Abstract— Facial Expression Classification is an interesting
research problem in recent years. There are a lot of methods
to solve this problem. In this research, we propose a novel
approach using Canny, Principal Component Analysis (PCA)
and Artificial Neural Network. Firstly, in preprocessing phase,
we use Canny for local region detection of facial images. Then
each of local region’s features will be presented based on
Principal Component Analysis (PCA). Finally, using Artificial
Neural Network (ANN) applies for Facial Expression
Classification. We apply our proposal method (Canny_PCA_ANN)
for recognition of six basic facial expressions on JAFFE database
consisting 213 images posed by 10 Japanese female models. The experimental result shows the
feasibility of our proposal method.

Index Terms— Artificial Neural Network (ANN), Canny,
Facial Expression Classification, Principal Component Analysis
(PCA).

I. INTRODUCTION

Facial Expression Classification is an interesting
classification problem. There are a lot of approaches to solve
this problem such as: using K-NN, K-Mean, Support Vector
Machine (SVM) and Artificial Neural Network (ANN). The
k-nearest neighbor (k-NN) or K-Mean decision rule is a
common tool in image classification but its sequential
implementation is slowly and requires the high calculating
costs because of the large representation space of images.
SVM applies for pattern classification even with large
representation space. In this approach, we need to define the
hyper-plane for pattern classification [13]. For example, if we
need to classify the pattern into L classes, SVM methods will
need to specify 1+ 2+ … + (L-1) = L (L-1) / 2
hyper-plane. However, SVM may be errors in the case of the
image are not in any classes, because SVM will classify it
into the nearest classes based on the calculation parameters.

Another popular approach is using Artificial Neural
Network for the pattern classification. Artificial Neural
Network will be trained with the patterns to find the weight
collection for the classification process [1]. This approach
overcomes the disadvantage of SVM of using suitable
threshold in the classification for outside pattern. If the
patterns do not belong any in L given classes, the
Artificial Neural Network identify and report results to the
outside given classes.

In this paper, we propose a solution for Facial Expression
Classification using Principal Component Analysis (PCA)
and Artificial Neural Network (ANN) like below:

II. FACIAL FEATURE EXTRACTION

A. Canny for local region detection

There are many algorithms for edge detection to detect
local feature such as: gradient, Laplacian algorithm and
canny algorithm. The gradient method detects the edges by
looking for the maximum and minimum in the first derivative
of the image. The Laplacian method searches for zero
crossings in the second derivative of the image to find edges.
The canny algorithm [9,12] uses maximum and minimum
threshold to detect edges. The algorithm include following
steps:

- Smoothing: using a Gaussian filter to smooth the
  image to remove noise. A Gaussian filter with \(\sigma = 1.4\)
is shown below:
Identifying gradients: First, approximating the gradient in the x- and y-directions by applying the Sobel-operator shown below:

\[
B = \frac{1}{159} \begin{bmatrix}
2 & 4 & 5 & 4 & 2 \\
4 & 9 & 12 & 9 & 4 \\
5 & 12 & 15 & 12 & 5 \\
4 & 9 & 12 & 9 & 4 \\
2 & 4 & 5 & 4 & 2
\end{bmatrix}
\] (1)

\[
H_x = \begin{bmatrix}
1 & 0 & 1 \\
-2 & 0 & 2 \\
-1 & 0 & 1
\end{bmatrix}
\]

\[
H_y = \begin{bmatrix}
1 & 2 & 1 \\
0 & 0 & 0 \\
-1 & -2 & -1
\end{bmatrix}
\] (2)

Then, applying the law of Pythagoras computes the edge strengths:

\[
|G| = \sqrt{G_x^2 + G_y^2}
\]

\[
|G| = |G_x| + |G_y|
\] (3)

Where \(G_x\) is the gradient in the x-direction and \(G_y\) is the gradient in the y-direction.

The direction of the edges:

\[
\theta = \arctan \left( \frac{|G_y|}{|G_x|} \right)
\] (4)

Edge tracking: All local maxima in the gradient image marked as edges, then using double threshold to determine strong edges and weak edges. Remove all edges that are not connected to a strong edge.

