A New Formulation of Face Sketch Multiple Features Detection Using Pyramid Parameter Model and Simultaneously Landmark Movement

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Summary
There are many cases when crimes happened, the criminals can not be identified. But with the help of the eyewitness reconstruction, the sketchers can make the suspects' face to help the identification. With this in mind, we propose a new formulation of face sketch multiple features detection. It is conducted by using the Pyramid Parameter Model and simultaneously landmark movements' improvement. Our proposed method is divided into four stages: training, create image gradient, shape initialization, and multiple features detection processes. The last stage is started by searching the maximum line gradient value between two landmarks. Thus, by using the Similarity Transformation Equation, the set of landmarks (shape) will be simultaneously moved. The movements are conducted by reducing the range and parameter value on each movement. This process is called Pyramid Parameter Model. The position of new landmark is enhanced by using simultaneously landmark movements on each shape. As the testing set, we use 50 halftone and 50 hatching face sketches. Each sketch is examined by using 38 landmarks of 7 features. The experimental results show that the average of detection rate is 93.28% for halftone and 93.03% for hatching face sketch.
Key words:
Pyramid Parameter Model, Maximum Line Gradient, Multiple Features Detection, Halftone and Hatching Face Sketches, police investigation.

1. Introduction

Criminals always bring the society disquiet, while, usually, the law enforcement only has a limited face database to identify the suspects. The best identification alternative is by sketching the suspect's face based on the eyewitness' reconstruction. The sketch can show characteristics of suspects. Hence, eyewitness and sketcher have crucial role. Regarding those conditions, it is needed to develop a new method for employing the sketches as the data to probe the suspect during the investigations.

Many face interpretation researchers tend to use the same modality as their training and testing data sets, for example those in [1-5], whereas in the suspect identification research should always use different modalities [2, 15, 16]. The training sets [15,16] used the halftone model drawn by employing the dark-to-bright gradation effect in order to achieve the desired plasticity [17]. The distance similarity from photo-sketch of the same person is larger than the one in photos of two different persons. This distance similarity is proportional to different modality; the larger the distance, the bigger the different. The difference modality of photo-sketch can be reduced by using Eigentransform [16]. Figure 1 shows that Eigentransform method only suitable for halftone face sketch training set but not for the hatching. Thus, this method can not used to reduce the different modality in order to produce a hatching-like face sketch.

We propose a new formulation for halftone and hatching face sketch multiple features detection using Pyramid Parameter Model and simultaneously landmark movement without involving the photo-to-sketch transformation process. In this method, set of landmarks, i.e. shape, move toward feature by using a range of translation, scaling, rotation and step values. The movement is repeated by decreasing the parameter ranges and value from previous movement(s). As the result of the Pyramid Parameter Model, the new landmark positions are being moved simultaneously based on maximum line gradient. This process is conducted to enhance the model.

The first contribution of our research is to build a new training purpose modelling system. Result of training can be used to relocate the initialization shape to a closer position with the features. The second, to build the model to detect face sketch multiple features, for both halftone and hatching face sketches, without involving the photo-to-sketch transformation process.

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Our proposed method uses Active Shape Model (ASM) as a reference. ASM has been used in many researchers, such as in the Vertebral Fracture Detection [18-24], Face Image Interpretation [6-11], and Model Building [12-14]. The main advantage of ASM, it is able to simultaneously detect feature based on the data training. Yet, it has several weaknesses. On ASM, the obtained model is changing only in the available variances in the training set. All changes outside the training set are not covered by the model. The shape initialization easily affects the final result. If the initial shape is suitable to ASM, it leads to the correct result. Otherwise, the final result will not be satisfactory. Moreover, ASM only uses data around the landmarks and does not utilize all available gray information across the object. It may be less reliable, although the model boundaries move to the places which have the most information (boundaries) [25, 27]. To overcome the weaknesses of ASM method, we use maximum line gradient as movement reference. The movement is being repeated by using Pyramid Parameter Model.

2. Active Shape Model (ASM)

Many researchers have researched on the analysis of texture patterns of the face image and have used many kinds of pattern analysis methods such as Principal Component Analysis (PCA) [31], Kernel PCA[1], and Independent Component Analysis (ICA) [32]. Although there were some methods that considered the shape variation of the face such as the Gabor Wavelet Jets, they concentrated on the analysis of holistic face texture assuming they are deal with only front view face image. Cootes have proposed a series of algorithms to overcome the limitations of the aforementioned shape and texture analysis methods such as the active shape model (ASM) [27, 28], and active appearance model (AAM) [20, 21, 22, 23]. The ASM alleviates the limitations of the previous shape analysis methods. It learns the shape variation of an object using a linear shape model from a set of training examples so that the linear shape model can produce a legal shape of the target objects without requiring the designer's prior knowledge on the target object.

