Example-Based Automatic Caricature Generation

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***Abstract*—Caricature is a popular artistic media widely used for effective communications. The fascination of caricature lies in its expressive depiction of a person's prominent features, which is usually realized through the so called exaggeration technique. This paper proposes a new example based automatic caricature generation system supporting the exaggeration of visual appearance features. The system comprises the construction of a learning database and the generation of caricatures. The construction of the learning database links the pairs of facial images and corresponding caricatures. Given an input face, the system automatically compute the feature vectors of facial parts and hairstyle, and search the learning database for the exaggerated parts by using the most prominent features. Experimental results show that our system can achieve the control over the degree of exaggeration and the exaggerated results can better represent the features of the subjects.**

Keywords- caricature; example-based; exaggeration; visual appearance facial feature;

I. Introduction

Caricatures serve as effective media for communication in many settings. These "deformed" images, which emphasize a person's most prominent features to make it easy for observers to identify the subject at a glance, range from artistic portraits to satirical or parodic illustrations and comics. People now use them as everything from gifts to resources for criminal investigations and satires of politicians. Caricatures are a highly individualized form of art, but not everyone is capable of drawing a caricature on his or her own. Given the challenges involved, people who want caricatures for personal use would benefit greatly from a generation system that anyone could use to produce caricatures without much difficulty. This paper proposes a new automatic caricature generation technique: an example-based caricature generation system that uses exaggerations of visual appearance features.

Since the 1980's, there are tremendous of research work have been conducted on the computer generation of caricature [1-2]. Most of early works, however, rely more or less on user's input for either extracting features from input face or controlling the style of resulting caricature. Recently, example based approaches [15, 16, 17, 18, 20] are attracting large attentions for its advantage of being able to reflect the unique style of individual artists. Those methods rely on training data comprising many sets of input images and their corresponding caricatures. They allow users to express divergent artistic styles by simply substituting the appropriate examples into the target product. To ensure successful learning, feature vector design becomes very important. Most of existing example based methods use eigenspaces defined via Primary Component Analysis (PCA) of face features. Since people normally concentrate on visual appearance features, such as the shape of individual parts (eyes, nose, and mouth, etc.) as well as the composite arrangement of those parts when they draw caricatures, methods that use eigenspaces may fail to reflect artists' styles fully. Our technique takes the example-based approach but also incorporates part-specific learning to enable the exaggeration of visual appearance features. Furthermore, new algorithms have been implemented to automatically compute the features of hairstyle which are not well addressed in the existing systems.

The remainder of the paper is organized as follows: after reviewing the related works in Section 2, Section 3 first presents the overall structure of proposed system and then describes the details of algorithms. Section 4 describes the results of experiments and Section 5 concludes the paper.

II. Related Research

There is a considerable amount of past research on computer generation of caricature. Generally, these existing studies fall into three broad categories: interactive, rule-based and example based.

Interactive methods give users the control over the features to be exaggerated as well as the degree of exaggeration, but on the other hand usually add more loads to users [3]. Also it can be difficult to produce ideal results for a user without the knowledge on caricature. Akleman et al. [4] provided a simple morphing template for the user to manually deform the facial features. Later, they improved the algorithm with a new deformation algorithm that uses simplicial complex [5]. Gooch et al. [6] converted a photograph to a simple line illustration, and then manipulated the feature grid imposed on the illustration.

Rule-based approaches simulate the predefined rules to draw caricature. Most rule-based methods produce an exaggerated representation by analyzing the subject's features and then manipulating an average model accordingly. The first such work by Brennan [7] puts 165 feature points on the "*average face*". The feature points are moved with an amount proportional to the difference from the corresponding reference points, and are connected to create a line-drawing caricature. Koshimizu et al. [8] applied the same idea in their interactive system (PICASSO) which can generate very impressive line drawing style caricatures. Chiang et al. [9]

proposed a method by morphing a caricature drawn by the artist based on the difference from average model. Mo et al. [10] used normalized deviation from the average model to exaggerate the distinctive features. Teseng et al. [11, 12] used both inter and intra correlations of size, shape and position features for exaggeration. They subdued some of the features to emphasize the other features. Chen et al. [13] considered the two relative principles described in [14], and proposed "T-Shape" rule for emphasizing the relative position among facial elements. They measured the similarity between the caricature and the photograph with Modified Hausdorff Distance and minimized the distance to improve their results.