In this research, we used Canny algorithm [9,12] to detect local regions for the facial expression features – left and right eyebrows, left and right eyes, and mouth. First, we crop the original image (256x256) into cropped image (85x85) only contain face. After applying histogram equalization, we use canny algorithm for local region detection. Figure 2 shows Facial Feature Extraction Process. Figure 3 shows a sample image, and figure 4 shows the local region detection for the facial features. Figure 5 shows results detected by edge detection using canny algorithm.
B. Principal Component Analysis for Facial Feature Extraction

After detected local feature, we used PCA to extract features for left and right eyebrows, left and right eyes, and mouth. These are the vector v1, v2, v3, v4 and v5. Eigenvector is combination of five vectors:

\[ V = \{v_1, v_2, v_3, v_4, v_5\} \] (5)

PCA is a procedure that reduces the dimensionality of the data while retaining as much as possible of the variation present in the original dataset. PCA uses a linear transformation that converts data from a high dimensional space (x) to a lower dimensional space (y):

\[
\begin{align*}
    y &= T x \\
    y_1 &= t_{11} x_1 + t_{12} x_2 + \ldots + t_{1n} x_n \\
    y_2 &= t_{21} x_1 + t_{22} x_2 + \ldots + t_{2n} x_n \\
    \vdots \\
    y_k &= t_{k1} x_1 + t_{k2} x_2 + \ldots + t_{kn} x_n \\
    T &= \begin{bmatrix}
        t_{11} & t_{12} & \cdots & t_{1n} \\
        t_{21} & t_{22} & \cdots & t_{2n} \\
        \vdots & \vdots & \ddots & \vdots \\
        t_{k1} & t_{k2} & \cdots & t_{kn}
    \end{bmatrix}
\end{align*}
\] (6)

Let \( X = \{x_1, x_2, \ldots, x_m\} \) are set of \( Nx1 \) vectors. The method runs in six steps:

- **Computing mean of sets \( x \):**
  \[
  \bar{x} = \frac{1}{M} \sum_{i=1}^{M} x_i \] (7)

- **Subtract the mean:**
  \[
  \varphi_i = x_i - \bar{x} \] (8)

- **Set the matrix** \( A = [\varphi_1, \varphi_2, \ldots, \varphi_M] \), then compute:
  \[
  C = AA^T = \frac{1}{M} \sum_{i=1}^{M} \varphi_i \varphi_i^T \] (9)

- **Computing the eigenvalues of \( C \):**
  \[ \lambda_1 > \lambda_2 > \ldots > \lambda_n \]

- **Computing the eigenvectors of \( C \):** \( u_1, u_2, \ldots, u_n \)
  \[
  x - \bar{x} = y_1 u_1 + y_2 u_2 + \ldots + y_n u_n = \sum_{i=1}^{N} y_i u_i \] (10)

- **Dimensionality reduction**
  \[
  \hat{x} = \bar{x} + \sum_{i=1}^{K} y_i u_i \] (11)

Where \( K << N \), \( u_i \) are \( K \) largest eigenvalues. The representation of \( x - \bar{x} \) into the basis \( u_1, u_2, \ldots, u_K \) is

\[
\begin{bmatrix}
    y_1 \\
    y_2 \\
    \vdots \\
    y_K
\end{bmatrix}
\]

III. FACIAL EXPRESSION CLASSIFICATION USING ARTIFICIAL NEURAL NETWORK

In this paper, we use Multi Layer Perceptron (MLP) Neural Network with back propagation learning algorithm.

A. Multi layer Perceptron (MLP) Neural Network

![Multi Layer Perceptron structure](image)

A Multi Layer Perceptron (MLP) is a function...
\[
\hat{y} = \text{MLP}(x, W), \text{with } x = (x_1, x_2, \ldots, x_n) \text{ and } \hat{y} = (\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_m)
\]

\[W \text{ is the set of parameters } \{ w_{ij}^L \}_{i,j,L} \cup \{ w_{0i}^L \}_{i,L} \]

For each unit \( i \) of layer \( L \) of the MLP. Integration:

\[s = \sum_{j} y_{j}^{L-1} w_{ij}^L + w_{0i}^L \]  

(12)

Transfer: \( y_j^L = f(s) \), where

\[f(t) = \frac{1}{1 + e^{-t}} \]  

(13)

On the input layer (\( L = 0 \)): \( y_j^0 = x_j \)

On the output layer (\( L = L \)): \( y_j^L = \hat{y}_j \)

The MLP uses the algorithm of Gradient Back-Propagation for training to update \( W \).

