Automatic Matting Using Edge Feature-Based Scribbles

Meidya Koeshardianto, *Member, IAENG,* Eko Mulyanto Yuniarno, *Member, IAENG,* and Mochamad Hariadi, *Member, IAENG*

***Abstract*—Foreground and background extraction, or commonly called matting, is still widely used in computer vision applications. Most of the matting, constraints of the foreground are determined manually. However, it is more efficient if done without human intervention. We proposed a method to determine constraint, scribbles, automatically using edge feature on image matting. Edge features are used to find gradient vector from each RGB color channel to obtain automatic scribbles. Our result will compare with a manual process using Mean Absolute Error (MAE). All of the experiment in this research were used several images from some previous work. The experimental result shows our proposed method has only differed 0,0336 from a current state of the art research and it done automatically without human effort.**

***Index Terms*—image matting, edge feature, automatic scribbles.**

I. Introduction

MANY applications in movie maker especially in visual effect animation have difficulties in putting the object on the real background scene. Extracting foreground technique has been used to obtain the object. Therefore, it could be composited with the background and taken in the real condition. The separation process between the foreground and background can be done using some techniques, such as image segmentation. Nevertheless, image segmentation [1], [2] results still cannot separate objects accurately. Image matting has been proposed as a solution to solve this problem of object separation.

Image matting is one of the methods that aim to do soft extraction. To get the alpha matte accurately of foreground that given as a constraint of an image. The earliest work in image matting was done by assuming the green color as the background [3]. However, this approach is rarely used in the recent image matting research because it has a limitation which cannot retrieve image foreground naturally.

Considering all the problem above, natural image matting was solved by proposing two thoughtful approaches that are supervised and unsupervised matting. The supervised methods need defined foreground and background constraints before applying the matting process. These methods have advantages that foreground and background can be determined accurately, but it requires effort for manual labeling using trimap or scribbles. Unsupervised matting reduces complexity by eliminating effort for labeling the constraints. However, in some cases, the results of the matting process are incompatible with user intention so that the extraction process does not match with their desire.

The main contribution of this paper implies a supervised approach without manual guidance. As shown in Figure.1, we overview of the proposed automatic image matting using edge feature-based scribbles. A simple way, there are two main steps to apply edge feature namely: edge feature subtraction and determining background model. The edge feature result will be used as the scribbles that obtained using three processes such as a determination of gradient of each color channel and direction, background subtraction, and thresholding. The evaluation results from our proposed will be compared with the Laplacian matting method using scribbles manually. The dataset used from previous research.

This paper has been divided into seven sections. The first section deals with our proposed methods and our contribution. Then, we review current research in image matting methods in section two. Section three explores laplacian formulation in automatic matting. Section four explanation detailed of the proposed method. Section five shows the automatic matting result furthermore we show more experiment analysis in section six. Moreover, in the last section, we conclude this research.

II. Current Research in Image Matting

Prior studies that have noted the important of matting methods was described by Potter [4] that take as input I is affected to be a composite of a foreground F and a background B as in (1). It is a color of the ith pixel that assumed to be a linear combination of the corresponding foreground and background colors.

$$I_i = \alpha_i F_i + (1 - \alpha_i) B_i \tag{1}$$

where $i = (x, y)$ and α_i is the pixel's foreground opacity.

In recent years, there has been an increasing amount of research on image matting that develops is emphasized mostly for automatic matting. The first method was extracting image automatically, as known unsupervised, that performed by Levin [5] with spectral matting. Then, [6] extend spectral matting by using modified spectral matting. All of them are automatically extracted by figure out the smallest eigenvectors of an appropriately defined Laplacian matrix. The smallest eigenvectors of the matting Laplacian extend the individual matting components of the image.

Several works [7], [8], [9], [10], [11] estimated unknown regions automatically by directly deal with a trimap. Wang et