An ASM was developed for the purpose of medical image analysis [13]. They became popular methods in the face image analysis research field because they are good at representing the variations of the shape and texture of non-rigid objects such as the human face. Cootes et al. used the term ASM as the name of the model fitting algorithm in their paper, where the model includes a *point distribution model* (PDM). The PDM is a kind of deformable shape model that consists of a linear model to explain the shape variation of the training data.

The first step in ASM is to form the model using the landmarks positions of the images in the training set. There are three steps to build the shape model which are Procrustes analysis, shape alignment, and PCA and shape model order reduction. The model uses some images in training set where the correct landmarks of the object have been defined by training process. After aligning the shape by Procrustes algorithm, the shape variations are described using Linear PCA [30].

The second step is searching, the shape model adjusts the shape suggested by the profile model to conform the legitimate shape. This operation is needed since the profile matches at each landmark are unreliable. For the image searching, an initial estimation of the shape is manually applied to an unseen image. The initial shape should hit the object edges in the unseen image and at the same time be reasonably short [26]. Then ASM uses the edge profile and the covariance matrix of the mean normalized derivatives generated in the last stage to find the best movement.

(a) (b) (c) (d)

Figure 1 Transformation Examples of Photo-to-sketch [15, 16]. (a) An Original Photo. (b) Reconstructed Photo. (c) Reconstructed Sketch. (d) The Original Sketch.

(a) (b) (c)

Figure 2 The Photo and Sketch Examples. (a) An Original Photo. (b) The Halftone Face Sketch. (c) The Hatching Face Sketch.

3. Proposed Method

This research divide into four stages: training, create image gradient of testing set, shape initialization, multiple features detection processes. The last stage divides into two stages. The first stage, shape moves simultaneously based on maximum line gradient, this process is repeatedly conducted using Pyramid Parameter Model. The process result will be improved by using simultaneously landmark movement. System framework can be seen in Figure (3)

If image training set is *I(x,y)* and the number of features to be detected is *k*, each feature is FT_j, where $j=1,2,...k$, then the overall features of training set can be modelled as follows

$$XT = FT_1 \bigcup FT_2 \bigcup \dots \bigcup FT_k = \bigcup_{j=1}^{k} FT_j \quad (1)$$

And landmarks of training set can be expressed using equation as follows

$$\begin{aligned} FT_1 &= \{(x_1, y_1), (x_2, y_2), ..., (x_{n1}, y_{n1})\} \\ FT_2 &= \{(x_1, y_1), (x_2, y_2), ..., (x_{n2}, y_{n2})\} \\ FT_3 &= \{(x_1, y_1), (x_2, y_2), ..., (x_{n3}, y_{n3})\} \\ FT_4 &= \{(x_1, y_1), (x_2, y_2), ..., (x_{n4}, y_{n4})\} \\ &. \\ &... \\ &... \\ FT_k &= \{(x_1, y_1), (x_2, y_2), ..., (x_{nk}, y_{nk})\} \end{aligned} \quad (2)$$

Where $n_i \in$ integer number and $i \in 1, 2, 3, \dots, k$. and n_i represents number of landmarks on each shape *j-th*. Figure 4 displays an example of model shape formed by landmarks on each training set. It can be shown that number of landmarks on face curvature, left eyebrow, right eyebrow, left eye, right eye, nose and lips are 9, 4, 4, 5, 5, 5, 6 respectively. It means that n_1=9, n_2=4, n_3=4, n_4=5, n_5=5, n_6=5 and n_7=6.

On the testing set, shape can be represented by using FS_i, where $i=1, 2, 3, \dots k$. Thus, shape of testing set can be modeled using equation as follows

$$XS = FS_1 \bigcup FS_2 .... \bigcup F_k = \bigcup_{j=1}^{k} FS_j \quad (3)$$

Landmark on testing set can be modelled using matrix equation

$$\begin{aligned} FS_1 &= \{(x_1, y_1), (x_2, y_2), ..., (x_{n1}, y_{n1})\} \\ FS_2 &= \{(x_1, y_1), (x_2, y_2), ..., (x_{n2}, y_{n2})\} \\ FS_3 &= \{(x_1, y_1), (x_2, y_2), ..., (x_{n3}, y_{n3})\} \\ FS_4 &= \{(x_1, y_1), (x_2, y_2), ..., (x_{n4}, y_{n4})\} \\ &. \\ &... \\ FS_k &= \{(x_1, y_1), (x_2, y_2), ..., (x_{nk}, y_{nk})\} \end{aligned} \quad (4)$$

