Face Sketch Synthesis by Style Transfer with Local Features

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Abstract

Face sketch synthesis is challenging as it is difficult to generate sharp and detailed textures. In this paper, we propose a new framework based on deep neural networks. Imitating the process of how artists draw sketches, our framework synthesizes face sketches in a cascaded manner in which a content image is first generated that outlines the shape of the face and key facial features, and textures and shadings are then added. We utilize a Fully Convolutional Neural Network (FCNN) to create the content image, and propose a local feature based style transfer to append textures. The local feature, what we call pyramid column feature, is a set of features at different convolutional layers corresponding to the same local image patch. We demonstrate that our pyramid column feature can not only preserve more sketch details than common style transfer method but also surpass traditional patch based approach. Our model is trained on CUHK student training data set and evaluated on other datasets. Quantitative and qualitative evaluations suggest that our framework outperforms other state-of-the-arts methods. In addition, despite of the small training data (88 face-sketch pairs), our model shows great generalization ability across different datasets and can generate reasonable results under practical situations.

1. Introduction

Face sketch synthesis has drawn a great attention from the community in recent years because of its wide range of applications. For instance, it can be exploited in law enforcement for identifying suspects from a mug shot database consisting of both photos and sketches. Besides, face sketch has also been widely used for entertainment purpose. For example, filmmakers could employ face sketch synthesis technique to ease the cartoon production process.

Unfortunately, there exists no easy solution to face sketch synthesis due to the big stylistic gap between photos and sketches. In the past two decades, a number of exemplar based methods [13, 10, 17, 18] were proposed. In these methods, an input photo is divided into patches and candidate sketches for each photo patch are selected from a training set. The main drawback of such kind of methods is that if the test image can't find a similar patch in the training set, they may lose some contents in the final result. For example, the sketches in the first row of Fig.1 fail to keep the hairpins. Besides, some methods [10, 18] clear away the textures when they try to eliminate the inconsistency between neighboring patches. Another potential risk is that the result may not look like the original photo, *e.g.* left eye in Fig. 1 (b). Recently, approaches [15, 16] based on convolutional neural network (CNN) were developed to solve these problems. Since these models directly gener-

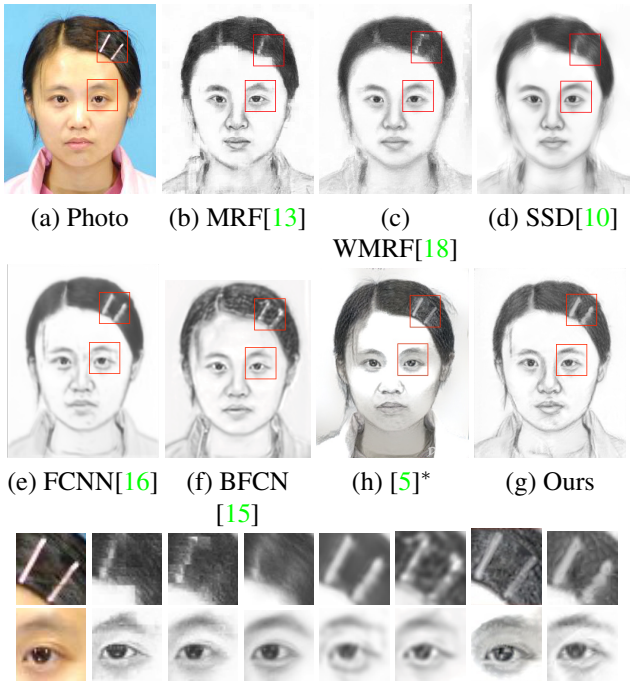


Figure 1. Face sketches generated by existing methods and the proposed method. Our method can not only preserve both hair and facial content, but also maintain sharp textures. (h)* is obtained from deep art website[1] by using the photo as content and a sketch from training set as style.

[1] https://deepart.io/

ates sketches from photo, they can maintain the structures and contents of the photos. However, the loss function of them are usually mean square error (MSE) or variation of it, which is responsible for the blur effect, *e.g*. Fig. 1 (e) and (f). The reason is that MSE prefers values close to mean, and is not suitable for texture representations. The popular neural style transfer provides a better solution for texture synthesis. But there are two obstacles towards directly applying such kind of method. First, it is easily influenced by illumination of the photo, see the face of Fig. 1 (h). Second, it needs a style image to give the global statistics of textures. If the given style doesn't coincide with target sketch, which we don't have, some side effects will occur, *e.g*. the nose in Fig. 1 (h). Extensive experiment and discussion is given in Section **??**.

