Then the top view’s scale factor $p_T (cm)$ is calculated with Equation \(2\)

\[
\alpha_T = \frac{2.5}{(W_T + H_T)/2}
\]  (2)

Where $W_T$ is the width of the bounding box $c_T$ and $H_B$ is the height of the
bounding box $c_T$.

For each food image $P_{T_i}$ ($i \in 1, 2, \ldots, m$), we try to find an image in set $P_{S_1}, P_{S_2}, \ldots, P_{S_n}$
with the same food type. If $type_{T_i}$ is equal to $type_{S_j}$ ($j \in 1, 2, \ldots, n$), $P_{S_j}$ will be
marked so that it won’t be used again; then $P_{T_i}$ and $P_{S_j}$ will be used to calculate
this food’s volume. We divide foods into three shape types: ellipsoid, column,
irregular. According to the food type $type_{T_i}$, we select the corresponding volume
estimation formula as shown in Equation 3.

\[
v = \begin{cases} 
\beta \times \frac{\pi}{4} \times \sum_{k=1}^{H_S} (L_S^k)^2 \times \alpha_S^3 & \text{if the shape is ellipsoid} \\
\beta \times (s_T \times \alpha_T^2) \times (H_S \times \alpha_S) & \text{if the shape is column} \\
\beta \times (s_T \times \alpha_T^2) \times \sum_{k=1}^{H_S} \left( \frac{L_S^k}{L_{MAX}^S} \right)^2 \times \alpha_S & \text{if the shape irregular}
\end{cases}
\]

In Equation 3, \( H_S \) is the height of side view \( P_S \) and \( L^k_S \) is the number of foreground pixels in row \( k (k \in 1, 2, ..., H_S) \). \( L_{MAX}^S = \max(L^k_S, ..., L^H_S) \), which records the maximum number of foreground pixels in \( P_S \). \( s_T = \sum_{k=1}^{H_T} L^k_T \) is the number of foreground pixels in top view \( P_T \), where \( L^k_T \) is the number of foreground pixels in row \( k (k \in 1, 2, ..., H_T) \). \( \beta \) is the compensation factor and the default value is 1.0. There will be a unique value for each food type.

2.5. Calorie Estimation

After getting volume of a food, we get down to estimate each food’s mass first with Equation 4.

\[
m = \rho \times v
\]

Where \( v (cm^3) \) is the volume of current food and \( \rho (g/cm^3) \) is its density value.

Finally, each food’s calorie is obtained with .

\[
C = c \times m
\]

Where \( m (g) \) is the mass of current food and \( c (Kcal/g) \) is its calories per gram.

3. Results and Discussion

3.1. Dataset Description

For our calorie estimation method, a corresponding image dataset is necessary for evaluation. Several food image datasets[13, 14, 15, 16] have been created so far. But current food datasets can not meet our requirements, so we use our own food dataset named ECUSTFD2.

2http://pan.baidu.com/s/1o8qDnXC
ECUSTFD contains 19 kinds of food: apple, banana, bread, bun, doughnut, egg, fired dough nut, grape, lemon, litchi, mango, mooncake, orange, peach, pear, plum, qiw, sachima, tomato. For a single food portion, we took several pairs of images by using smart phones; each pair of images contains a top view and a side view of this food. For each image, there is only a One Yuan coin as calibration object. If there are two food in the same image, the type of one food is different from another. For every image in ECUSTFD, we provide annotations, volume and mass records.

3.2. Object Detection Experiment

In this section, we compare the object detection results between Faster R-CNN and another object detection algorithm named Exemplar SVM(ESVM) in ECUSTFD. At first, we divide ECUSTFD images into two sets. In order to avoid using train images to estimate volumes in the following experiments, the images of two sets are not selected randomly but orderly. The numbers of training images and testing images are shown in Figure 2. And we use Average Precision(AP) to evaluate the object detection results. In testing set, Faster R-CNN’S mean Average Precision(mAP) is 93.0% while ESVM’S mAP is only 75.9%, which means that Faster R-CNN is up to the standard and can be used to detect object.

3.3. Food Calorie Estimation Experiment

In this section, we present our food calorie estimation results. Due to the limit of experimental equipments, we can not get food’s calorie as a reference; and our experiments just verify the volume estimation results and mass estimation results. First we need to get the compensation factor $\beta$ in Equation 3 and $\rho$ in Equation 4 for each food type with the training sets. $\beta$ are calculated with Equation 6.

$$\beta_k = \left( \frac{\sum_{i=1}^{N} V_i}{\sum_{i=1}^{N} v_i} \right)$$  (6)
Where $k$ is the food type, $N$ is the number of volume estimation. $V_{ik}$ is the real volume of food in the $i$th volume estimation and $v_{ik}$ is the estimation volume of food in the $i$th volume estimation.

$$
\rho_k = \left( \frac{\sum_{i=1}^{N} M_{ik}}{\sum_{i=1}^{N} v_{ik}} \right)
$$

Where $k$ is the food type, $N$ is the number of mass estimation. $M_{ik}$ is the real mass of food in the $i$th mass estimation and $v_{ik}$ is the estimation volume of food in the $i$th mass estimation.

The shape definition, estimation images number, $\beta$, $\rho$ of each food type are shown in Figure 1. For example, we use 122 images to calculate parameters for apple, which means that $N = 122/2 = 61$ volume estimation results are used to calculate $\beta$.