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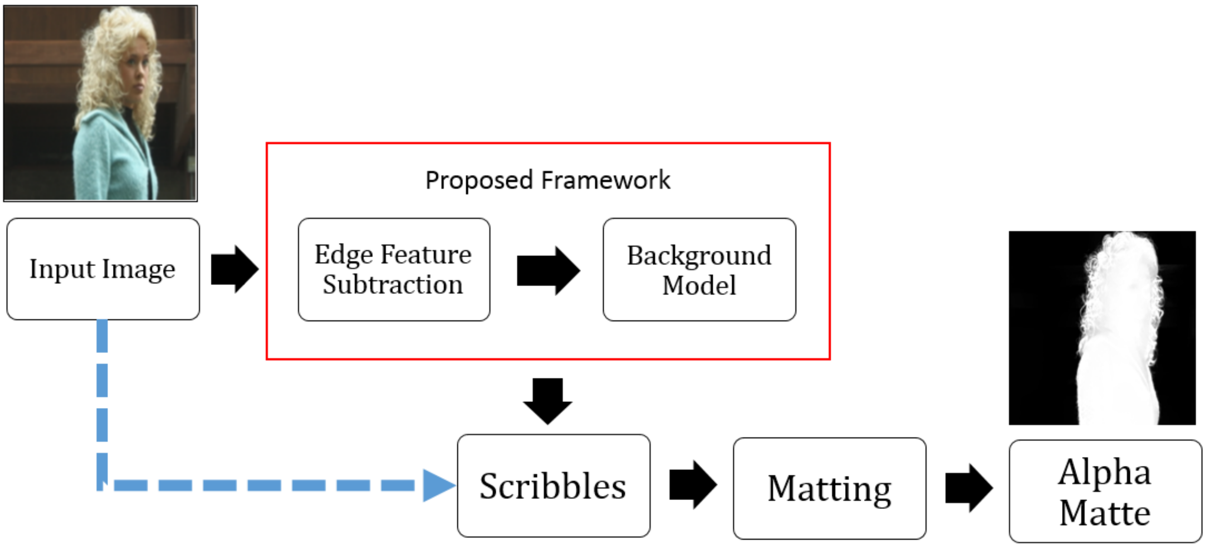

Fig. 1. We propose a method that can obtain alpha matte automatically. The blue lines show the conventional supervised matting process that needs manual scribbles. The red box is the current feature for automatic scribbles building.

al. [7] use depth information from a ToF camera. Rhemann et al. [8] suggested an interactive trimap segmentation via energy minimization. Refine a binary mask and a depth map of RGB-D images has done by He et al. [9] iteratively. Kim et al. [10] considers the geometry constraint across multi-view images with fractional boundaries.

There are also trying to use template matting [12], meaning constraints provided based on feature matching that has been given. Even lately, research on automatic matting is still done by some researcher. In [11] by assigning automatically trimap that used to recognize target automatically and [13] has used image matting to advance the image quality of synthetic aperture imaging via energy minimization by estimating the foreground and the background.

Most of the techniques used in automatic matting have the same problem of determining the foreground and background to be extracted. This paper attempt to show that determining foreground and background using edge features and modified the extraction formula [14] can be changed supervised matting process to be run automatically.

III. Problem Formulation in Automatic Matting

Base in (1), the color of the i^{th} pixel is decomposed into two layers, called F and B, which are blended linearly. This is known as the compositing equation and the acceptance allows (1) to be rewritten by expressing α as a linear function of I:

$$\alpha_i \approx aI_i + b, \forall i \in w, \tag{2}$$

where $a = \frac{1}{F-B}$, $b = -\frac{B}{F-B}$ and w is a small window. By minimizing the cost function the liniear coefficients a, b and α can be estimated.

$$J(\alpha, a, b) = \sum_{j \in i} \left(\sum_{i \in w_j} (\alpha_i - a_j - b_j)^2 + \epsilon a_j^2 \right) \tag{3}$$

where w_j is a small window around pixel j and ϵ is small constant for regularization term on a_j. Later, in experiments we only used a window size of 3×3 to enable the propagation of intensity information by defining affinities among a small number of neighboring pixels. Using Theorem 1 in [14], a_j and b_j can be eliminated from (3) to yield a cost function that is dependent only on α:

$$J(\alpha) = \alpha^T L\alpha \tag{4}$$

where α is an $N \times 1$ vector, and L is an $N \times N$ Laplacian matrix, in which the (i, j)th entry can be defined in eq.5

$$\sum_{k|(i,j)\in w_k} \left(\delta_{ij} - \frac{1}{|w_k|} \left(1 + \frac{1}{\frac{\epsilon}{|w_k|} + \sigma_k^2} (I_i - \mu_k)(I_j - \mu_k) \right) \right), \tag{5}$$

N is the number of pixels in the target object, δ_{ij} is Kronecker delta, μ_k and σ_k^2 are the mean and variance respectively of the intensities in the window w_k, and $|w_k|$ is the number of pixels in w_k. Then alpha matte can be solved with

$$\alpha = \arg\min \alpha^T L\alpha + \lambda(\alpha^T - b_s^T) D_s(\alpha - b_s) \tag{6}$$

where λ is some large number, D_s is a diagonal matrix in which diagonal elements are 1 for constrained pixels and 0 for the other pixels, and b_s is a vector that contains the specified alpha values for the constrained pixel. In linear system (6) can be written

$$(L + \lambda D_s)\alpha = \lambda b_s \tag{7}$$

In the supervised method, a variable b_s can be obtained manually. A process from supervised to unsupervised can be conducted through determining variable automatically. So that, the process that solves the problem is called automatic scribbles. To extract alpha matte in this research, the parameter b_s from equation (7) have to be generated automatically using a constraint on the object which is provided by edge feature subtraction and the background model. The generated scribbles indicate foreground ($\alpha = 1$) and background pixels ($\alpha = 0$).