3.1 Training

Training is conducted to determine the average value for all of landmark, landmark variance average based on center point of training set. If the training set *I(x,y)*, $\exists\, x,y$ is landmarks training set and $x,y \in$ landmark, then feature landmarks of training set can be determined its average value of x and y using equation

$$\overline{x_i} = \frac{\sum_{j=1}^{n} x_{i,j}}{n} \quad (5)$$

$$\overline{y_i} = \frac{\sum_{j=1}^{n} y_{i,j}}{n} \quad (6)$$

$i=1..m$, where m is the number of training set and $j=1..n$, where n is the number of landmarks on each training set. By using for all training set, the average value of x and y can be calculated using equation

$$\overline{X} = \frac{\sum_{i=1}^{m} \overline{x_i}}{m} \quad (7)$$

$$\overline{Y} = \frac{\sum_{i=1}^{m} \overline{y_i}}{m} \quad (8)$$

Minimum and maximum value of x and y can be used to determine difference of maximum and minimum deviation average by using equation

$$\overline{\Delta\sigma_x} = \frac{\max(\overline{x}) - \min(\overline{x})}{2} \quad (9)$$

$$\overline{\Delta\sigma_y} = \frac{\max(\overline{y}) - \min(\overline{y})}{2} \quad (10)$$

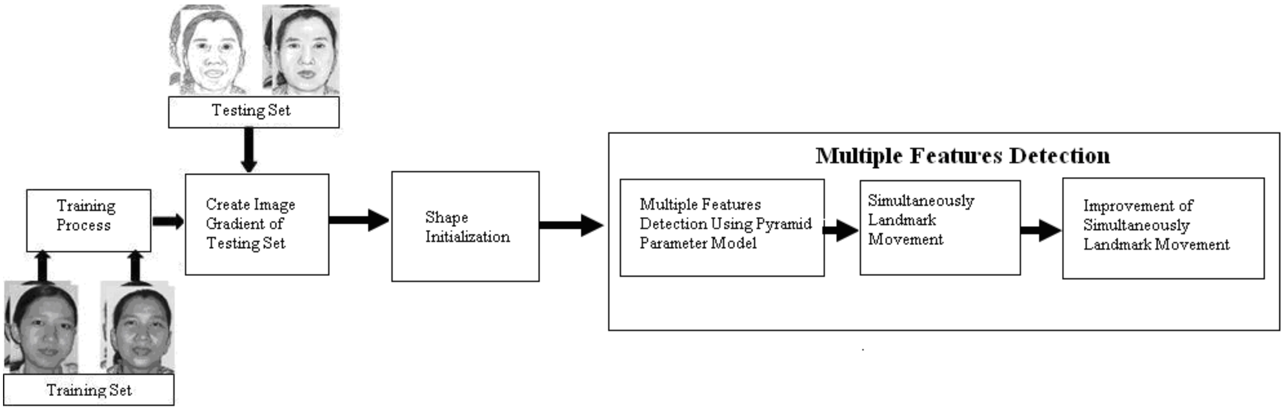


Figure 3 System Framework

And set of mass centre for each landmark of training set in each image can be determined by using subtraction origin landmark to average value

$$xv_i = x_{i,j} - \overline{x_i} \quad (11)$$

$$yv_i = y_{i,j} - \overline{y_i} \quad (12)$$

By using Equation (11) and (12), hence, the total landmark variance of *x* and *y* can be calculated using equation.

$$\sigma x_{i,j} \leftarrow \sigma x_{i,j} + xv_i \quad (13)$$

$$\sigma y_{i,j} \leftarrow \sigma y_{i,j} + yv_i \quad (14)$$

The result of Equation (13) and (14) can be used to obtain the landmark variance average of *x* and *y* by using equation

$$\overline{\sigma x}_j = \frac{\sigma x_j}{n} \quad (15)$$

$$\overline{\sigma y}_j = \frac{\sigma y_j}{n} \quad (16)$$

While the difference of variance deviation average of *x* and *y* for each training set can be calculated as follow

$$\Delta\delta x_j = \frac{(\sigma xMax_j - \sigma xMin_j)}{2} \quad (17)$$

$$\Delta\delta y_j = \frac{(\sigma yMax_j - \sigma yMin_j)}{2} \quad (18)$$

Where $\sigma xMin_j = \min(xv_{i,j})$, $\sigma xMax_j = \max(xv_{i,j})$, $\sigma yMin_j = \min(yv_{i,j})$ and $\sigma yMax_j = \max(yv_{i,j})$. Equation (7), (8), (15), and (16) will be used to form shape initialization. Equation (7), (8), (9), (10), (15), (16), (17), and (18) will be used to detect multiple features of face sketch.