Then we use the images from the testing set to evaluate the volume and mass estimation results. The results are shown in Table 2. We use mean volume
| Food Type         | shape   | estimation image number | $\beta_k$ | $\rho_k$ |
|-------------------|---------|-------------------------|-----------|----------|
| apple             | ellipsoid | 122 | 1.13 | 0.88    |
| banana            | irregular | 82  | 0.64 | 0.59    |
| bread             | column   | 26  | 0.70 | 0.13    |
| bun               | irregular | 32  | 1.14 | 0.43    |
| doughnut          | irregular | 42  | 1.38 | 0.42    |
| egg               | ellipsoid | 30  | 1.00 | 1.16    |
| fired dough twist | irregular | 48  | 1.30 | 0.77    |
| grape             | column   | 24  | 0.25 | 0.25    |
| lemon             | ellipsoid | 34  | 1.11 | 1.04    |
| litchi            | irregular | 30  | 0.98 | 0.95    |
| mango             | irregular | 20  | 1.24 | 1.33    |
| mooncake          | column   | 64  | 1.04 | 1.24    |
| orange            | ellipsoid | 110 | 1.12 | 0.99    |
| peach             | ellipsoid | 48  | 1.07 | 1.09    |
| pear              | irregular | 72  | 1.12 | 1.09    |
| plum              | ellipsoid | 82  | 1.22 | 1.19    |
| qiwi              | ellipsoid | 54  | 1.11 | 1.09    |
| sachima           | column   | 54  | 1.13 | 0.25    |
| tomato            | ellipsoid | 46  | 1.20 | 1.07    |

error to evaluate volume estimation results. Mean volume error is defined as:

$$ME^i_v = \frac{1}{N_i} \sum_{j=1}^{N_i} \frac{v_j - V_j}{V_j}$$  \hspace{1cm} (8)

In Equation 8 for food type $i$, $2N_i$ is the number of images Faster R-CNN recognizes correctly. Since we use two images to calculate volume, so the number of estimation volumes for $i$th type is $N_i$. $v_j$ is the estimation volume for the $j$th pair of images with the food type $i$; and $V_j$ is corresponding real volume for the
## Table 2: Volume and Mass Estimation Experiment Results

| Food Type       | image number | estimation volume | mean | mean volume estimation error (%) | mean mass estimation error (%) |
|-----------------|--------------|------------------|------|----------------------------------|-------------------------------|
| apple           | 158          | 332.78           | 320.65 | -3.65                           | 263.60                       | 250.02                       | -5.15 |
| banana          | 92           | 162.17           | 128.13 | -20.99                          | 146.61                       | 116.92                       | -20.25 |
| bread           | 20           | 155.00           | 102.03 | -34.17                          | 29.04                        | 18.71                        | -35.57 |
| bun             | 56           | 247.50           | 237.02 | -4.23                           | 78.19                        | 89.91                        | 15.00  |
| doughnut        | 10           | 166.00           | 197.58 | 19.03                           | 63.44                        | 59.44                        | -6.31  |
| egg             | 42           | 52.38            | 56.40  | 7.67                            | 61.20                        | 65.80                        | 7.51   |
| fired dough twist | 38         | 64.74            | 70.73  | 9.26                            | 40.60                        | 41.72                        | 2.76   |
| grape           | 26           | 240.00           | 203.98 | -15.01                          | 219.50                       | 203.07                       | -7.48  |
| lemon           | 112          | 96.79            | 100.54 | 3.88                            | 94.24                        | 94.71                        | 0.49   |
| litchi          | 46           | 43.48            | 45.35  | 4.30                            | 44.01                        | 44.38                        | 0.84   |
| mango           | 38           | 80.53            | 91.89  | 14.12                           | 90.58                        | 98.66                        | 8.92   |
| mooncake        | 68           | 70.00            | 55.04  | -21.37                          | 64.01                        | 65.81                        | 2.82   |
| orange          | 100          | 240.00           | 266.37 | 10.99                           | 218.44                       | 234.69                       | 7.44   |
| peach           | 72           | 106.67           | 116.53 | 9.25                            | 111.29                       | 117.81                       | 5.86   |
| pear            | 70           | 266.86           | 265.57 | -0.48                           | 256.43                       | 257.12                       | 0.27   |
| plum            | 94           | 100.00           | 115.98 | 15.98                           | 105.14                       | 112.92                       | 7.41   |
| qiwi            | 60           | 122.00           | 127.19 | 4.25                            | 122.30                       | 124.68                       | 1.95   |
| sachima         | 96           | 147.29           | 136.85 | -7.09                           | 31.89                        | 30.13                        | -5.50  |
| tomato          | 120          | 171.00           | 199.40 | 16.61                           | 180.55                       | 179.21                       | -0.74  |

Mean mass error is defined as:

$$ME_{Mi} = \frac{1}{N_i} \sum_{j=1}^{N_i} \frac{m_j - M_j}{M_j}$$ (9)

In Equation 9 for food type $i$, the number of mass estimation for $i$th type is $N_i$. $m_j$ is the estimation volume for the $j$th pair of images with the food type $i$; and $M_j$ is corresponding real mass for the same pair of images.
Volume and mass estimation results are shown in Figure 2. For most types of food in our experiment, the estimation results are closer to reference real values. The mean error between estimation volume and true volume does not exceed $\pm 20\%$ except banana, bread, mooncake. For some food types such as pear, our estimation result is close enough to the true value. The mass estimation results are almost the same as the volume estimation results. But for some food types like mooncake and tomato, the mass estimation errors are less than the volume estimation errors. And the way we measure volume needs to be blamed due to drainage method is not accurate enough. All in all, our estimation method is available.

4. CONCLUSION

In this paper, we provided our calorie estimation method. Our method needs a top view and side view as its inputs. Faster R-CNN is used to detect the food and calibration object. GrabCut algorithm is used to get each food’s contour. Then the volume is estimated with volume estimation formulas. Finally we estimate each food’s calorie. The experiment results show our method is effective.

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