IV. Proposed Framework for Automatic Scribbles

The proposed framework begins with two main processes namely edge feature subtraction and background model

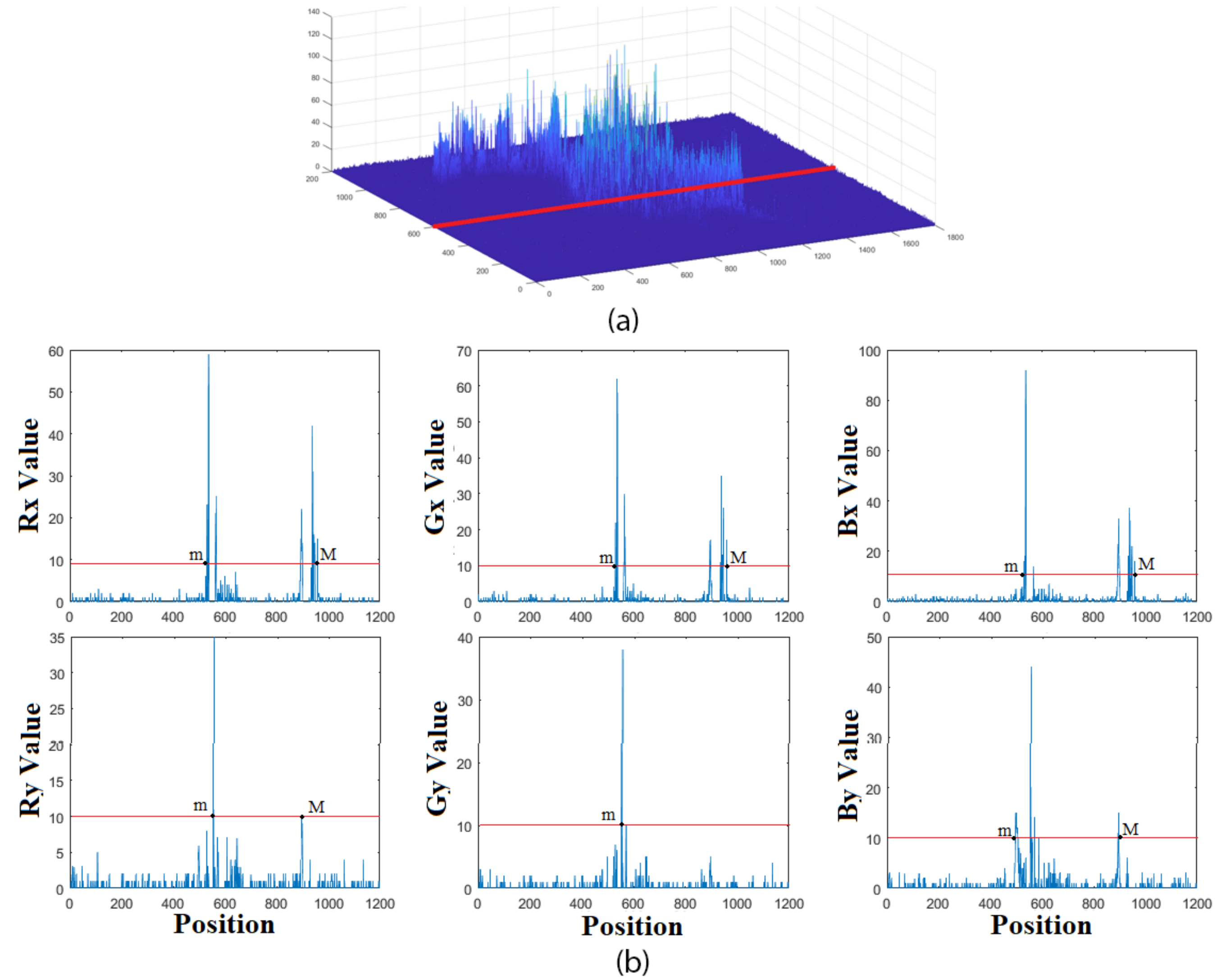

Fig. 2. The result of foreground model from each color channels after background subtraction process with each corresponding mean direction. (a) Represent result foreground model in 3D. (b) First and second row represent red line from (a) on horizontal and vertical RGB edge magnitude respectively in 2D. Variable m and M are the beginning and the ending position magnitude for background model. The detail explanation will be further discussed in subsection IV-B

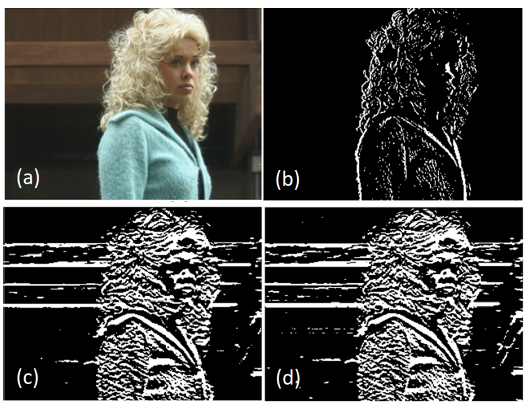

Fig. 3. The result of gradient change for different methods of edge detection. (a) Original Image (b) our proposed, (c) and (d) gradient model using Prewitt and Sobel. Original image from [14]

building. On the subsection, edge feature subtraction consists of several processes particularly edge detection, background subtraction, and thresholding.

