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An Approach to Face Shape Classification for Hairstyle Recommendation

Wisuwat Sunhem
Faculty of Information Technology
King Mongkut's Institute of Technology Ladkrabang
Bangkok 10520, Thailand
Email: wisuwat.sun@gmail.com

Kitsuchart Pasupa
Faculty of Information Technology
King Mongkut's Institute of Technology Ladkrabang
Bangkok 10520, Thailand
Email: kitsuchart@it.kmitl.ac.th

***Abstract*—It is important to choose a good hairstyle for women because it can enhance their beauty, personality, and confidence. One of the most important factors to consider for choosing the right hairstyle is the individuals face shape. An effective face shape classification can be used for constructing a hairstyle recommendation system. This paper presents a classification approach that divides face shapes into 5 different shapes: round, oval, oblong, square, and heart. This approach, which is based on an Active Appearance Model (AAM) and a face segmentation technique, produces a set of features that can be evaluated by several popular machine learning methods, namely, Linear Discriminant Analysis (LDA), Artificial Neural Networks (ANN), and Support Vector Machine (SVM). Our results show that the Support Vector Machine with Radial Basis function kernel was the best algorithm that predicted accurately up to 72%.**

***Keywords*—hairstyle recommendation; face shape classification; machine learning**

I. INTRODUCTION

Hairstyle is what we, especially women, think of when we want to have a new look-a new hairstyle can invigorate a persons look. On the other hand, a wrong hairstyle might make someones look unattractive and make her or him lose confidence. Many people prefer to choose their new hairstyle from magazines without knowing which one really suits their face. It is difficult to cope with a bad haircut. If it is too short, it takes quite a while for the hair to grow long enough for trying a new hairstyle. Therefore, it would be better if we know our face shape and features well before our next visit to a salon [1]. Women who have similar face shape have similar hairstyles that will make them look good.

Face can be classified into 5 shapes: oval, round, oblong, square, and heart [1]. Each shape can look good with several different hairstyles. A guide to determine face shapes was introduced by a beauty expert [2]. However, her guideline is vague and ambiguous and can lead to misclassification of shapes. Moreover, it is not accurate like a mathematical model.

A well-known and powerful technique, "Active Appearance Model" (AAM), can create a statistical model of the shape and grey level appearance of an object. Recently, there was an attempt to use AAM to identify face shapes for facial expression recognition [3], but that attempt is not applicable for constructing a hairstyle recommendation system. A face shape classification from 3D human data was conducted by Sarakon *et al.* (2014) but the purpose of their research was not applicable to hairstyle recommendation [4]. Therefore, we introduce a novel approach to automatically identify face shapes for hairstyle recommendation here. This approach utilizes an AAM [5] and face segmentation technique [6] to extract a set of discriminative features. It was then used with several machine learning techniques to classify face shapes.

This paper is structured as follows: Section II presents the background of techniques used in this paper–AAM and face shape determination rules; Section III describes experimental procedures that includes data collection, feature extraction and experimental settings; Section IV discussed the results, followed by the conclusion in Section V.

II. METHODOLOGY

A. Face Shape Determination Rules

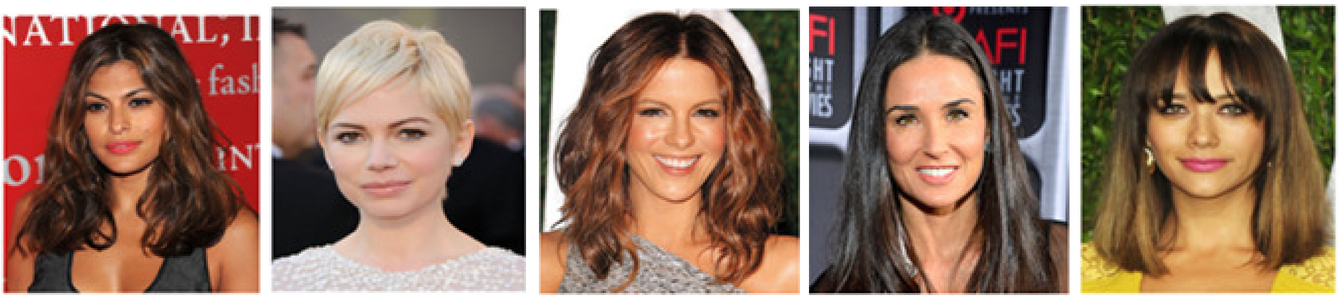
Face can be classified into 6 shapes: round, square, oblong, heart, oval, and diamond [2]. Each shape can be identified by the following rules:

- Heart-shaped face: The width of the forehead is greater than the width of the jawline and the chin may be pointy.
- Square-shaped face: the widths of the forehead, cheekbones, and jaw are equal and there is a sharp jawline.
- Round-shaped face: the widths of the forehead, cheekbones, and jaw are equal and the jaw is slightly round as opposed to angular.
- Oblong-shaped face: the height of the face is very long compared to the width.
- Oval-shaped face: the ratio of the height to width is 3/2.
- Diamond-shaped face: the widths of the forehead and the jaw are equal but the cheekbones are wider than them.

These rules are imprecise and difficult to represent mathematically so it can lead to misclassification.

B. Active Appearance Model

Active Appearance Model (AAM) is a statistical model that represents texture and shape of an interesting object that will undergo a feature extraction procedure. This model can be trained with the texture and shape at chosen landmark points in a training image. It can then be used to find landmark points in other images.



(a) Oval-shaped face (b) Round-shaped face (c) Oblong-shaped face (d) Square-shaped face (e) Heart-shaped face

Fig. 1: Sample images labeled by experts.

AAM is based on Active Shape Model (ASM) concept which uses principal component analysis (PCA) to process landmark points in an image and calculate a mean shape. However, ASM does not use texture information. ASM is very simple but it is not robust when applied to unseen images. AAM improves on ASM performance and robustness by using both shape and texture information.

III. Experimental Framework

A. Data Collection

We collected a dataset of 1,000 images of women's faces with different shapes-such as oval and oblong-from Google Image Search. These images were labeled by volunteers. Eight undergraduate students in our university whom we had recruited were tested whether they were qualified to label this set of image. We explained to the students prior to the test how to determine face shapes according to the guideline in Section II-A.

This work intended to provide a way for constructing a hairstyle recommendation system that was inspired by In-Style.coms article [1]. This article discusses perfect hairstyles for 5 face shapes. Unfortunately, it does not show a guideline for determining face shapes. Hence, we applied Derric's guideline (2011) [2] described in Section II to 5 shapes mentioned in [1]. The 6th face shape, diamond-shaped, in Derric's classification is not mentioned in [1], therefore, we simply ignored it. Two advantages of using only 5 shapes are the following: it made it easier for participants to identify shapes because a diamond-shaped face is very similar to a heart-shaped face, and two, a diamond-shaped face has the same proper hairstyles as those that a square-shaped face has [2]. Besides, an expert [8] have not mentioned that there exists a diamond-shaped face.

The participants were asked to match a number of images of face shapes, already labeled by two experts [8], [9], with descriptive labels, and only the participants who were able to match 8 out of 10 face shapes correctly were chosen to help constructing a valid dataset. Some examples of the images used are illustrated in Figure 1. The only six participants who successfully passed the test were asked to help constructing a valid dataset from the 1000-image dataset. Images that were described by the same label chosen by 4 out of 6 participants were included in the valid dataset which we then skimmed down to 500 images, 100 each for 5 classes of shapes.

B. Feature Extraction

We obtained a discriminative feature set by extracting the valid dataset with FaceTracker software [7]. This software's AAM algorithm selected 60 points in an image of a face that outline the features of the face clearly. Unfortunately, these points did not include the forehead, hence we were not able to identify the top of the face with this software. An example of the output from the software is shown in Figure 2a. In order to identify a point indicating the hairline, we used a face segmentation technique based on color region [6] that separated hair and forehead as shown in Figure 2b. This technique does not find points outlining features well, but it can give a good point for separating hair from forehead, so we were able to find a hairline position as shown in Figure 2c.