For an artist, the procedure of sketching a face usually starts with outlining the shape of the key facial features like the nose, eyes and mouth. Textures and shadings are then added to regions such as hair lips, and bridge of the nose to give sketches a specific style. Inspired by this and neural style transfer [4], we propose a new framework for face sketch synthesis that can overcome the aforementioned limitations. In our method, the outline of a face is delineated by a feed-forward neural network, and textures and shadings are then added by a style transfer approach. Specifically, we design a new architecture of Fully Convolutional Neural Network (FCNN) which contains inception layers [11] and convolution layers with batch normalization [6] to outline the face (Section **??**). For the texture part, we first divide the feature maps of the target sketch in each layer into a fixed size grid and combine features from different layers but at the same grid location into a pyramid feature column (Section **??**). These pyramid feature columns can be generated by local sketch patches from the training set. A target style is then computed by assembling these pyramid columns. Since we only want the statistics characteristics of these local sketch patches similar to the target sketch, it is not difficult to find them (Section **??**). Our approach is superior to the current state-of-the-art methods in that

- It is capable of generating more stylistic sketches without introducing over smoothing artifacts
- It can well preserve the content of the test photo.

2. Related Work

2.1. Face Sketch Synthesis

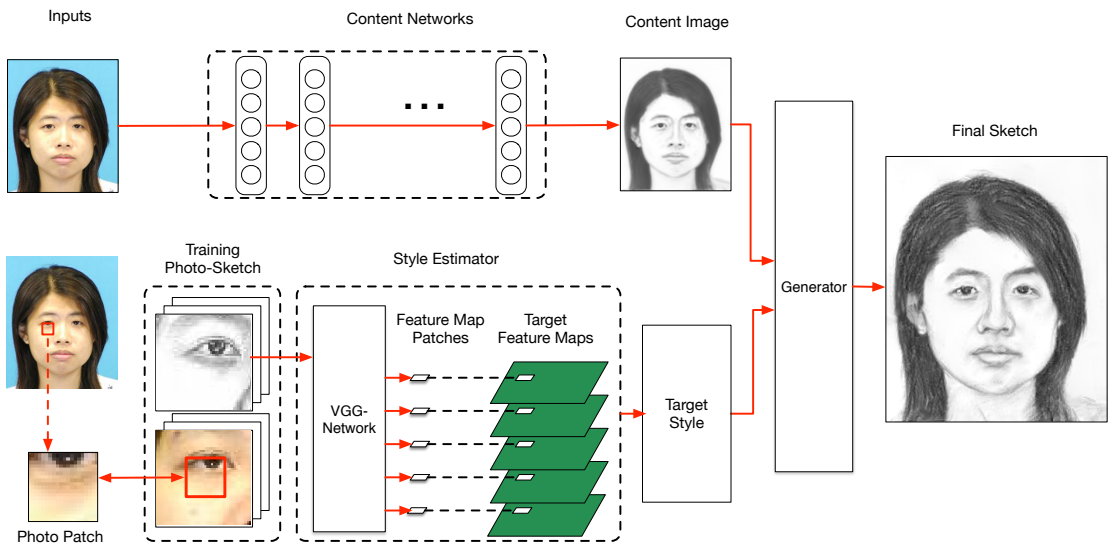
Based on the taxonomy of previous studies [10, 18], face sketch synthesis methods can be roughly categorized into profile sketch synthesis methods [1, 2, 14] and shading sketch synthesis methods [8, 10, 12, 13, 16, 17, 18]. Compared with profile sketches, shading sketches are more expressive and thus more preferable in practice. Based on the assumption that there exists a linear transformation between a face photo and a face sketch, the method in [12] computes a global eigen-transformation for synthesizing face sketches from face photos. This assumption, however, does not always hold since the modality of face photos and that of face sketches are quite different. Fortunately, Liu et al. [8] found that the linear transformation holds better locally and therefore they proposed a patch based method to perform sketch synthesis. A MRF based method [13] was proposed to preserve large scale structures across sketch patches. Variants of the MRF based methods were introduced in [17, 18] to improve the robustness to lighting and pose, and to render the ability of generating new sketch patches. In addition to these MRF based methods, approaches based on guided image filtering [10] and feed-forward convolutional neural network [16] are also found to be effective in transferring photos into sketches. A very recent work similar to ours is done by Zhang *et al*. [15]. They proposed a two branch FCNN to learn content and texture respectively and then fusion them through a face probability map. Although their results are impressing, the sketch texture is not natural and the facial components are smoothed.