A. *Edge Feature Subtraction*

The basic idea identifying foreground and background area on an image is used first derivative differential numerics or commonly called the first gradient. It detects a changing in the intensity of pixel value within a short distance.

Edge Detection: Edge detection is the most significant the current feature is in the process of forming gradients. Gradients are formed not based on all components of the color channel which are usually directly made gray-scale, however in this study, gradient establish was done on each color channel.

Let I^c as an image where $c \in [R, G, B]$ is color channel. We denote ∇I^c as gradient of an image from each different direction. Gradient from each different direction can be computed by the expected value of horizontal and vertical direction.

$$\nabla I^c = \begin{bmatrix} \dfrac{\partial I^c}{\partial x} \\ \dfrac{\partial I^c}{\partial y} \end{bmatrix} = \begin{bmatrix} F_h^c \\ F_v^c \end{bmatrix} \tag{8}$$

where ∇F_h^c and ∇F_v^c are gradient direction towards hori-

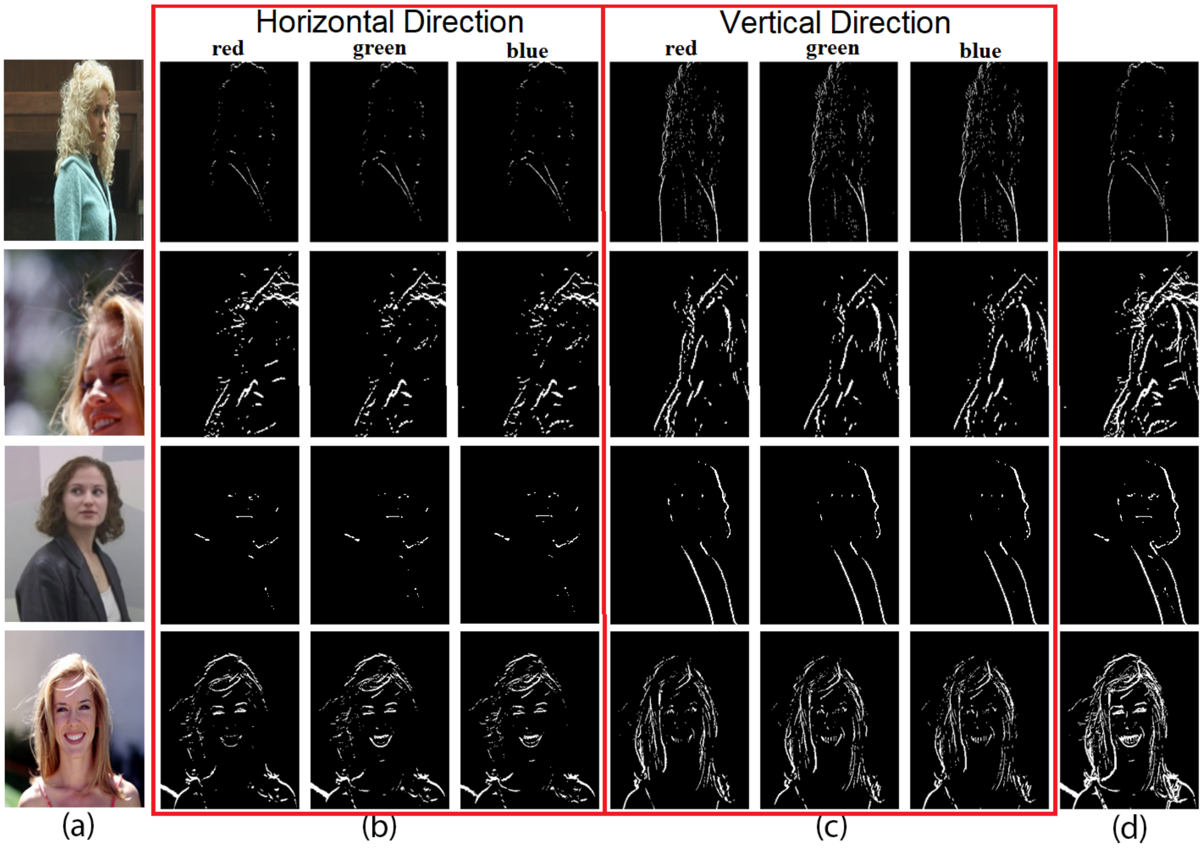

Fig. 4. We show detail edge feature for each color channel magnitude and direction. (a) Input image, (b) and (c) gradient horizontal and vertical direction from each color channel, (d) Final result of foreground scribbles. Input image from [14]

zontal and vertical can be written from

$$\begin{aligned} \nabla F_h^c &= \frac{\partial I(x,y)}{\partial x} = \lim_{\Delta x \to 0} \frac{f(x+\Delta x, y) - f(x,y)}{\Delta x} \\ \nabla F_v^c &= \frac{\partial I(x,y)}{\partial y} = \lim_{\Delta y \to 0} \frac{f(x, y+\Delta y) - f(x,y)}{\Delta y} \end{aligned} \tag{9}$$