After we were able to find all of the points necessary for identifying features of the face as shown in Figure 3, nineteen attributes were extracted from these points as shown in Table I. We denote the i^{th} point as $p^{(i)}$; its coordinates as $({p_x}^{(i)}, {p_x}^{(j)})$; and the distance between $p^{(i)}$ and $p^{(j)}$ as $d(p^{(i)}, p^{(j)})$.

C. Experimental Settings

The valid dataset was normalized by z-score according to the equation

$$z_i = \frac{x_i - \mu}{\sigma}, \tag{1}$$

where μ is the mean of each attribute across all instances while σ is the standard deviation of each attribute. The dataset was then randomly divided into a training set and a test set. The ratio of the number of instances in the training set to that in the testing set was 9 to 1. Prediction features of the dataset are evaluated by the following 3 methods:

(i) Linear Discriminant Analysis (LDA): LDA is a simple statistical model that can be used to find a linear combination of features. LDAs one-versus-all scheme for multi-class classification problem was applied in this study.

(ii) Artificial Neural Networks (ANN): The parametric model of machine learning which can generate both lin-

(a) AAM (b) Face Segmentation based on color (c) Proposed technique

Fig. 2: Output images processed by different algorithms.

TABLE I: A SET OF PROPOSED DISCRIMINATIVE FEATURES FOR FACE-SHAPE CLASSIFICATION

Index	Description	Formula
1	Ratio of the height of a face to the width	$f_1 = \frac{d(p^{(9)}, p^{(18)})}{d(p^{(1)}, p^{(17)})}$
2	Ratio of the distance between left jaw and right jaw to the width of the face	$f_2 = \frac{d(p^{(5)}, p^{(13)})}{d(p^{(1)}, p^{(17)})}$
3	Ratio of the distance between chin and bottom of mouth to the distance between left jaw and right jaw	$f_3 = \frac{d(p^{(9)}, p^{(19)})}{d(p^{(5)}, p^{(13)})}$
4–11	Angle the x-axis makes with the straight line from a facial feature point to the chin point (the only facial-feature points considered start at right ear down to the chin)	$f_i = tan^{-1}(\frac{\lvert {p_y}^{(i-3)} - {p_y}^{(9)}\rvert}{\lvert {p_x}^{(i-3)} - {p_x}^{(9)}\rvert})$; $i = 4, ..., 11$
12–19	Angle the x-axis makes with the straight line from a facial-feature point to the chin point (the only facial-feature points considered start at left ear down to the chin)	$f_i = tan^{-1}(\frac{\lvert {p_y}^{(i-2)} - {p_y}^{(9)}\rvert}{\lvert {p_x}^{(i-2)} - {p_x}^{(9)}\rvert})$; $i = 12, ..., 19$

ear and non-linear classifier with multi-layer perceptron concept.

(iii) Support Vector Machine (SVM): SVM is one of popular machine learning methods that separates a dataset into two classes with a linear hyperplane. It can accommodate non-linear data by utilizing a “Kernel trick”. We only investigated linear function and radial basis function (RBF) kernels of SVM in this work. SVMs one-versus-one scheme was used in this work for multi-class classification task.

All of these algorithms have parameters that needed to be tuned. To tune them, we employed an m-fold cross-validation (CV) method and got optimal models that generalize well with the test set. In particular, grid searching for estimator parameters was employed, and 5-fold CV was applied to the training set to validate the parameters found. In ANN case, we varied the number of layers from 1 to 5 and the number of neurons in each layer from 1 to 30. In SVM case, the range of C parameter was $\{10^{-4}, 10^{-3}, 10^{-2}, \ldots, 10^{2}, 10^{3}, 10^{4}\}$ and that of RBF kernel γ parameter was $\{10^{-4}, 10^{-3}, 10^{-2}, \ldots, 10^{2}, 10^{3}, 10^{4}\}$. After the optimal parameters had been obtained, models with these parameters were trained with the training set and then used to evaluate the test set.