2.2. Style Transfer with CNN

Texture synthesis has long been a challenging task. Traditional method can only imitate repetitive patterns which has a strong limitation. Recently, Gatys *et al*. [4, 5], studied the use of CNN in style representation (including texture and color) where a target style is computed based on features extracted from an image using the VGG-Network and an output image is generated by minimizing the difference between its style and the target style. It can transfer any style to any images, and the results are impressive. Justin *et al*. [7] further accelerated this process by learning a feed forward CNN in the training stage. These methods represent textures by a multi-scale gram matrix of feature maps. Since gram matrix cares more about global statistics, if the style is very different from the photo, it usually breaks the local structures. Although it is not a big deal in artistic style, it can't be tolerated in face sketch synthesis. In [3], Chen and Schmidt propose a different patch based style transfer method which is better at capture local structures. However, it is still not suitable for this task. Our style transfer mechanism is inspired by but different from these works [4, 5, 7] in that our target style is extracted from many image patches rather than from a single style image. Note that there usually does not exist a single style image in the training set that matches all properties of the test image.

3. Methodology

Our method can be classified as a shading synthesis method. The steps of our method are summarized in Fig. 2. First, a preprocessing step as described in [13] is carried



(a)

Figure 2. The proposed method contains two branches which take an photo aligned by the eyes as inputs. The content network outputs a content image and the style estimator generates a target style. The final sketch is generated by combing the target style with the content image.

out for all photos and sketches in a training set to align the centers of two eyes. A test photo $\mathcal{I}$ is then fed into two branches, namely the content network and the style generator, respectively. The content network converts the test photo into a content image $\mathcal{C}$, where facial features and the shape of the face are outlined with the global arrangement of the facial features preserved. It is not necessary that the style of the content image resembles a real sketch, but the shapes of different features such as noses, eyes, mouthes and hair, should be delineated. The style estimator takes the test photo as input and utilizes photo-sketch pairs in the training set to generate a target style $\mathcal{S}$ which we want to transfer to the final sketch. Given $\mathcal{C}$ and $\mathcal{S}$, we generate a sketch $\mathcal{X}$ that combines the content information in $\mathcal{C}$ with the style representation $\mathcal{S}$. This is formulated as an optimization problem over an energy function taking both $\mathcal{C}$ and $\mathcal{S}$ into considerations. Details will be explained in the following subsections.

3.1. Content Image Generation

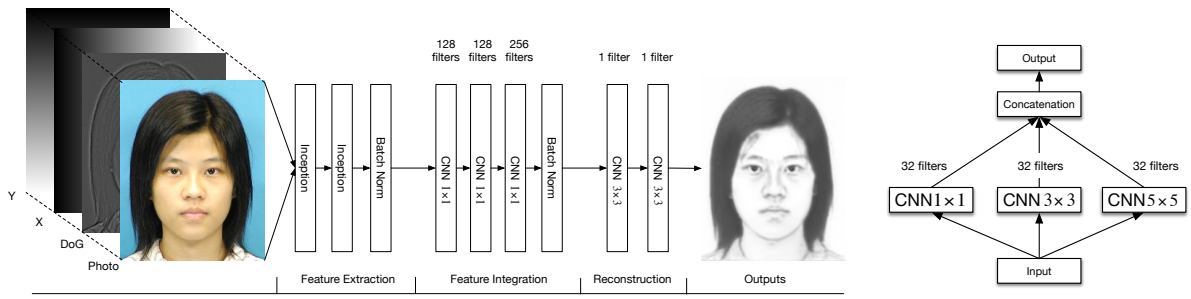
We use CNN to build our content network (see Fig 3). In addition to the test photo, two location channels containing spatial information (i.e., x and y coordinates) and a difference of Gaussian (DoG) channel containing edge information are fed into the content network. As pointed out in [13], face sketch synthesis algorithms benefit from integrating features from multiple resolutions. We employ an inception module inspired by the GoogLeNet [11] to extract features. It concatenates feature maps generated from filters with different spatial resolutions. Our inception unit contains 3 CNN filter groups, with each group having 32 filters. The filters in these 3 groups have a size of (1×1), (3×3) and (5×5) respectively (see Fig. 3(b)). The output features are then fed to a three-layer-CNN for feature integration, where the size of all filters are fixed at (1×1). Finally, the integrated features are used to reconstruct the content map by a two-layer-CNN with the filter size being 3×3. A mirror padding is carried out before the convolution operation when necessary to ensure the output feature map is the same size as the input. It is observed that the output of the content net outlines the shapes of the facial features, but its style does not look like sketches. For example, there exists no texture in the hair region and there is a lack of shadings to convey 3D information.