3.2 Create Image Gradient of Testing Set

Image Gradient is used to form pixel gradation, so that shape can move toward edge features. To obtain feature edge, image will be processed by using the second derivative. Its result will be used to form image gradient using the first derivative. Edges are considered image pixels where intensity change is local maximum. The first derivative can be written as equation

$$\nabla I = \frac{\partial G(x,y)}{\partial x} + \frac{\partial G(x,y)}{\partial y} \quad (19)$$

The second derivative is computed by the Laplacian operator, and edges are obtained by finding the Laplacian of an image and locating the pixels that separate positive and negative regions.

$$G = \nabla^2 I = \frac{\partial^2 G(x,y)}{\partial x^2} + \frac{\partial^2 G(x,y)}{\partial y^2} \quad (20)$$

Figure (5) show halftone and hatching face sketch, and the gradient image of each sketch.

3.3 Landmark Initialization

Result of training can be used to relocate the initialization shape to a closer position with the features. We propose to determine the shape landmark initialization based on the overall landmark average value and the landmark variance average on each training set. The result of landmark initialization is new landmark coordinates as center point the training set. This process can be modeled as

$$X_j = \overline{X} + \overline{\sigma x}_j \quad (21)$$

$$Y_j = \overline{Y} + \overline{\sigma y}_j \quad (22)$$

Where *j=1..n* and *n* is number of landmarks for each training set. Both equations are the justification model of the overall training set considering the variance average of all landmarks to x and y value averages. Figure 6 shows the Point Distribution Model (PDM) of training set, centre of point, and shape model initialization.

3.4 Feature Detection

Feature detection is the feature landmark searching process on face sketch. In this research, the features detected are the face curvature, right eyebrow, left eyebrow, right eye, left eye, nose, and lip. Seven shapes which are used to extract multiple features can represent face sketch characteristics. Feature detection divides into two stages: Pyramid Parameter Model and Simultaneously Landmark Movement.

3.4.1 Pyramid Parameter Model

We propose to detect multiple features by using Pyramid Parameter Model. This method is similar with the Multi Resolution Image Search Method [29]. Our proposed method employs the parameters range of detection process in multi-resolution fashion. Those parameters are translated, scaled, and their *step* of value in a pyramidal model. The smaller the parameter range, the better the detection result. Illustration of the Pyramid Parameter Model can be seen in Figure 7.

On detection process using Pyramid Parameter Model, shapes move simultaneously by using Similarity Transformation. It can be expressed using equation:

$$X_i = M(S_i, \phi)[X_{ref}] + t_i \tag{23}$$

where

$$M(S_i, \phi) = S\begin{pmatrix} \cos(\phi) & -\sin(\phi) \\ \sin(\phi) & \cos(\phi) \end{pmatrix}$$

Whereas shape movement direction moves based on maximum line gradient. Principally, the greater line gradient value, the greater its energy.

Consider the landmarks are $\{(x_1, y_1), (x_2, y_2), \ldots \ldots .(x_n, y_n)\}$, if two landmarks ($i$-th and $(i+1)$-th) are consecutive, namely the first landmark is (x_i, y_i) and the second one is (x_{i+1}, y_{i+1}). We propose a formulation to define the line gradient of the two landmarks by using equation as follows

$$\Delta xy = \begin{cases} |y_i - y_{i+1}|, if\,|y_i - y_{i+1}| > |x_i - x_{i+1}| \\ |x_i - x_{i+1}|, if\,|y_i - y_{i+1}| \le |x_i - x_{i+1}| \end{cases} \tag{24}$$

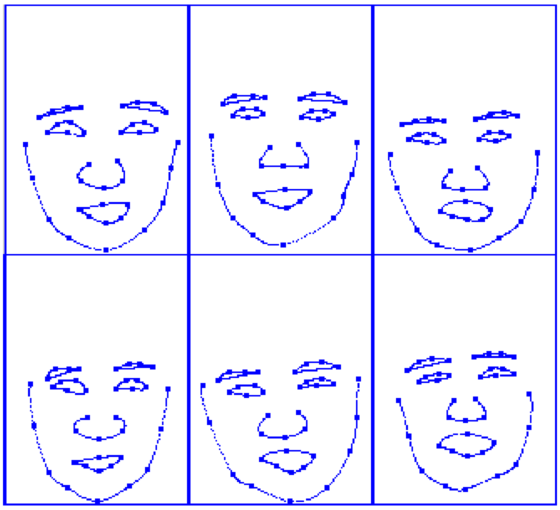


Figure 4 Shape Model Using 38 Landmarks on The Training Set.