IV. Results and Discussion

For each algorithm, its confusion matrices for the training and test sets are shown in Table II– IX. These matrices reveal that round-shaped faces were often predicted as square-shaped one and vice versa. Oval-shaped faces tended to be most difficult to classify correctly as the classifier was the least accurate when applied to this face shape. Overall, SVM-RBF algorithm is the best machine learning algorithm for predicting face shape as it achieved 70.67% and 72.00% accuracies for predicting the training and test sets, respectively, as shown in Table X. It is clear that using SVM with a non-linear function gave better results than with a linear function. LDAs performance was the worst among all classifiers, only 64.89%

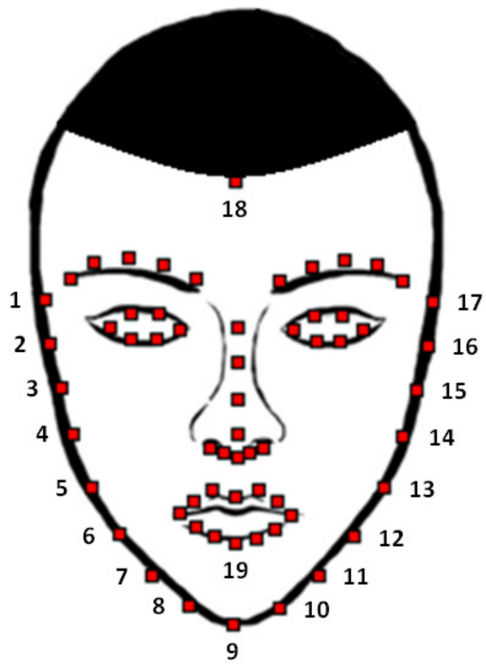


Fig. 3: Sixty-one Points that Trace Facial Features Generated by Our Proposed Approach.

and 58.00% accurate for the training and test sets, respectively. In this work, noises such as facial expression that can cause misidentification were not taken into account. They may be the cause of the significant classification error of the results.

TABLE II: THE CONFUSION MATRIX OF LDA ON TRAINING DATA

True Label	Predicted Label					
	Round	Oval	Oblong	Square	Heart	Accuracy(%)
Round	59	3	0	24	4	65.56
Oval	10	28	28	9	15	31.11
Oblong	0	3	82	1	4	91.11
Square	14	1	3	72	0	80.00
Heart	4	11	17	7	51	56.67

TABLE III: THE CONFUSION MATRIX OF LDA ON TEST DATA

True Label	Predicted Label					
	Round	Oval	Oblong	Square	Heart	Accuracy(%)
Round	7	1	0	1	1	70.00
Oval	2	5	1	0	2	50.00
Oblong	0	1	4	1	4	40.00
Square	2	0	0	8	0	80.00
Heart	0	3	1	1	5	50.00

We analyzed the weights of our proposed feature sets generated by LDA and SVM-Linear as shown in Figure 4 and Figure 5, respectively. Of note is that the importance feature for SVM-Linear was not for LDA. LDA gave the importance to f_{15} while SVM-Linear gave it to f_1. Since SVM-Linear performed better than LDA, we reasoned that the importance of the feature from SVM-Linear was more valid than LDA.

TABLE IV: THE CONFUSION MATRIX OF ANN ON TRAINING DATA

True Label	Predicted Label					
	Round	Oval	Oblong	Square	Heart	Accuracy(%)
Round	64	6	0	16	4	71.11
Oval	8	49	11	10	12	54.44
Oblong	0	4	78	3	5	86.67
Square	16	5	2	67	0	74.44
Heart	7	26	9	5	43	47.78

