Ramen as You Like

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\textbf{Abstract}

In recent years, a large number of images are being posted on SNS. The users often synthesize or modify photos before uploading them. However, the task of synthesizing and modifying photos requires a lot of time and skill. In this demo, we demonstrate easy and fast image synthesis and modification through "sketch-based food image generation". The proposed system uses pix2pix to generate realistic food images based on sketched images, and DeepLab V3+ for real image segmentation. A user can create a realistic food image easily and fast by sketching a mask image consisting of food elements. In addition, a user can also edit a mask image automatically generated from a real photo food photo, and generate a modified food image. For training, we created a new dataset of ramen photos annotated with pixel-wise labels for image generation and segmentation. In this demo, we propose a sketch-based interactive food image generation/editing system using an image-to-image translation network called "pix2pix" [2] and semantic segmentation network called "DeepLab V3+" [1]. At the conference site, we will demonstrate an interactive food image generation/editing system, “Ramen as You Like”, based on sketched images and segmentation images in a web browser (Fig. 1). Note that the system can treat with any kinds of the datasets containing pixel-wise labels such as the MS-COCO dataset, although we focus on ramen images at present.

\section{Method}

\subsection{Image Generation}


Our generation network is based on “pix2pix” with U-Net. The input of the network is the channel-concatenated feature map of 15-channel binary masks (Fig.2).

The objective function used Eq.1 as adversarial loss and Eq.2 as L1 loss. Eq.3 shows the overall loss function.

\begin{align}
\mathcal{L}_{cGAN}(G, D) &= \mathbb{E}_{x,y} [\log D(x, y)] + \\
&\quad \mathbb{E}_{x,z} [\log (1 - D(x, G(x, z)))], \quad (1) \\
\mathcal{L}_{L1}(G) &= \mathbb{E}_{x,y,z} [\| y - G(x, z) \|_1], \quad (2) \\
G^* &= \arg \min_G \max_D \mathcal{L}_{cGAN}(G, D) + \lambda \mathcal{L}_{L1}(G), \quad (3)
\end{align}

where \(x\) and \(y\) present input data of set of mask image and real image, \(z\) present random noise vector.

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2.2 Image Segmentation

DeepLab V3+ [1] is a semantic segmentation model with an encoder-decoder structure consisting of a powerful encoder module and a simple yet effective decoder module. We used DeepLab V3+ as a segmentation network to generate a semantic mask from a real photo for sketch-based image editing. We trained the model with the ramen dataset.

![Fig. 2 A U-Net-based ramen image generator.](image)

Fig. 2

![Fig. 3 Some images and mask images in the ramen dataset.](image)

Fig. 3

3. EXPERIMENTS

3.1 “UEC-RamenSeg” Dataset

We have created a new dataset which consists of ramen images and corresponding pixel-wise segmentation masks (Fig.3). The mask images contain 15 classes of pixel-level semantic labels, which represent background, bowl, soup, spoon, chopsticks and toppings including cut egg, seaweed, sliced roasted pork and so on. We prepared 520 pairs of original ramen images and mask images, of which 500 pairs images were used to train a generation network and a segmentation network. The remaining images were used to test.

![Fig. 4 The results of ramen image generation from sketch image drawn by the user.](image)

Fig. 4

![Fig. 5](image)

Fig. 5

3.2 Results of Ramen Generation and Editing

Fig.4 shows the results of ramen images generated from sketch images drawn by users. Users can freely draw the size of the bowl and the amount of soup, select the soup type, add/remove spoon, chopsticks and toppings in the mask images, and convert them into realistic images instantly (less than 1 second). This shows that users can draw ramen images as they like interactively with the proposed system. In addition, distorted bowl can be generated as shown in the two rightmost examples of Fig.4, while all bowls were in circle shapes in the training image set.

![Fig. 4](image)

Fig. 4

![Fig. 5](image)

Fig. 5

Fig.5 shows the work flow of modifying and regenerating the segment result image of the actual image.

they like such as adding/removing toppings and changing soup taste. Finally, we obtained the modified ramen images Users can semantically edit the generated masks by adding, removing, changing each element, which is easier than editing raw photos directly.

4. CONCLUSION

We have presented an application which can generate and modify food images from mask images sketched interactively. It employs an image-to-image translation network and semantic segmentation network.

For future work, we plan to extend this system to other domains than ramen. Regarding the food domain, we plan to extend it for the healthy purpose such as reducing the amount of over-calorie meals and changing unhealthy meals to healthy ones by replacing high-fat foods with vegetables.

References