Under a rule-based method, reflecting differences in drawing styles normally requires making changes to parameter extraction processes and creation rules for each style. While example-based methods rely on training data comprising many sets of input images and their corresponding caricatures, they allow users to express divergent artistic styles by simply substituting the appropriate examples into the target product. The example-based method proposed by Liang et al. [15] separates a portrait into two models—polyline-based shapes and shading-based textures—and learns from a collection of actual professional portraits to refine and integrate both models, thereby converting the input facial image into a caricature. Shet et al. [16] used cascade correlation neural network to learn the exaggeration degree of caricaturist. Liu et al. [17] applied PCA to obtain the principle components of the facial features, and then used Support Vector Regression (SVR) to predict the result for given a face image. They further proposed a non-linear mapping model using semi-supervised manifold regularization learning [18].

In rule-based and example-based methods alike, feature vector design plays an integral part in improving overall caricature quality. Many existing caricature generation techniques use eigenspaces defined via PCA. However, when people draw caricatures, they normally concentrate on visual appearance features such as the shape of individual parts (eyes, nose, and mouth, etc.) as well as the composite arrangement of those parts. In that sense, methods that use eigenspaces may fail to reflect artistic styles fully. Our study takes the example-based approach but incorporates part-specific learning to enable the exaggeration of visual appearance features.

III. PROPOSED METHOD

Figure 1 provides an overview of the proposed method, which comprises the construction of a learning database and the generation of caricatures. The construction of the learning database uses pairs of facial images and corresponding caricatures as input. Based on geometrical shape information, extracted from the facial image using the active shape model (ASM) for facial feature points detection [21], and hair regions, extracted using our original method, our construction process calculates visual appearance feature vectors and links them to the corresponding caricature parts. Given that males and females have different facial features, we created new ASM average models for males and females, respectively, in order to improve ASM fitting accuracy. Figure 2 shows the control points of the ASM model that we used in our system.