In equation (9), Δ is distance from each pixel that assume $\Delta x = \Delta y = 1$. Then each ∇F can be defined as

$$\begin{aligned} \nabla F_h^c &= f(x+1,y) - f(x,y) \\ \nabla F_v^c &= f(x,y+1) - f(x,y) \end{aligned} \tag{10}$$

So that, refer to (8) each vector the first differential numeric from each direction can be written as

$$\begin{aligned} \nabla . F_h^c &= \left[\frac{\partial}{\partial x} \frac{\partial}{\partial x} \frac{\partial}{\partial x}\right] \begin{bmatrix} R \\ G \\ B \end{bmatrix} = \left[\frac{\partial R}{\partial x} + \frac{\partial G}{\partial x} + \frac{\partial B}{\partial x}\right] \\ \nabla . F_v^c &= \left[\frac{\partial}{\partial y} \frac{\partial}{\partial y} \frac{\partial}{\partial y}\right] \begin{bmatrix} R \\ G \\ B \end{bmatrix} = \left[\frac{\partial R}{\partial y} + \frac{\partial G}{\partial y} + \frac{\partial B}{\partial y}\right] \end{aligned} \tag{11}$$

Then, by applying (11) we have μ_i^c as mean that could be calculated which is the average of each ∇F_h^c and ∇F_v^c values.

Background Subtraction: Both of edge magnitude and direction changes are taken into account in the next phase of background subtraction. For removing salt and pepper noise, we subtract the current F_h^c and F_v^c difference images from the corresponding mean images.

$$\begin{aligned} BS_h^c &= |\nabla . F_h^c - \mu_h^c| \\ BS_v^c &= |\nabla . F_v^c - \mu_v^c| \end{aligned} \tag{12}$$

Each color channel obtains the various magnitude of edge feature. We compare our scribbles generating a method with other two edge algorithm: Sobel and Prewitt. The effect of background subtraction can be seen in Figure.3. Our proposed is slightly different from the common edge method which visually shows the better result to obtain the foreground model.

Thresholding: The last sequence process of the edge feature is determining threshold where is very important in deciding the foreground results. From (12) we put into account threshold from each color channel.

$$H^c = \begin{cases} 1, & \text{if } BS_h^c > \tau, \\ 0, & otherwise \end{cases}$$

$$V^c = \begin{cases} 1, & \text{if } BS_v^c > \tau, \\ 0, & otherwise \end{cases}$$

We define τ as a threshold for each direction where H^c and V^c are horizontal and vertical edge direction. Then, the foreground scribbles S_f can be written as

$$S_f = \sum^c H^c + V^c \tag{13}$$

or

$$S_f = \prod^c H^c V^c \tag{14}$$

In this research, we proposed S_f with two types, namely sum, and multiplication process. We cannot only do the sum process but also the multiplication process all the energy terms to derive the foreground scribbles as we call edge