(a) (b)

Figure 5 (a) Halftone and Hatching Face Sketches (b). Gradient of each Face Sketch

On the last landmark, between (x_n, y_n) and (x_1, y_1) can be computed using equation

$$\Delta xy = \begin{cases} |y_n - y_1|, if\,|y_n - y_1| > |x_n - x_1| \\ |x_n - x_1|, if\,|y_n - y_1| \le |x_n - x_1| \end{cases} \tag{25}$$

The distance between two landmarks (d) can be determined using equation

$$d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \qquad (26)$$

Equation (26) will be used to determine the iteration number of gradient calculation along the line. The gradient average along the line can be written by using equation

$$y_j = y_1 + j/d * (y_2 - y_1) \qquad (27)$$

$$x_j = x_1 + j/d * (x_2 - x_1) \qquad (28)$$

$$\overline{G}(x,y) = \frac{\sum_{j=1}^{d} G_j(x_j, y_j)}{d} \qquad (29)$$

The result of gradient average is re-evaluated using equation

$$LG(x,y) = \begin{cases} \overline{G}(x,y) * (d-1)/(D+\beta), \ if \ \Delta\text{xy} < D \\ \overline{G}(x,y), \text{if } n \geq d-1 \end{cases} \qquad (30)$$

Where $D=d-1$. If the maximum line gradient lies on the i-th landmark, then the average value of translation, scale and rotation will be updated using equation

$$\overline{x}_{New} \leftarrow tx \qquad (31)$$

$$\overline{y}_{New} \leftarrow ty \qquad (32)$$

$$Sx_{Max} \leftarrow Sx \qquad (33)$$

$$Sy_{Max} \leftarrow Sy \qquad (34)$$

$$\phi_{Max} \leftarrow \phi \qquad (35)$$

3.4.1 Improvement of Simultaneously Landmarks Movement

On the previous process, shape was moved simultaneously toward feature being searching for. To improve this process, we propose to improve the movement result by using simultaneously landmark movement. For each landmark will be moved, it will be normalized first using equation

$$\begin{aligned} y_i &= ty + \overline{\sigma y}_{i,j} \\ x_i &= tx + \sigma x_{i,j} \end{aligned} \qquad (36)$$

$$\begin{aligned} y_{i+1} &= ty + \overline{\sigma y}_{(i+1),j} \\ x_{i+1} &= tx + \sigma x_{(i+1),j} \end{aligned} \qquad (37)$$

Consider n set of landmarks, For each two landmarks which each other consecutive *i-th* and *(i+1)-th* can be computed line gradient using Equations (24), (26), (27), (28), (29), and (30). Whereas on the first and the last landmark can be computed line gradient using Equations (25), (26), (27), (28), (29), and (30). The iteration procedure is using the $-\phi$ until ϕ angle range, $-S$ until S scale range for both x and y, $\overline{X}$ $-dx$ until $\overline{X}$ $+dx$ translation range for x, and $\overline{Y}$ $-dy$ until $\overline{Y}$ $+dy$ translation range for y. The movement of landmarks on each shape is calculated using Equation (23) based on the values translation, scale and rotation from maximum line gradient. The landmark variance average will be updated using equation

$$\overline{\sigma x}_{(i+1)} = \overline{\sigma x}_{(i)} + (\overline{x}_{(i+1)} - \overline{x}_i) \qquad (38)$$

$$\overline{\sigma y}_{(i+1)} = \overline{\sigma y}_{(i)} + (\overline{y}_{(i+1)} - \overline{y}_i) \qquad (39)$$

3.5 Algorithm System

Our proposed method is divided into training, create image gradient of testing set, shape initialization, and multiple features detection processes. On the first step, training set is processed using Algorithm 1. To get gradient image and shape initialization can be used Algorithm 2 and 3 respectively. Shape Initialization will be moved simultaneously using algorithm 4. Last stage is started by simultaneously landmark movement using Algorithm 5, and the new landmark result will be used to improved landmark movement using Algorithm 6

Algorithm 1. Training Process Algorithm

1. $\forall I(x,y)$, $\exists$ x,y and $x,y \in$ number of landmarks, compute x and y average for training set using Equation (5) and (6).
2. Calculate x and y average for training set and landmark using Equation (7) and (8)
3. Calculate difference of maximum and minimum average deviation using Equation (9) and (10)
4. $\forall j$, $j \in$ training set and $\forall I$, $i \in$ landmark
   Compute mass centre using Equation (11) and (12),
   Compute total of mass centre using Equation (13) and (14).
   Determine mass centre maximum and minimum.
5. $\forall i$, $i \in$ number of landmarks compute landmark variance average using Equation (15) and (16)
6. Compute x and y variance deviation using Equation (17) and 18

Algoritmh 2. Create Image Gradient of Testing Set

1. $\forall I(x,y)$, $I \in$ Testing set, do step 2
2. Determine edge feature using Equation (20)
3. Determine edge gradient using Equation (19)

Algorithm 3. Landmark Initialization Algorithm

1. $\forall i,\ i\in$ number of landmarks do step 2
2. Compute landmark initialization using Equation (21) and (22)