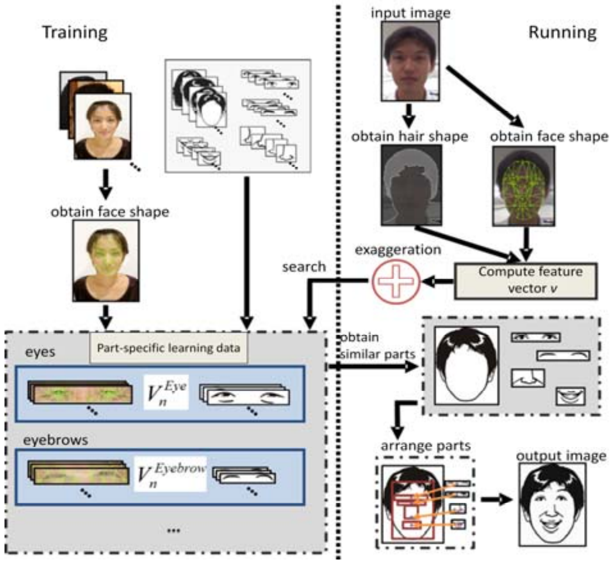


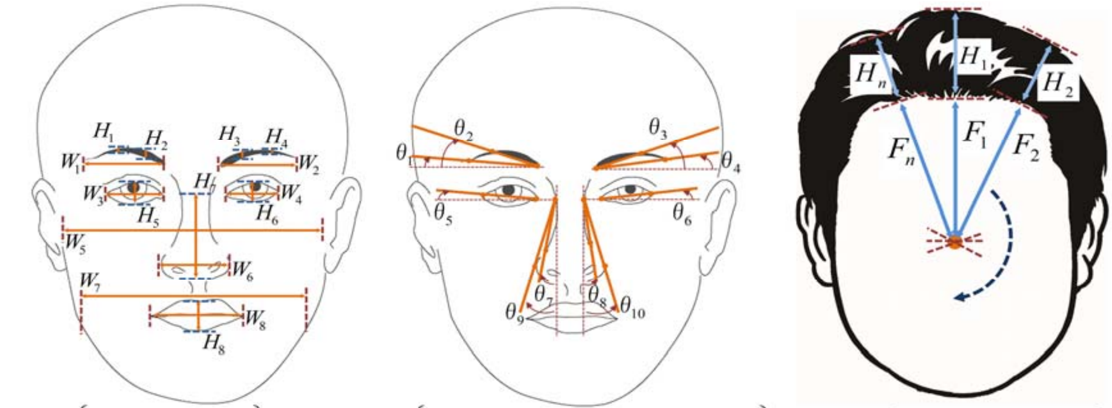
Figure 1. System framework

Figure 2. The control points of the ASM model used in the proposed system

When generating caricatures, our system first calculates a feature vector for each part using the method same as that used for the database construction step. Next, the system performs exaggeration processing on the feature vectors and uses the exaggerated feature vectors to search the example database for the exaggerated parts. Finally, the system arranges the gathered caricature components to generate a caricature.

A. Designing and extrcting visual appearance feature vectors

Humans perceive faces based more on characteristic information—large, thin, and drooping, for example—than on precise shape information. For our study, we sought advice from professional caricaturists on the features of five facial parts (eyebrows, eyes, nose, mouth, and hair) and incorporated that input into the design of our visual appearance feature vectors, which are shown in Figure 3. The feature vectors for the different parts all have different



$$Eye = \left\{ \frac{H_5}{W_3}, \theta_5, \frac{H_5}{W_3}, \theta_6 \right\} \quad Eyebrow = \left\{ \frac{H_1}{W_1}, \frac{H_2}{W_1}, \theta_1, \theta_2, \frac{H_3}{W_2}, \frac{H_4}{W_2}, \theta_3, \theta_4 \right\} \quad Hair = \left\{ \frac{H_1}{F_1}, \frac{H_2}{F_2}, \dots, \frac{H_n}{F_n} \right\}$$

$$Mouth = \left\{ \frac{W_8}{W_7}, \frac{H_8}{W_8} \right\} \quad Nose = \left\{ \frac{W_6}{W_5}, \frac{H_7}{W_6}, \theta_7, \theta_8, \theta_9, \theta_{10} \right\}$$

Figure 3. The feature vectors used in the proposed system

numbers of dimensions, with the coordinates for each dimension normalized to the range of real numbers from 0.0 to 1.0

The eyebrow features that have the strongest visual impact are thickness and angle. As eyebrow thickness normally tapers off gradually near the side of the head, our system measures vertical thickness at two locations: the inner end of the eyebrow and the outer end of the eyebrow. Eyebrow angle, meanwhile, varies according to the change in vertical position on the outer end relative to the vertical position of the inner end. We thus select two points on the outer end and measure the angles of the straight lines connecting the two selected points to the inner end. Eyes also have two main defining traits: shape characteristics (thin, slit eyes or large eyes, for instance) and angle characteristics (eyes that slant upward or eyes that droop downward, for example). Shape features are defined by the aspect ratio of the eye, while angle features are defined by the angle of the straight line connecting the inner corner of the eye and the outer corner of the eye. Nose shape corresponds to the ratio between nose width and nose height, while nose size depends on the ratio of nose width to overall face width. The amount of space between the nose and mouth is another person-to-person variable; as shown in Figure 3, we also incorporate two types of top-down angles into the features. For the mouth feature, we use the ratio between mouth width and mouth height to define shape and the ratio between mouth width and overall face width to define size.

To determine the hair feature vector, one first needs to extract the hair region. However, the sheer person-to-person diversity of hairstyles has prevented researchers from developing a hairstyle-extraction equivalent of the ASM method for facial shape extraction. For our study, we implemented our own original hair region extraction method. First, we use a region growing algorithm to segment the image into regions. The algorithm places multiple seeds on the image, expands the seeds along gradients, and then divides the image into regions according to the boundaries that form where the gradients are high. The number of image regions thus equals the number of seeds placed on the image.