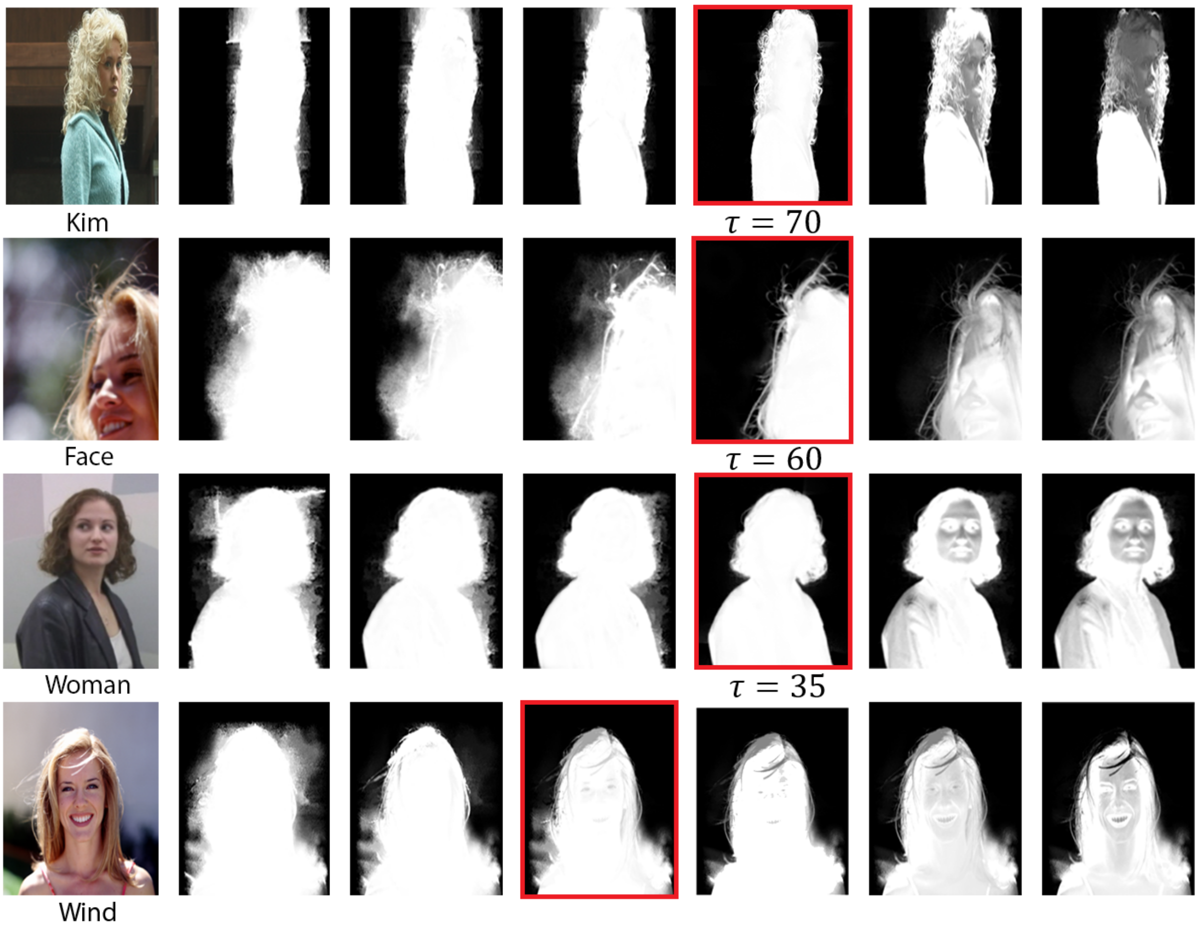

Fig. 5. **Qualitative comparison result:** We compare the result of alpha matte with various threshold. The images were processed using 80 iteration where the best result of alpha matte is in red box.

TABLE I
COMPARISON PROCESSING TIME BETWEEN UNSUPERVISED, SUPERVISED, AND OUR PROPOSED

Image Data	Image Size	Spectral [5]	Closed Form [14]	Our method
Kim	238×318	70,5366	6,8906	7,2221
Face	165×137	25,9910	5,2498	5,2699
Woman	212×165	35,9130	8,0105	8,0528
Wind	254×254	133,1572	7,4317	7,8649

feature subtraction. This process can not be assigned as a convolution matrix such as a Prewitt and Sobel edge feature. Moreover, this is the main reason why we do not process an edge detection on gray-scale first. The detailed result of our proposed it is already proofed in Figure.4. A more detailed explanation about scribbles dependency will be further discussed in section VI.

B. Background Model

In the background model, another part of scribbles, derived from equation (13) that we have argued foreground area $F \in [m_x < S_f < M_x]$ where m_x and M_x are beginning and ending position magnitude in one linear direction as shown in Figure.2 (R_x value). Starting now, we can define the model $\forall i \in I \rightarrow B = [i|i \in F']$ then the scribbles background S_b can be written as

$$S_b \in \{m_i - d < S_f < M_i + d\} \tag{15}$$

Or it can be written as 2D direction as

$$S_b = \sum_{x=0}^{m_x-d} \sum_{y=0}^{m_y-d} S_b(x,y) + \sum_{x=M_x+d}^{X} \sum_{y=M_y+d}^{Y} S_b(x,y) \tag{16}$$

where d is distance between magnitude with background region.

V. AUTOMATIC MATTING RESULT

The effectiveness of our proposed method will be evaluated by state-of-the-art a supervised method that needs manual scribbles. The premise to be proved, we ignore the work of the user to draw scribbles, the proposed method could be run automatically. After that, we compare our proposed methods with other two methods such as closed form matting as supervised matting and spectral matting as unsupervised matting to evaluate the performance and accuracy. We used the result alpha matte from closed form matting as ground truth. All experimental results were carried