3.2. Sketch Style Generation

3.3. Style Representation

The style features of sketches are extracted using the VGG-Network [9], a CNN that was originally designed for visual object recognition tasks, and was later used for texture feature representation in [4]. Here we use the intermediate feature maps extracted by the convolutional layers and max-pooling layers in the VGG-19 network just before the fully connected layers.

In the VGG-Network, convolutional layers extract features and max-pooling layers down-sample the features such that the following convolutional layers extract features in a lower resolution. We extract the outputs of the first convolutional layers at different resolutions for the computation



(a) (b)

Figure 3. Illustration of the content network for generating a content image. The numbers above the building block denote the number of CNN filters. (a) The architecture of content network. (b) The inception module in (a) contains three groups of filters with different sizes.

of style. Following the terminology in [4], these layers are referred to as "conv1_1", "conv2_1", "conv3_1", "conv4_1", and "conv5_1", respectively, from the lowest level to the highest level. Define $L_s = \{$conv1_1, conv2_1, conv3_1, conv4_1, conv5_1$\}$. Since the VGG-Network is originally designed for color images, while sketches are gray scale images, we modify the first layer of VGG-Network for gray scale images by setting the filter weights to

$$W^k = W_r^k + W_g^k + W_b^k \tag{1}$$

where W_r^k, W_g^k, and W_b^k are weights of the kth filter in the first convolutional layer for the R, G and B channels respectively, and W^k is the weight of the kth filter in the first convolutional layer of our modified network. Note that we keep the bias in our modified network the same as that in the original VGG-Network. Denote the feature map of the final sketch $\mathcal{X}$ in the lth layer (in matrix form) by $F^l(\mathcal{X})$, where the element at the mth row and the nth column is the activation of the mth filter at location n. We use the gram matrix as our style representation. A gram matrix is a summary statistics of feature maps discarding the spatial information, and is originally designed for texture synthesis [4]. The gram matrix at layer l is given by:

$$G^l(\mathcal{X}) = F^l(\mathcal{X}) \cdot \left(F^l(\mathcal{X})\right)^T \tag{2}$$

where $G^l(\mathcal{X}) \in \mathcal{R}^{M_l \times M_l}$, and M_l denotes the number of filters in layer l. A multi-resolution style representation is obtained by combining the gram matrices at different layers: $\mathcal{S}(\mathcal{X}) = \{G^l(\mathcal{X})\}$ where $l \in \{$conv1_1, conv2_1, conv3_1, conv4_1, conv5_1$\}$. This style information is useful in guiding the sketch synthesis, especially in the texture region such as hair and shadings around the nose, eyes and mouth.

3.4. Target Style Generation via Multi-resolution Grouping

There usually does not exist a candidate image in the training set that perfectly matches a given test photo in style. We hence propose a patch based method to estimate the style of the final sketch. Denote the feature maps (of the lth layer) used to estimate the style of the final sketch by A^l. In our patch based method, we divide A^l into a grid where each grid cell (feature map patch) at layer $conv5\_1$ contains only one pixel. Since the pooling size is 2×2, we choose the sizes of feature map patches at the next lower layer twice of that at the current layer. Thus, the sizes of the feature map patches at layer $conv1\_1$, $conv2\_1$, $conv3\_1$, $conv4\_1$ and $conv5\_1$ are 16×16, 8×8, 4×4, 2×2 and 1×1, respectively. We introduce a multi-resolution feature descriptor by grouping feature map patches having the same grid indices i, j at different layer index l together as a pyramid column, U_{ij}. The photos and sketches are resized so that both the number of rows and columns are dividable by 16. A^l can then be represented as a hyper-grid U with the cells being U_{ij}. Similarly, we divide the test photo and the final