Our system automatically sets seeds for three regions: the skin region, the hair region, and the "other" region. The automatic setting process uses ASM control points and follows the steps below.

Setting the skin region seed

First, the system obtains the skin color from the ASM control points located on the tip of the nose, cheeks, and other positions that best represent the subject's skin color. The system then looks at the colors of the points that have a high probability of corresponding to skin, such as the areas just inside the tip of the nose, the cheeks, and the facial profile, and places skin region seed as appropriate.

Setting hair region seed

Based on the safe assumption that the hair region lies on the upper portion of the subject's head, the system uses the ASM control points on the upper portion of the head to set hair region seed. Forehead size varies from person to person, however, so the control points do not always lie in the hair region. In order to obtain points in the hair region only, the system compares the skin color obtained in the preceding step with the colors of the control points in question. If a control point corresponds to skin color, the system gradually moves the point until it reaches the hair portion.

Setting "other" region seed

First, we assume that the person in the input image is positioned near the center of the image and that a background is visible behind the person. Based on this assumption, the system places "other" region seed near the top edge, left edge and right edge of the image. The system does not place a seed near the bottom edge, as a subject's hair might extend to the bottom of the image. However, a person's hair is normally parted by his or her face, neck, or chest. This means that the middle portion of the bottom edge that intersects with the line extending straight down from the center of the subject's face often lies in an "other" region outside the hair region. The system thus places seeds in this area, as well.

(a) Seeds setting results (b) Segmentation results (c) Hairstyle feature vector

Figure 4. example of obtaining a hair region and its feature vector

Figure 4 illustrates an example of using the above procedure to divide regions. Figure 4(a) shows the results of the automatic seed setting results. There are several seeds in the Figure. The light gray circles on the subject's hair are the hair region seeds; the dark gray circles on the subject's face are the skin region seeds; and the black circles on the top, left edge, and center-bottom area are seeds indicating "other" regions. Figure 4(b) shows the results of segmentation using the proposed algorithm. The brightly colored area at the top of the subject's head is the area that the system determined to be the hair region. As the Figure shows, the system successfully obtained the general shape of the subject's hair.

The system then uses the obtained hair region to calculate the feature vector for capturing the visual appearance of the hairstyle. Generally, hairstyle types fall into basic length categories: short, semi-short, semi-long, and long are several examples. In other words, how far a person's hair goes down his or her head is one important feature of the person's hairstyle.

In addition to length, volume is another key element of how a person's hairstyle looks. To establish a feature vector that expresses both length and volume, our method involves drawing straight radial lines out from the center of the face at certain angle intervals and using the distance separating the two intersections between each line and the hair region boundary (see Figure 4(c)). As Figure 5 shows, the system uses the proportion between H_i (the distance between the two intersections) and F_i (the distance from the interior intersection to the center). H_i value of 0 means that there is no hair around the face, while an H_i value of greater than 0 indicates the volume of the hair. This makes it possible to deal with volume and length in a uniform fashion. The hair feature vector created when straight lines are drawn at angle intervals of $(2\pi)/n$ has n dimensions.

B. *Searching for similar parts*

Using the feature vectors defined above, the system calculates the distance between the parts of input image and the parts of the examples in the learning database, and then searches for similar parts. This requires comparisons of feature vectors that include dimensions with different properties, such as length ratios and angles. For our method, we thus normalize each feature vector on the feature axis in advance.

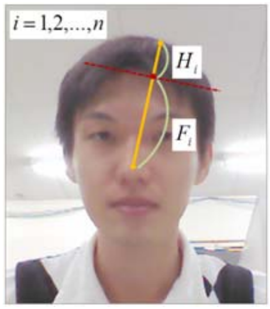


Figure 5. Hairstyle feature vector

We use the Euclidian norm (L2) to calculate the distances between vectors, taking the part with the lowest Euclidian norm as the similar part. Formula (1) expresses face part similarity, where the vectors for comparison are $V^{in} = (v_1^{in}, v_2^{in}, \ldots, v_n^{in})$ and $V^{db} = (v_1^{db}, v_2^{db}, \ldots, v_n^{db})$, respectively.