Algorithm 4. Simultaneously Shape Movement Using Pyramid Parameter Model

1. $\forall p,\ p\in 1..$Pyramid Level do 2
2. $\forall \phi,\ \ \phi\in\{min(\phi_{train})..max(\phi_{train})\}$ do step 3
3. $\forall\ Sx,\ \ Sx\in\{min(Sx_{train})..max(Sx_{train})\}$ and $\forall\ Sy,\ Sy\in\{min(Sy_{train})..max(Sy_{train})\}$ do step 4
4. $\forall\ tx,\ tx\in\{(\overline{X}-dx)..(\overline{X}+dx)$ and $\forall\ ty,\ ty\in\{(\overline{Y}-dy)..(\overline{Y}+dy)\}$ do step 5 and 6
5. $\forall\ i,\ i\in$ number landmarks compute new landmark using Equation (23)
   if i<number of landmarks
      Do Equation (36)
      Compute total line gradient *(LineGrad)* using Equation (24), (26), (27), (28), (29) and (30)
   else
      Do Equation (37)
      Compute total line gradient *(LineGrad)* using Equation *(25), (26), (27), (28), (29)* and *(30)*
   end if
6. If the maximum *(LineGrad)* lies on the *i-th,* Update maximum scaling, maximum rotation and maximum translation using Equation (31), (32), (33), (34) and (35)
7. Based on step 6, determine new landmark $\forall\ i,\ i\in$ landmark using Equation (23)

Algorithm 5. Landmark Movement on each shape

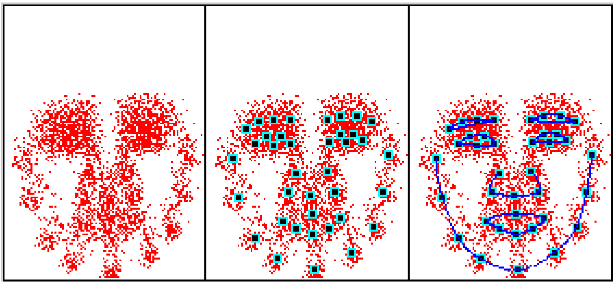
1. $\forall k,\ k\in$ number of features do step 2
2. $\forall\ tx,\ tx\in\{(\overline{X}-dx)..(\overline{X}+dx)$ and $\forall\ ty,\ ty\in\{(\overline{Y}-dy)..(\overline{Y}+dy)\}$ do step 3
3. $\forall\, i,\ i\in$ number of Landmarks do step 4 and 5
4. *if* i<number of Landmarks
      Do Equation (36)
      Compute total line gradient *(LineGrad)* using Equation (24), (26), (27), (28), (29) and (30)
   else
      Do Equation (37)
      compute total line gradient *(LineGrad)* using Equation (25), (26), (27), (28), (29) and (30)
   end if
5. If the maximum *(LineGrad)* lies on the *i-th* landmark Update maximum translation using Equation (31) and (32).
6. $\forall\ i,\ i\in$ Number of Landmark do Equation (23) using parameter as result of step 5 and do step 7
7. $\forall$p, p$\in$features, update the landmark variance average using Equation (38) and (39)

Algorithm 6. Improvement of landmark movement on each shape

1. $\forall k,\ k\in$ number of features do step 2
2. $\forall\phi,\ \phi\in\phi_{min}..\ \phi_{max}$ do step 3
3. $\forall Sx,\ Sx\in Sx_{min}..Sx_{,max}$ and $\forall Sy,\ Sy\in Sy_{min}..Sy_{,max}$ do step 4
4. $\forall\, tx,\ tx\in\{(\overline{X}-dx)..(\overline{X}+dx)$ and $\forall\ ty,\ ty\in\{(\overline{Y}-dy)..(\overline{Y}+dy)\}$ do step 5
5. $\forall\, i,\ i\in$ number of landmark do Equation (23)
6. $\forall\, i,\ i\in$ number of landmark do 7
7. *if* i<number of landmark
      Do Equation 36
      Compute total line gradient *(LineGrad)* using Equation (24), (26), (27), (28), (29) and (30)
   else
      Do Equation 37
      Compute total line gradient *(LineGrad)* using Equation *(25), (26), (27), (28), (29)* and *(30)*
   end if
8. If the maximum *(LineGrad)* lies on the *i-th* landmark Update maximum translation using Equation (31), (32), (33), (34) and (35).
9. $\forall\ i,\ i\in$ number of Landmarks do Equation 23 using parameter as result of step 8
10. $\forall$p, p$\in$features, update the landmark variance average using Equation 38 and 39

4. Experimental Result and Discussion

To test our proposed method, we use seven features: face curvature *(FT_1)*, right eyebrow *(FT_2)*, left eyebrow *(FT_3)*, right eye *(FT_4)*, left eye *(FT_5)*, nose *(FT_6)* and lip *(FT_7)*. Each feature is given by 9, 4, 4, 5, 5, 5, and 6 landmarks. Thus, the number of landmarks is 38. Landmark for each feature can be seen in Figure 8.