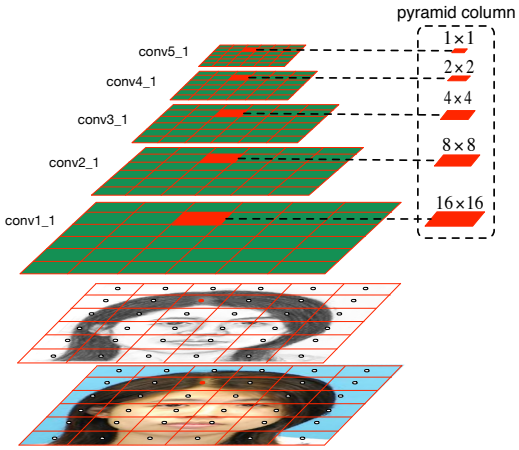


Figure 4. Illustration of pyramid column. Feature maps of the final sketch, A^l, are divided into patches according to the size of the smallest feature map. A pyramid column U_{ij} consists of feature map patches at different layer having the same grid indices i and j. The input photo and the final sketch are divided into patches where centers C_{ij} are denoted as dots. U_{12} and C_{12} are colored in red as an example.

sketch, respectively, into a grid with the same dimension as U. Denote the centers of these patches as C_{ij}. U_{ij} is hence a multi-resolution feature descriptor for a sketch region centered at C_{ij} (see Fig. 4). To estimate U_{ij}, a sketch patch in the training set is fed to the VGG-Network and a pyramid column is composed from the resulting feature maps. This process consists of two steps: (1) find a matching sketch patch from the training set S_{ij} for U_{ij} and (2) feed S_{ij} to VGG-Network and compose U_{ij} from the resulting feature maps.

Find Matching Sketch Patch

Inspired by previous works [13, 18], we examine the similarity in appearance of photo patches to find a matching sketch S_{ij} for U_{ij}. Denote a patch centered at C_{ij} in the test photo as Ψ_{ij}. If a patch centered at $\tilde{C}_{ij}$ in the kth photo in the training set has the smallest Euclidean distance from Ψ_{ij} in term of color channels, a sketch patch, S_{ij}, centered at $\tilde{C}_{ij}$ is extracted from the sketch paired with the kth photo in the training set. The size and position of S_{ij} are determined by the region associated with U_{ij} which is calculated according to the architecture of the VGG-Network and location of C_{ij}. For non-boarder cells, S_{ij} is a sketch patch of size 144×144 centered at $\tilde{C}_{ij}$. For cells near boarders, the region associated with U_{ij} is the intersection of a sketch patch of size 144×144 centered at C_{ij} with the whole sketch. Therefore, S_{ij} is a patch from the kth sketch containing $\tilde{C}_{ij}$ such that the location of $\tilde{C}_{ij}$ in S_{ij} is the same as the location of C_{ij} in the region associated with U_{ij} (see Fig. 5).

Estimate Pyramid Column

We compose an estimate for U_{ij} from the resulting feature maps obtained by feeding S_{ij} to the VGG-Network. Specifically, after feeding S_{ij} to the VGG-Network, we form a hyper-grid $\tilde{U}$ on the resulting feature maps. The pyramid column corresponding to $\tilde{C}_{ij}$ is selected as an estimation to U_{ij}. This pyramid column is the cell that contains $\tilde{C}_{ij}$ when projecting S_{ij} onto $\tilde{U}$.

After A^l are estimated, we calculate the target gram matrices by: $\{G_t^l = A^l \cdot \left(A^l\right)^T\}$ where $l \in L_s$.