$$\sum_{i=1}^{n} (v_i^{in} - v_i^{db})^2 \qquad (1)$$

As the presence or lack of hair has a significant impact on a person's visual appearance, our system calculates similarity based on both the Euclidean norm for the feature vector and an item that reflects the differences in hair presence in the corresponding direction. Formula (2) expresses hair similarity for use in the search process.

$$\sum_{i=1}^{n} \left(v_i^{in} - v_i^{db}\right)^2 + r \sum_{i=1}^{n} \left(\delta\left(v_i^{in}\right) - \delta\left(v_i^{db}\right)\right)^2 \qquad (2)$$

$$\text{Where} \quad \delta(v) = \begin{cases} 0 (v = 0) \\ 1 (v \neq 0) \end{cases}$$

In Formula (2), r is a coefficient for adjusting the weight of differences in hair presence.

Using the formulas above, the system calculates the similarity between each feature vector obtained from the input image and the corresponding feature vector from the database and then uses the most similar item as a caricature part.

C. *Exaggerating feature vectors*

In order to preserve the artistic style in which specific parts were drawn, our method achieves exaggerated depictions by exaggerating the visual appearance feature vectors of the various parts and using the exaggerated vectors to obtain similar part caricatures from the example database. As shown in Figure 6, for each part in the input image, our system calculates its difference from the average of the database in the feature vector space. Finally, the system shifts the feature vector in the direction of the difference vector in accordance with the required exaggeration level and uses the resulting feature vector for search purposes.

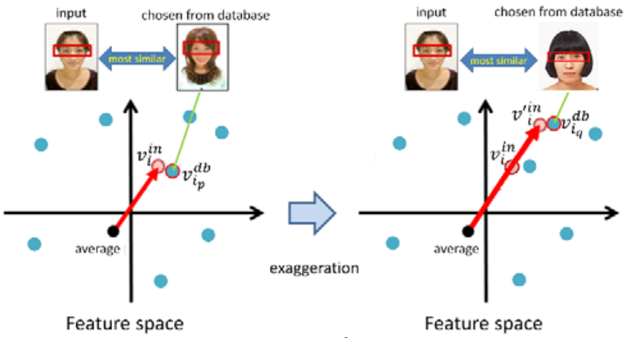


Figure 6. Exaggerating feature vectors

Although it is logical to assume that a feature is more prominent when there is a larger difference between the corresponding feature vector dimension and the average, the relationship also depends on the distribution of coordinate values in said dimension. Mo et al. [10] proposed a method that supplements the subject's variations from the average face with the distribution of his or her features themselves, which thereby determines exaggeration quantities. Methods that rely solely on differences from the average face sometimes fail to generate accurate caricatures because there is no mechanism for assessing the prominence of a given feature difference relative to other feature differences. Consider, for example, the horizontal spans of a person's eyes and mouth. Assume that the difference from the average for both features is 2 cm. As mouth width generally varies more broadly from person to person than eye width does, a 2-cm variation in eye width would represent a more prominent feature than a 2-cm variation in mouth width would. Exaggerating the features with the largest deviations from the standard distribution thus makes it possible to capture a subject's distinctive features more accurately. Our system uses the distribution of example data in the database to normalize the difference for each dimension, thereby making it possible to calculate difference vectors that produce more prominently exaggerated features.

The following formula determines the coordinate value for each dimension, where *V'* is the exaggerated feature vector.

$$v_i' = v_i^{in} + k\left(\frac{v_i^{in} - m_i}{\sigma_i}\right) \tag{3}$$

Where

$v^{in} = \{v_1^{in}, v_2^{in}, \dots, v_n^{in}\}$: Feature vectors for the input image