(a) (b) (c)

Figure 6 (a) Point Distribution Model. (b) Centre of Point Distribution Model. (c) Shape Model Initialization.

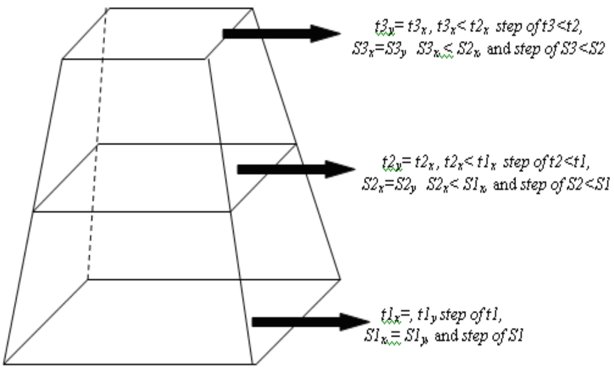


Figure 7 Pyramid Parameter Model

The training set contains 50 people, 13 of them are men and the other 37 are women. The face image size is 110x150 pixels. The training set use 3 poses: normal, open smiling and close smiling.

Testing set is the sketch image drawn by sketcher in the form of halftone and hatching face sketch on frontal position. We use 50 halftone and 50 hatching face sketches. Figure 9 shows the example result of six people from training set. Figure 10 and 11 describe experimental result of halftone and hatching face sketches respectively. The First row shows initial shape. On the Second, third and fourth row show experimental result from the first, second and third movements using Pyramid Parameter Model. Last row describes improvement of simultaneously landmark movement.

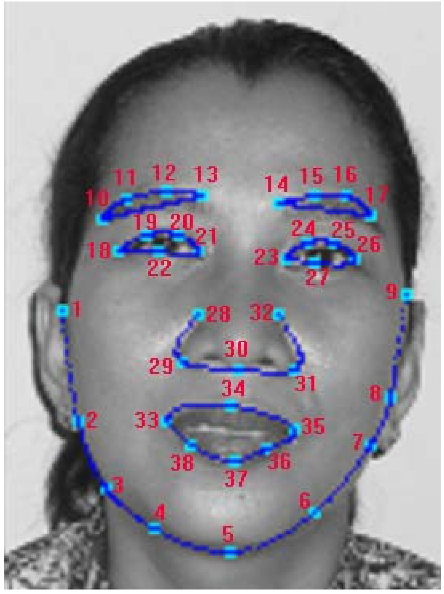


Figure 8 Landmark Distribution Of Face Photo Image

Figure 9 Images Training Photo Sample

In this research, the first movement of Pyramid Parameter Model, translation parameters value *(t_x and t_y)* used are $t_x=t_y= \pm(xAvgDev+4)$ with *step=4*. The second movement, $t_x=t_y=\pm 1$ with *step=1*. And the third movement, $t_x=t_y= \pm 0.5$ with *step=0.5*. Scaling parameter value used are $S_x=S_y=$[*0.8* until *1.2*] with *step=0.1*, $Sx=S_y=$[*0.9* until *1.1*] with *step=0.5*, $Sx=S_y=$[*0.95* until *1*] with *step=0.25.* Whereas rotation parameter value *(ϕ)* for each stage is not changed, because testing set used is frontal position. The last movement, landmarks simultaneously moved toward maximum line gradient and the result of movement will be improved by updating the variance average.

4.1. Experimental Result Using Halftone Face Sketch

Based on experimental result, the average of detection rate percentage of halftone face sketch each feature is listed in Table 1. The highest detection rate percentage is on the left eye, while the lowest one is the face curvature.

Table 1 Detection Rate of Multiple Features Detection of Halftone Face Sketch Using Proposed Method

Features	Detection Rate Percentage On Movement (%)			
	1st	2nd	3rd	4th
Face Curvature	68.67	80.89	82.89	84.44
Right Eyebrow	79.50	87.50	90.50	91.50
Left Eyebrow	91.50	98.00	98.50	98.50
Right Eye	95.60	97.60	98.00	98.00
Left Eye	99.60	100	100	100
Nose	84.80	87.20	92.80	93.20
Lips	72.67	84.00	87.00	87.33
The average of Detection Rate	84.62	90.74	92.81	93.28

In this experiment, recognition rate increases on each movement. The average of detection rate increases 90.74%-84.62%=6.12% from the first to the second movement. The third movement, the average of detection rate increases 92.81%-90.74%=2.07%. The last, the average of detection rate increases 93.28%-92.81%=0.47%. It means, our proposed method can increase detection rate on each movement without photo-to-sketch images transformation process.