4. Combine Style with Content

To generate a sketch that combines the content image with the estimated style, we adopt the methodology described in [4]. Specifically, we minimize a loss function consisting of a style loss, a content loss and a component loss. The style loss is defined as the difference between the gram matrix of the final sketch and the target gram matrix i.e.,

$$\mathcal{L}_s(\mathcal{X}) = \sum_{l \in L_s} \frac{1}{M_l^2 N_l^2} \left\| G^l(\mathcal{X}) - G_t^l \right\|_2^2 \qquad (3)$$

where N_l denotes the number pixels in the feature map at layer l. The content loss is defined based on the difference between the feature map of the sketch and that of the content image at layer conv1_1:

$$\mathcal{L}_c(\mathcal{X}) = \left\| F^{\text{conv1\_1}}(\mathcal{X}) - F^{\text{conv1\_1}}(\mathcal{C}) \right\|_2^2. \qquad (4)$$

Human is able to distinguish different people from key components such as eyes, nose and mouth, which indicates that these features are the most discriminative parts of a face. Specific styles or textures are usually used to emphasize these components, for example, sharp edges with shadings at the two sides of the nose are used to convey 3D information. To better transfer styles of these components, we employ a component loss to encourage the key component style of the final sketch being the same as the target key component style. Since two eyes are placed at fixed positions, the key components lie roughly within a rectangular region taking the positions of two eyes as vertices. Key component style is given by gram matrices calculated within feature map regions $\mathcal{R}$ corresponding to the key components. These regions are specified by hyper-grid cells U_{ij} whose C_{ij} are inside the rectangular region. More specifically, a target style for the key component is calculated: $\{\hat{G}_t^l = A_c^l \cdot \left(A_c^l\right)^T\}$ where A_c^l is the composed feature map patch in A^l corresponding to the key components, $l \in L_s$. The style of the key components in final sketch $\hat{G}^l(\mathcal{X})$ is calculated in exactly the same manner. The component loss is hence defined as:

$$\mathcal{L}_k(\mathcal{X}) = \sum_{l \in L_s} \frac{1}{M_l^2 \hat{N}_l^2} \left\| \hat{G}^l(\mathcal{X}) - \hat{G}_t^l \right\|_2^2 \qquad (5)$$

where $\hat{N}_l$ denotes the number of pixels in the feature map region $\mathcal{R}$ at layer l. The total loss we minimize is

$$\mathcal{L}_t(\mathcal{X}) = \alpha \mathcal{L}_c + \beta_1 \mathcal{L}_s + \beta_2 \mathcal{L}_k \qquad (6)$$

where α, β_1 and β_2 are the weighting factors for content, style and component losses respectively. The minimization is carried out using L-BFGS. Instead of using random noises, we use the content image as a starting point, which will make the optimization process converge much faster.

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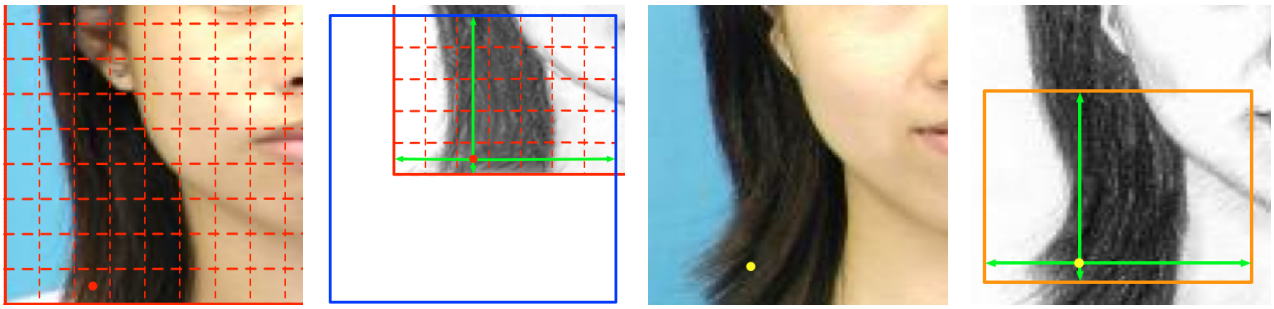

Figure 5. Find a matching patch for boarder cells. (a) The center C_{ij} of a boarder cell is denoted as the red dot in the photo. (b) The region associated with U_{ij} is the intersection of the blue square with the sketch. The distances between C_{ij} to the intersection boarders are denoted by green lines. (c) $\tilde{C}_{ij}$ denoted as a yellow dot is located by examining photo similarity. (d) The distances of $\tilde{C}_{ij}$ to boarders of S_{ij} equal to the distances of C_{ij} to boarders of intersection region in (b) such that the location of $\tilde{C}_{ij}$ in S_{ij} is the same as the location of C_{ij} in the region associated with U_{ij}.

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