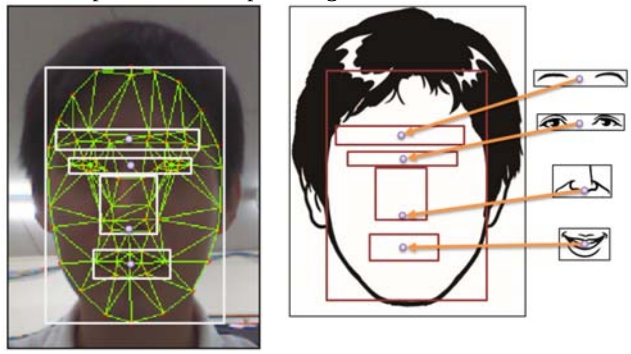
$M = \{m_1, m_2, \dots, m_n\}$: Example data average

$\{\sigma_1, \sigma_2, \dots, \sigma_n\}$: Example data standard deviation

In Formula (3), k is a coefficient for determining the overall exaggeration rate. Setting k to a positive value exaggerates the subject's features, while setting it to a negative value brings the subject's features closer to the average.

D. Arrange the part images

After obtaining caricatures for all the parts from the example database, the system places the caricatures accordingly and generates output. The obtained ASM control point information provides a basis for calculating the positional relationships between parts in the input image. Our method thus uses this control point information to arrange the caricature parts in the output image.


(a) Obtaining the corresponding position from the input image

(b) Placing items in the obtained positions

Figure 7. Part image placement

The process of obtaining positional information from ASM control points is as follows. First, the system obtains the bounding rectangle for the control points that constitute each part. Next, the system determines where each part lies on the face by calculating the position of the bounding rectangle for each part relative to the bounding rectangle for the profile.

After obtaining positional information from the input image, the system uses the profile caricature to obtain the rectangle indicating the range of the face. Finally, the system completes the caricature by placing the caricature images for the various parts based on the positional information.

Figure 7 illustrates part placement. Figure 7(a) depicts the process of obtaining the bounding rectangles and corresponding coordinates from the ASM control points in the input image. The system generally uses the central coordinates for each rectangle, but the nose is one exception: the system uses the coordinates corresponding to the position at the very bottom of the nose itself. Figure 7(b) illustrates the process of placing caricature parts based on the obtained position information. By matching the obtained coordinates with the corresponding coordinates in the parts, the system places the parts in the caricature.

IV. EXPERIMENT

A. Results and discussions

We built a prototype system and test it with an example data sets comprising pairs of input images and caricatures for 21 males and 10 females, provided by a company that makes caricatures for commercial use. Figure 10 shows several results generated with the prototype system. Figure 10(b1, c1, d1) are the caricature results for an input image of Prime Minister Abe. We applied exaggerations to the caricature, creating the image in Figure 10(c1). One can see that the hair in the caricature has a bit more volume overall than the hair in the input image, but the hair in both images comes down to the subject's ears. The system successfully obtained the general shape of the subject's hair. Looking at the facial features in the images, one can see that the characteristics of the eyebrows in the original picture—somewhat thick and slightly drooping—are evident in the caricature. Although the system selected eyes for the caricature that were slightly bigger and more horizontally even than the eyes in the input image, the differences are relatively minor. The nose also exhibits some similarities and differences: the caricature does a reasonable job of reflecting the gradual top-to-bottom widening of the nose but is too wide overall. The nasolabial folds (smile lines) also extend in different directions, but this is because the system does not currently include a method for obtaining facial wrinkles and folds. The mouth selected for the caricature, meanwhile, is slightly larger than the mouth in the input image. For comparative purposes, we created a caricature with exaggerated features (Figure 10(d1)) and a version with averaged (by setting k in Formula (3) to a negative value) features (Figure 10(b1)). The face in the input image has narrower, slightly droopier eyes than the example average, so the exaggerated depiction makes those features even more prominent. In the averaged image, on the other hand, the eyes are slightly bigger and more horizontally even. The exaggerated depiction also makes the subject's mouth smaller, while the averaged version makes it appear bigger.