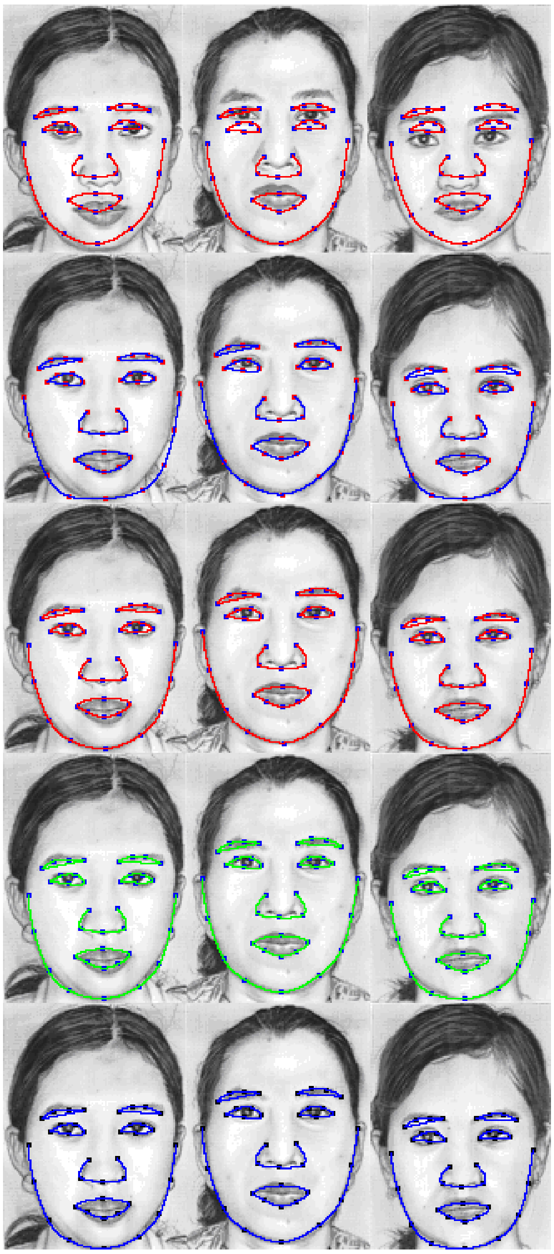


Figure 10 Experiment Result from the Halftone Face Sketch.

4.2 Experimental Result Using Hatching Face Sketch

The second experiment, we use hatching face sketch. It does not have gradation, because hatching face sketch is created from dash line, regularly and repeatedly, therefore role of image gradient forming is very importance. Detection rate of the experimental result can be seen in Table 2. The highest detection rate percentage occurs on the Left Eyebrow, while the lowest one occurs on the lips.

Figure 11 Experiment Result from the Hatching Face Sketch.

Table 2 Detection Rate of Multiple Features Detection of Hatching Face Sketch Using Our Proposed Method

Features	Detection Rate Percentage On Movement (%)			
	1st	2nd	3rd	4th
Face Curvature	79.78	88.22	90.44	91.33
Right Eyebrow	90.00	94.50	96.00	96.00
Left Eyebrow	95.50	98.50	98.50	98.50
Right Eye	90.40	92.80	95.20	96.40
Left Eye	91.20	93.60	96.80	96.80
Nose	75.60	84.80	89.20	89.20
Lips	72.00	78.00	81.33	83.00
The average of Detection Rate	84.93	90.06	92.50	93.03

Based on Table 2 can be shown that, the average increment of detection rate on the second, the third and the last movement are 90.06-84.93=5.13%, 92.5-90.06=2.44%, and 93.03-92.5 = 0.53%, respectively. It means, our proposed method can be used to detect multiple features of hatching face sketch without involving the photo-to-sketch transformation process.

4.3 Discussion

On the halftone face sketch, the biggest error rate occurs on the face curvature feature. It has smaller line gradient value than another feature (for instance ear, neck). Thus landmarks move toward wrong direction and the face curvature shape is moving downward and it lies on the edges of upper side of another object. The biggest error rate on the hatching face sketch occurs on the lip feature. This is caused by the presence of incisions around the lips which have greater gradient than the lips, thus shape move way the lip feature.

5. Conclusion and Future Work

Based on experimental results can be inferred.

a. The proposed face sketch multiple features detection employs simultaneously landmark movement which is supported by multi resolution for the parameter setting in pyramidal model.
b. If a shape lies on a region which has no gradation, it will not be able to move toward desired feature. This problem mostly occurs on hatching face sketches, but the use of gradient image has increased detection rate.
c. We are able to create an effective method to detect face sketch multiple features, for both halftone and hatching, without involving the photo-to-sketch transformation process.
d. Though the training and testing set have different modality and photo-to-sketch images transformation process is disregarded, the experimental result give detection rate of 93.28% and 93.03% for halftone and hatching face sketch respectively.
e. From the first to the last movement, the average of detection rate is increasing 8.66% for halftone and 8.1% for hatching face sketch.

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