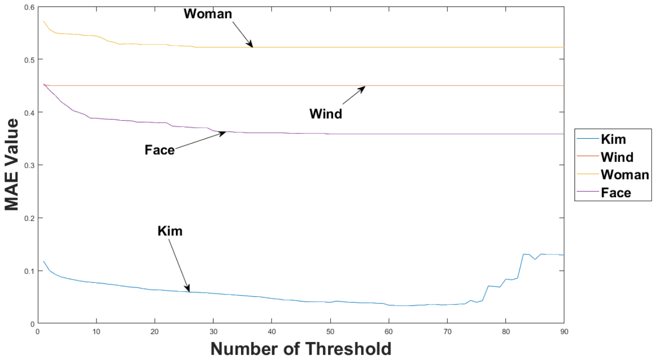

Fig. 6. Quantitative comparison: MAE value of alpha matte between our approach and Close form method. A small value indicates that our proposed is similar to Closed form result.

out on a PC with Intel(R) Core(TM) i5-8250U@1,6 GHz and 8 GB memory, NVIDIA GeForce 940MX (4GB) graphics card.

We use the Laplacian matting [14] to extract foreground from the image for proofing our concept implementation in automatic constraint building. In Figure.5, we demonstrate our automatically generated alpha matte that is used four images of Kim, Face, Woman and Wind as test images that come from [14]. We do the proposed model to get the best alpha matte with some various threshold setting. In this experiment, set threshold parameters lie on $10 < \tau < 90$ to generate an alpha matte. The red box in Figure.5 indicates the best result from our proposed for images Kim, Face, Woman, and Wind respectively. We did not provide a threshold value For Wind image in Figure.5 because the best result alpha matte has not been found yet.

In the next scenario, we have compared processing time from our proposed with closed-form matting [14] as a supervised matting and spectral matting [5] as another automatic matting algorithm to evaluated performance and accuracy. Table I shows that the proposed method was much shorter than spectral matting and not much different from closed-form matting. Moreover, spectral matting needs the support of high capacity memory, so it is not fit in processing bigger image, while the memory consumption in the proposed method is relatively smaller and can quickly process the larger images.

There are several methods of measuring the similarity between two objects. For quantitative evaluation performance of our method we used Mean Absolute Error (MAE) that was used in [15] and [16]. MAE is defined as:

$$MAE = \frac{1}{XY}\sum_{x=1}^{X}\sum_{y=1}^{Y}|\alpha(x,y) - \overline{\alpha}(x,y)| \qquad (17)$$

where $\overline{\alpha}$ is alpha matte result from Closed-form and α is our proposed result.

In Figure.6 shows that detailed MAE result of alpha matte from each data image between our approach and Closed-form. Approaching the closed-form result could have MAE a minimum value.

VI. Experimental Analysis

In this section, we present an experimental analysis of the proposed method. Several things conveyed, namely comparison of the alpha matte result between image matting and segmentation and scribbles dependency against the alpha matte result. The last subsection in this section describes the limitation of the framework.

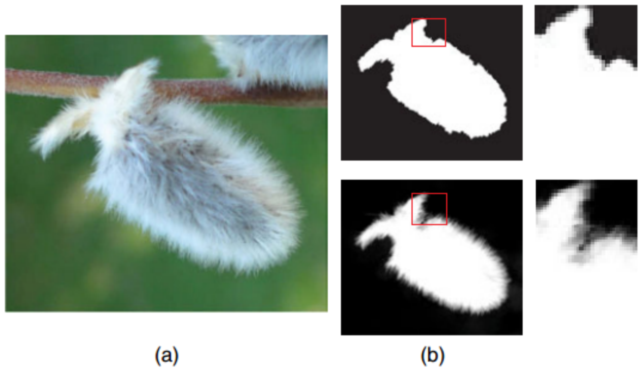

Fig. 7. The image (a) and alpha matte obtained from image segmentation (b, top row) and alpha matte from image matting (b, bottom row).

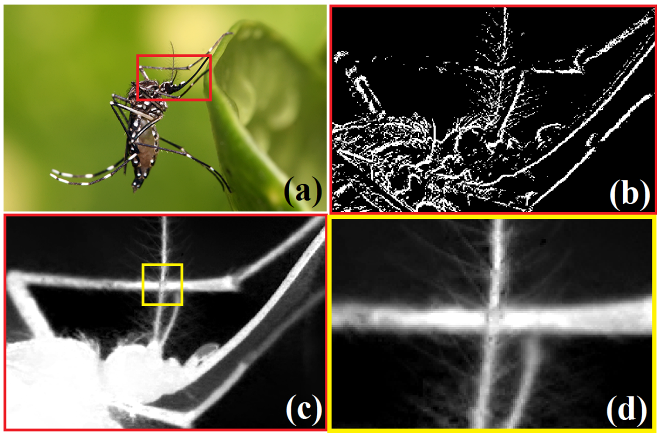

Fig. 8. Detail alpha matte result from automatic matting using edge feature-based scribbles.