Figure 10(b2, c2, d2) shows the caricature results for an input image of Deputy Prime Minister Aso. Figure 10(d2) illustrates the results of the exaggeration process, which produced changes in the appearance of the subject's eyebrows and nose. Although the subject's eyebrows started out basically level, the exaggerated version made them droop slightly. The nose in Figure 10(d2) is a different part from those used in the other caricatures, but the shape is essentially the same. In the averaged version, the eyebrows, eyes, and nose are different. The Figure also shows that the eyebrows grew gradually more arched as they approached the average model, while the eyes move from a slit shape to a larger, more open shape. The closer the image gets to the average model, the more gradual the top-down spread of the area under the nose becomes. These results suggest that the system could produce an exaggerated representation of the Deputy Prime Minister Aso image, as well, particularly with regard to the subject's eyes and eyebrows. As all the caricatures used as examples for the present study were of smiling faces, however, the system generated a smiling caricature for Prime Minister Abe's face even though the subject is not smiling in the input image. Future research will thus need to construct databases that account for cases where a subject's smile affects features that are generally similar when the subject is not smiling. In addition, the current implementation of the system does not take nasolabial folds (smile lines) into consideration. However, given that the example data used in the experiment included images containing nasolabial folds, the end results produced some caricatures with nasolabial folds that did not do a good job of capturing the subject's actual features. These lines are vital to conveying the subject's age and other characteristics, so we plan to improve the implementation by treating nasolabial folds as individual, independent parts.

B. *Subject evaluation experiment*

We conducted a subject experiment to validate the effectiveness of the proposed method. First, we generated three caricature images for each facial image (an averaged caricature, a caricature with no exaggerations, and a caricature with exaggerations). We then used the Thurstone method of pair comparisons to determine which caricature most closely resembled the original image. We showed each subject a set of three visual stimuli, as shown in Figure 8. The image in the middle was the original facial image, and the images to the left and right were two caricature images randomly selected from the set of three caricature images for the corresponding facial image. We had the subjects choose the caricature image (the image on the left or the image on the right) that most closely resembled the image in the middle. Totally three ($_3C_2$) sets of such images are presented to subject for each input image.

Figure 8. A set presented to a subject

15 university students volunteered as the subjects. Each of the 15 subjects provided answers on five input face images. Thus the total number of test instances was 225 (15 x 5 x 3). Table 1 shows the evaluation results in a pair comparison format. When the subjects compared caricatures with no exaggerations and averaged caricatures, for example, 51 subjects deemed the caricatures with no exaggerations to strike a stronger resemblance with the original image. The figure in each Table cell thus represents the number of times the subjects indicated that the caricature for that column more closely represented the original image than the caricature for the corresponding row. Figure 9 is a bar scale showing the results of a Thurston method-based analysis. The left side of the scale represents a lower winning rate, while the right side of the scale represents a higher winning rate. In addition to demonstrating the ranking of the different choices in a set, the Thurstone method also uses the spacing between the various choices to show relative differences in winning rate. As shown in Figure 9, the highest winning rate (the highest percentage of subjects deeming the images in that category to be the closest representations of the source image) belonged to the caricatures with exaggerations.

TABLE I. EVALUATION EXPERIMENT RESULTS

Times	Averaged caricature	Caricature with no exaggerations	Caricature with exaggerations
Averaged caricature	0	51	48
Caricature with no exaggerations	24	0	41
Caricature with exaggerations	27	34	0

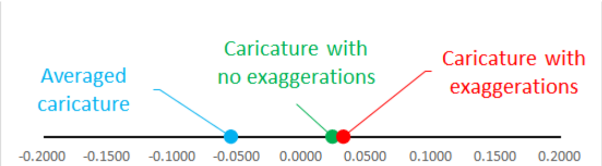


Figure 9. Results of Thurstone method-based analysis

V. CONCLUSION

The proposed method aims to facilitate the process of reflecting an artist's style by using the facial visual features captured by the artist. Our experiment, which used a limited example data set, showed that the method is capable of generating exaggerations of parts that feature prominently in subject faces. Although the experiment did not use an extensive collection of example data, companies engaged in collaborative research have already built stores of example data images numbering into the tens of thousands. Moving forward, we plan to gather more example data and conduct subjective evaluation experiments to design feature vectors for dealing with the exaggeration of facial parts arrangement, which is considered to be even more important than individual facial parts.