B. Structure of MLP Neural Network

MLP Neural Network applies for seven basic facial expression analysis signed MLP_FEA. MLP_FEA has 7 output nodes corresponding to anger, fear, surprise, sad, happy, disgust and neutral. The first output node give the probability assessment belong anger.

MLP_FEA has 200 input nodes corresponding to the total dimension of five feature vectors in \( V \) set.

The number of hidden nodes and learning rate \( \lambda \) will be identified based on experimental result.

IV. EXPERIMENTAL RESULT

We apply our proposal method for recognition of six basic facial expressions on JAFEE database consisting 213 images posed by 10 Japanese female models. We conduct the fast training phase (with maximum 200000 epochs of training) with the learning rate \( \lambda \) in \( \{0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9\} \) and the number of hidden nodes in \( \{5, 10, 15, 20, 25\} \) to identify the optimal MLP_FEA configuration. The precision of classification see the table below:

| Hidden Nodes | Learning rate \( \lambda \) |
|-------------|-----------------|
| 5           | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| 10          | 80  | 78  | 75  | 71  | 72  | 75  | 77  | 71  | 74  |
| 15           | 77  | 75  | 74  | 80  | 81  | 81  | 80  | 82  | 78  |
| 20           | 78  | 75  | 78  | 74  | 75  | 75  | 82  | 81  | 80  |
| 25           | 68  | 71  | 70  | 71  | 68  | 70  | 72  | 71  | 71  |

It is easy to see that the best classification with \( \lambda = 0.3 \) and the number of hidden nodes = 10. Therefore, we develop ANN with 10 hidden nodes and \( \lambda = 0.3 \) to apply for recognition of six basic facial expressions.
Based on the above optimal MLP_FEA configuration, we conduct the training with error = $10^{-2}$ and obtained the result below:

| Feeling   | Correct Classifications | Classification Accuracy % |
|-----------|--------------------------|---------------------------|
| Anger     | 9/10                     | 90                        |
| Fear      | 8/10                     | 80                        |
| Surprise  | 9/10                     | 90                        |
| Sadness   | 9/10                     | 90                        |
| Joy       | 8/10                     | 80                        |
| Disgust   | 9/10                     | 90                        |
| Neutral   | 8/10                     | 80                        |

The average facial expression classification of our proposal method (Canny_PCA_ANN) is 85.7%. We compare our proposal methods with Rapid Facial Expression Classification Using Artificial Neural Network [10], Facial Expression Classification Using Multi Artificial Neural Network [11] in the same JAFFE database.

This method (Canny_PCA_ANN) improved the Classification Accuracy than Rapid Facial Expression Classification Using Artificial Neural Networks [10] and Facial Expression Classification Using Multi Artificial Neural Network [11] (only used ANN).

This method does not need face boundary detection process perfectly. We used Canny for search local regional (left – right eyebrow, eyes and mouth) directly.

V. CONCLUSION

In this paper, we suggest a new method using Canny, Principal Component Analysis (PCA) and Artificial Neural Network (ANN) apply for facial expression classification. Canny and PCA apply for local facial feature extraction. A facial image is separated to five local regions (left eye, right eye, left and right eyebrows and mouth). Each of those regions’ features is presented by PCA. So that image representation space is reduced.

Instead of using ANN based on the large image representation space, ANN is used to classify Facial Expression based on PCA representation. So the training time of ANN is reduced.

To experience the feasibility of our approach, in this research, we built recognition of six basic facial expressions system on JAFFE database consisting 213 images posed by 10 Japanese female models. The experimental result shows the feasibility of our proposal system.

However, this approach uses ANN for classifying and the number of hidden nodes is identified by experience. It required the high calculating cost for learning process.

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