A. Comparison with Image Segmentation

Image matting being at the intersection of image segmentation is challenging to extract the foreground from an image. Image segmentation provides a binary alpha matte that contains only two value there are 1 for foreground and 0 for the background. Different from image segmentation, in image matting, alpha matte provides the value foreground between 0 and 1. In Figure. 7(b) shows that the degradation of alpha matte changes in the image matting is smoother than image segmentation.

However, it does not mean that the image segmentation algorithm has been replaced by the image matting. There are implementations in some instances such as fingerprint recognition, facial, and retina blood detection. It is better to use image segmentation instead of matting image. So, this technique depends on usage during implementation.

B. Scribbles Dependency Analysis

In this section, we analyze scribbles dependency. Therefore, the use of constraints such as scribbles on the supervised method is necessary and could be a major factor for the extraction result. More detail in defining foreground can produce better alpha matte.

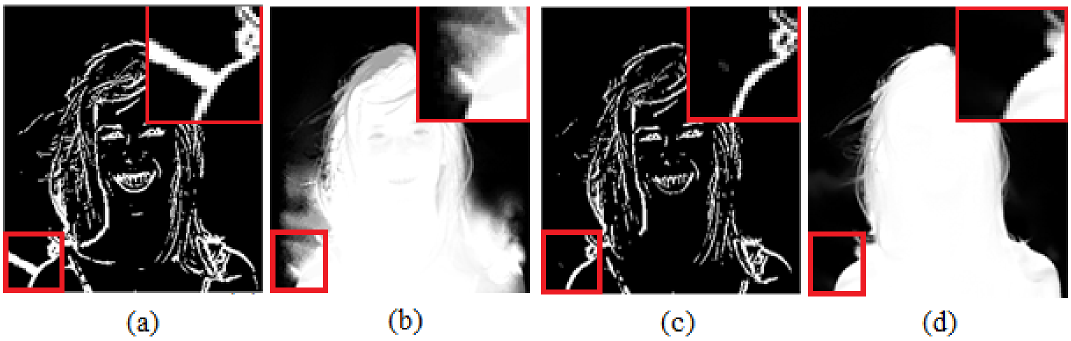

Fig. 9. We compare the benefit between the sum process and the multiplication process. The alpha matte result (b) was obtained from scribbles (a) using the sum process. By multiplication process further improves the alpha matte result (d) from scribbles (c).

From the input image in Figure.8, the detail foreground definition as scribbles has shown in Figure.8b and obtained an accurate alpha matte as shown in Figure.8c. The Edge feature in (13) can define the foreground of the sum of the magnitude of each color channel so that it can determine the smallest area of the image. As shown in Figure.8d is detailed proboscis and labium mosquito from Figure.8c. This determination can be done manually only with professional labor so that in some instances our framework is needed to construct better alpha matte.

Nevertheless, this finding is contrary to the previous result which was obtained detailed scribbles. As shown in Figure.5, The result of alpha matte from Wind image data appears to be unaffected by (13). There is some foreground region was defined as background. We analyze scribbles in (13) that used the sum process of each color channel as shown Figure.5 (bottom). Interestingly, the image Wind was observed by applying from (14), the confusion of the alpha matte result in the Wind image data using (13) can be improved.

The effect of (14) is further to eliminating pixels that formed from H^c and V^c compared to (13). The result of the multiplication process as shown in Figure.9 obtain F which is only determined pixel value from both directions that are in V^c and H^c. In this observed, not everything can be done directly using (14) because of the affect scribbles that formed. In some other cases, more significant the elimination of scribbles results in not being able to show the foreground correctly. Another parameter that affects foreground formation is the threshold value. Determination threshold of the foreground model significantly influences the formation of scribbles.

Notwithstanding these occurrences, in this proposed suggests that scribbles building is started with (13 and threshold determination. Then, if the result of alpha matte is still unsatisfactory, then we use (14). Hence, the errors in determining the background and foreground can be eliminated and significantly affect the results of alpha matte.

VII. Conclusion

An automatic matting method was proposed using edge feature-based to establish the automatic scribbles as constraints on supervised matting. The edge feature demonstrated that an accurate alpha matte could be obtained automatically in order to reduce human effort. Comparing the results alpha matte from our proposed method with the supervised matting have only differed 0,0336 in MAE score that shows it can be tolerated visually.

Our proposed has not obtained minimum MAE result in wind image. It because some background area was determined as a foreground. This challenge has been improved by modifying the sum process into the multiplication process with condition that scribbles building is started with summing process and threshold determination then if the result of alpha matte is still unsatisfactory then we use multiplication process.

The finding in this paper is subject to at least two limitations. First, when the gradient between foreground and background is rather low, our method may not work well. Second, we assume foreground and background have sufficient gradient distance such that beginning and the end magnitude edge energy can be determined. If this assumption is violated, it is challenging to utilize scribbles properties and then our approach is not much adequate as shown in Figure.10.

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Fig. 10. Failure case. (a) Input image. (b) Our proposed failure determine foreground and background. (c) The result of alpha matte

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