VI. ACKNOWLEDGEMENTS

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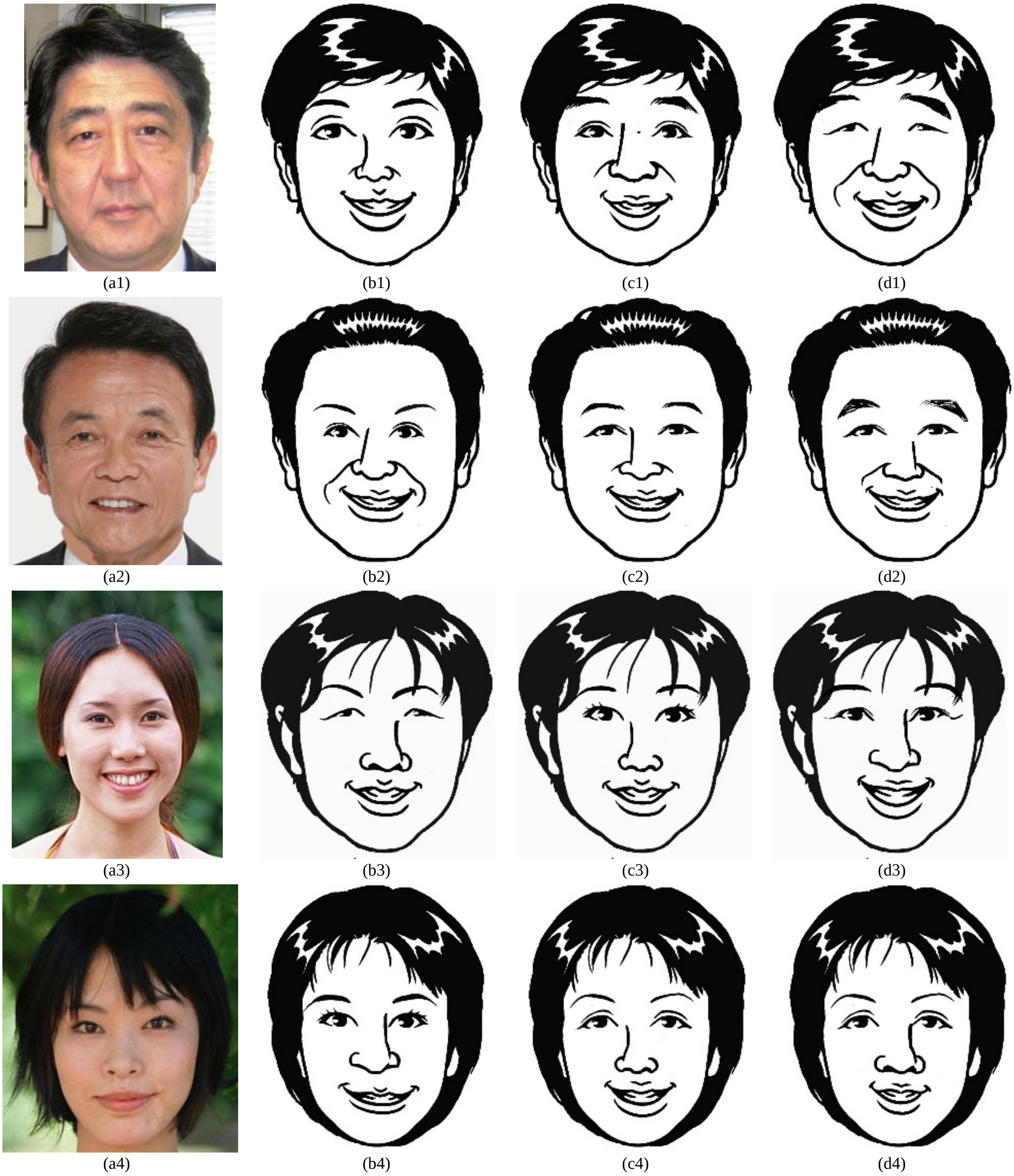

(a) (b) Averaged caricature (c) Caricature with no exaggerations (d) Caricature with exaggerations

Figure 10. Results