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### A Review on Image-Based Estimation of Real Food Size for Accurate Food Calorie Estimation

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**ABSTRACT:** In this paper, we review our works on image-based estimation of real size of foods for accurate food calorie estimation which including three existing works and two new works: (1)"CalorieCam" which is a system to estimate realfood size based on a reference object, (2) Region segmentation based food calorie estimation, (3) "AR Deep CalorieCam V2" which is based on visual inertial odometrybuilt in the iOSARKit library, (4) "Depth CalorieCam" which employs stereo cameras on iPhone X/XS, and (5)"RiceCalorieCam" which exploits rice grains as referenceobjects. Especially, the last two new methods achieved 10% or less estimation error, which was enough for robust foodcalorie estimation.

#### **I.INTRODUCTION**

In food image recognition, CNN-based methods haveachieved great improvement in recent years and somesmartphone applications employ them. However, in mostof the calorie estimation, the estimated calories are just associated with the estimated food categories and these applications often require users to enter information such as sizeor volume, there are problems that it is a troublesome and subjective evaluation. Currently, no applications which can estimate food calories automatically exist. Although most of the image recognition tasks includingfood category recognition have been almost solved due togreat progress of CNN based image recognition methods, fully-automatic food calorie estimation from a food photo has still remained an unsolved problem. We think that foodcalorie estimation not only helps people's health a lots, butalso is promising as a new problem of image recognitionstudies. In this paper, we review three of our works related tofood size estimation, and propose two new methods for foodsize estimation.

- (1) "CalorieCam" which is a reference-object-based food calorie estimation system.
- (2) Weakly-supervised segmentation based food calorie estimation
- (3) "AR DeepCalorieCam V2" which is a real food size and calorie estimation system based on visual inertial odometory implemented in iOSARKit.
- (4) "DepthCalorieCam" (new system) which is a food calorie estimation system exploiting iPhone stereo cameras.
- (5) Rice grain based size estimation (new method) which uses rice grained the size of which are usually almost the same as a reference object.

#### **II.CALORIECAM**

"CalorieCam" [1] is an image-based calorie estimation system which estimate food calories automatically by simply taking a food photo from the top with a pre-registered reference object. Taking into account usability and mobility of a system, we implemented the system as a stand-alone mobile application running on a normal Android smartphone.

To estimate food calorie from a single image, a userneeds to register a size-known reference object in advanceand to take a food photo with the registered reference object. As a reference object, we assume a personal belongingwhich we are always carrying such as a wallet and a creditcard-size card in a wallet (except a smartphone for taking a meal photo). After taking a meal photo with а referenceobject. the system carries out segmentation of food items and the pre-registered reference object. Because the realsize of the reference object is known (e.g. In case of acredit-cardsize object, the size is 85.6mm x 54mm.), thesystem can estimate the real size of each detected food itemsby comparing the



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number of pixels of the reference objects and the detected food items. By using the estimated real size and the equations to calculate food calorie from their size, the system finally estimates the calorie of the food items in the real photo. Figure 1 shows an example of usage and ascreen-shot of the proposed system.



Figure 1. (Upper) A user taking a food photowith the reference object. (Lower) A screen shot

#### **III.WEAKLY-SUPERVISED SEGMENTATION BASED CALORIE ESTIMATION**

In the previous work, we assumed that one meal photocontains only one dish. This means we have to recognize dishes one by one for the case of multiple dishes. Then, in this work we introduced CNN-based region proposal tocope with multiple-dish meals. We estimate calories fromsegmentation results by taking account of area ratios of multiple foods. With our method, we can estimate food calories for a photo without multiple-view photos and specific reference objects such as wallets and cards.

The proposed method on CNN-based region detectionconsists of the following steps as shown in Fig.2:

- Apply selective search [6] and obtain 2000 boundingbox proposals at most.
- Group them and select bounding boxes.
- Perform back propagation over the pre-trained CNNregarding all the selected bounding boxes.
- Obtain saliency maps by averaging BP outputs within each group
- Extract segments based on the saliency maps withGrabCut
- Apply non-maximum suppression (NMS) to obtainfinal region results.



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Figure 2. The processing flow of the proposed method.

After region segmentation, we choose a base food regionthe real size of which is expected to the same as the standarddish in the database from the segmentation results of multiple foods. We do not fix the category of a base food so thatthere are a lot of pattern in food combination. Therefore, we define the priorities of food items for choosing a basefood class. We decide the priorities based on a tendencyof unchanging food volumes. Some food volumes changefrequently, while some foods volume rarely change. Forexample, in "Teishoku" which is Japanese traditional foodcombo menu, we can often change the volume of "rice" asoptions, while we cannot change "miso-soup" volume ingeneral. In this case, "miso-soup" is more appropriate for abase food. In this way, there are difference in tendency ofunchanging food volumes and we defined food ranking thevolume of which are relatively stable as a high priority classfor choosing a base food class. After selecting a base foodthe actual size and calorie is assumed to be known, we calculate calories of other dishes than the dish of the base foodby comparing the number of pixels between each dishes andthe dishes of the base food taking account of calorie densities which depends on food categories.

#### **IV.RICE GRAIN BASED SIZE ESTIMATION**

In this work, we propose CNN-based real size estimation from boiled rice grains images. We use grains of boiled riceas a reference object and construct a CNN-based method that input a patch image of boiled rice grains images and output real size of a side of an input patch image. Figure 8shows examples of real size annotated boiled rice photos, and Figure 3 shows the architecture of our network. The architecture of our network is based on VGG16 As shown in the Figure 3, it has an output layer composed of a single unit that outputs a real size. An input image isa patch image cropped from boiled rice grains image and the output is a real size of a side of the input patch image. In this work, since the input patch image is  $244 \times 244$ , theoutput the real size for 224 pixels. The real size estimation is treated as a regression problem. Generally, in the regression problem, a mean square error is used as the loss function. In this work, we use themean square error shown in the Equation (1).

$$L = \frac{1}{n} \sum_{k=1}^{n} (x_k - y_k)^2$$



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Conv layers (VGG16) Fc layers

Figure 3. Our network that estimate a real sizefrom boiled rice grains images.

Table 1. The	e results of th	e real size	estimation	from	boiled	rice	grains	images
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Evaluation data.	abs. err.(cm/224pixels)	rel. err.(%)	corr.	$\leq 5\%$ err.(%)	$\leq 10\%$ err.(%)	$\leq 20\%$ err.(%)
Camera:COOLPIX, Small amount of water	0.212	7.182	0.958	41.667	75.000	91.667
Camera:COOLPIX, Medium amount of water	0.178	6.550	0.973	43.333	76.667	93.333
Camera:COOLPIX, Large amount of water	0.197	6.668	0.962	48.333	78.333	90.000
Camera:iPhone8 Plus, Small amount of water	0.127	5.652	0.945	50.000	75.000	98.333
Camera: iPhone8 Plus, Medium amount of water	0.170	7.512	0.903	43.333	68.333	88.333
Camera:iPnone8 Plus, Large amount of water	0.105	4.800	0.967	58.333	88.333	98.333

#### **V.CONCLUSION**

In this paper, we reviewed our three previous works andproposed two new works. Currently, DepthCalorieCam is the most promising approach. However, large-scale calorieannotated 3D food volume data is needed to extend the system into large-scale categories, which is very costly and time-consuming. In addition, the rice grain based method is also promising for meals containing white steamed rice. Especially it is appropriate for Japanese foods.

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