TABLE V: THE CONFUSION MATRIX OF ANN ON TEST DATA

True Label	Predicted Label					
	Round	Oval	Oblong	Square	Heart	Accuracy(%)
Round	8	1	0	1	0	80.00
Oval	1	5	2	1	1	50.00
Oblong	0	2	6	1	1	60.00
Square	2	1	0	7	0	70.00
Heart	1	2	3	0	4	40.00

TABLE VI: THE CONFUSION MATRIX OF SVM-LINEAR ON TRAINING DATA

True Label	Predicted Label					
	Round	Oval	Oblong	Square	Heart	Accuracy(%)
Round	61	5	0	19	5	67.78
Oval	7	48	10	5	20	53.33
Oblong	0	5	73	3	9	81.11
Square	14	9	1	63	3	70.00
Heart	5	19	7	4	55	61.11

TABLE VII: THE CONFUSION MATRIX OF SVM-LINEAR ON TEST DATA

True Label	Predicted Label					
	Round	Oval	Oblong	Square	Heart	Accuracy(%)
Round	9	1	0	0	0	90.00
Oval	1	4	3	0	2	40.00
Oblong	0	2	7	0	1	70.00
Square	2	1	0	7	0	70.00
Heart	1	2	2	0	5	50.00

TABLE VIII: THE CONFUSION MATRIX OF SVM-RBF ON TRAINING DATA

True Label	Predicted Label					
	Round	Oval	Oblong	Square	Heart	Accuracy(%)
Round	70	4	0	13	3	77.78
Oval	7	53	9	3	18	58.89
Oblong	0	4	76	0	10	84.44
Square	19	8	1	60	2	66.67
Heart	4	19	4	4	59	65.56

TABLE IX: THE CONFUSION MATRIX OF SVM-RBF ON TEST DATA

True Label	Predicted Label					
	Round	Oval	Oblong	Square	Heart	Accuracy(%)
Round	9	0	0	1	0	90.00
Oval	1	6	2	0	1	60.00
Oblong	0	2	7	0	1	70.00
Square	1	1	0	8	0	80.00
Heart	1	2	1	0	6	60.00

V. CONCLUSION

In this paper, we present a novel approach to face shape classification for constructing a hairstyle recommendation system.

TABLE X: PERFORMANCES OF MACHINE LEARNING ALGORITHMS USING THE PROPOSED FEATURES

Algorithm	Accuracy(%)	
	Training Set	Test Set
LDA	64.89	58.00
ANN	66.89	60.00
SVM-Linear	66.67	64.00
SVM-RBF	**70.67**	**72.00**

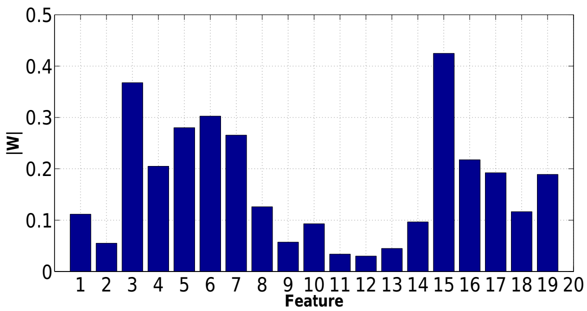


Fig. 4: The weights of features from LDA.

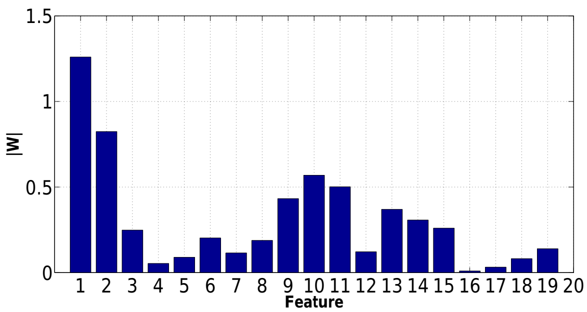


Fig. 5: The weights of features from SVM-Linear.

A set of discriminative features and an analytical procedure have been introduced for classifying face shapes by several machine learning algorithms. Using these features, the SVM-RBF algorithm was able to classify 5 face shapes at 72% of accuracy.

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