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Neutral expression synthesis using kernel active shape model

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Article Info	ABSTRACT
  	This paper presents a modified kernel-based Active Shape Model for neutralizing and synthesizing facial expressions. In recent decades, facial identity and emotional studies have gained interest from researchers, especially in the works of integrating human emotions and machine learning to improve the current lifestyle. It is known that facial expressions are often associated with face recognition systems with poor recognition rate. In this research, a method of a modified kernel-based active shape model based on statistical-based approach is introduced to synthesize neutral (neutralize) expressions from expressional faces, with the aim to improve the face recognition rate. An experimental study was conducted using 3D geometric facial datasets to evaluate the proposed modified method. The experimental results have shown a significant improvement on the recognition rates.

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1. INTRODUCTION

Successful face recognition systems should have the ability to handle multiple variations [1] that possibly exist within a range of different images of the same face [2], such as facial expressions [3] and occlusions [4]. By integrating facial expressions in facial synthesis for face recognition, the performance of the system, in terms of face identification, can be improved. Existing successful facial recognition systems [5-7] utilized expressionless or neutralize facial expression as training set to achieve a higher rate of recognition. Facial expression synthesis is a method for constructing new face shape from a given face without affecting facial characteristics of the initial face [6]. Synthesizing facial expression is a challenging task and would require high computational to generate a realistic facial expression. According to [8], the performance of expressive face recognition with a single neutral sample in gallery per subject could be enhance by synthesizing neutral facial expression. Other than the synthesis of facial expression, 3D face model has also been used to synthesize facial aging [9]. The target face is synthesized to a specific age parameter before performing face recognition.

There are various approaches [10-13] that have been proposed to synthesize better facial expressions. These include statistical-based approaches [14, 15]. Most of the approaches incorporated linear method, such as the Principal Component Analysis (PCA) [16] or nonlinear method, such as Kernel PCA [17]. PCA is used for various purposes such as for extracting facial features [18] from an input, transforming the extracted data to represent a face model and subsequently extended in applications for instance in the face recognition system. However, several issues arise in linear methods and that the linear transformations may lead to some information lost along the way [19]. Apart from that, the nature of human face is too complex to be expressed by using only linear methods. Kernel PCA allows a generalization of the linear method to reduce dimension in a nonlinear way. Schölkopf et al. [17] proposed the kernel PCA which has then became widely used for nonlinear feature extraction method in the face recognition system and to develop a nonlinear

shape model of faces. The kernel is equivalent to the method applied in Support Vector Machine [20], and it has been proven to be useful for various applications in de-noising [21] and data classification [22].

The synthesis of expressions through statistical model is based on a collection of faces database. It could be done because of two important factors: the input data and the shape parameters. The shape parameter is derived via a shape model to be used as input data for other process such as face identification or geometric manipulation. Several examples of statistical-based method are the Active Shape Model (ASM) [14] and morphable model [11]. ASM is one of the well-known methods used in computer vision for discovering deformation pattern of an object by iteratively deforms to fit an example of object into a new image [14]. A set of points is used to represent the object and then controlled by the shape model so that the variation can be seen in a training set of labelled examples. The ASM uses PCA to capture the statistics of the training shapes. Due to the limitation of PCA as linear model [15], kernel PCA is favored as nonlinear alternative to linear PCA as pre-image for model construction in ASM. Existing researches recognize the critical role of kernel method used in [21, 23-25], and therefore gave motivation of this study to explore the potential of kernel in the synthesis of facial expressions. Kernel PCA is also valued for its simplicity and it is easy to implement [23]. As pointed out in previous works done by [21, 26], there are more hidden information that could be extracted by substituting kernel PCA into the ASM instead of using only PCA.

Motivated by the flexible modelling using statistical tools from statistical-based approach, this paper presents a proposed modified kernel-based method for synthesizing and neutralizing expressions for the purpose of improving the recognition rates of face recognition. The proposed method is known as the modified kernel-based Active Shape Model (mKASM). The statistical measure is adopted based on kernel ASM to derive the nonlinear shape model parameters for pre-model construction and added an identity parameter into the model to synthesize neutral expression.

2.   RELATED WORK

To date, several studies have investigated ASM in the medical and industrial domains. Cootes et al. [14] introduced ASM to derive a model from resistor shapes. The research is extended to face applications - modelling a facial shape [26], thoracic vertebrate [27] and nematode worm [28]. To the best of our knowledge, the closest work to our study is by Agianpuye and Minoi [6], whereby they implemented ASM to synthesize neutral expression in 3D geometric face datasets. The difference is that their study is based on the conventional linear method, whereas in this work, we will be using the nonlinear perspective of ASM. Research to date has not yet determine the application of kernel ASM for 3D neutral face synthesis. Although kernel ASM has already been used in [26, 28] to construct nonlinear statistical model of 2D face images. On the contrary, this study explores the potential of kernel ASM in geometric 3D face surfaces.

3.   RESEARCH METHOD

3.1. The 3D face dataset

The dataset used is from Binghamton University i.e. the BU3DFE [29]. In the dataset, there are 54 subjects consisting of males and females. In the dataset, there are common emotional facial expressions with its varying intensity. The seven emotional expressions including neutral expression are angry, happy, fear, sad, disgust, and surprise. Excluding the neutral face, each of the other expressions has four levels of expression's intensity. The total number of faces in this dataset is 1350. The levels of intensity in each facial expression allow a wide range of facial expressions that represents a subject/person's expression. Pre-processing was done on the datasets before further processing to remove unwanted holes and spikes that present in the raw face data. Using only raw data may only lead to inaccurate results. Additionally, unclean data might also give a false the recognition rates [4]. In our experiment, the BU3DFE dataset has been pre-processed using [29]. Following on is the implementation of the neutralization of facial expression synthesis using the proposed mKASM method.

3.2. The proposed modified kernel active shape model

This section will explain the method used in this research, from preparing training sets until the generated new synthesized neutral face. The first step is to prepare a training set from the selected face dataset. Each group represents one facial expression and it is denoted as G. Group E can be any facial expression taken from the datasets. Hence, a vector of $G_E = [x_1 y_1 z_1, \ldots, x_n y_n z_n]$, where n is the number of faces in each training set. The ASM uses a point distribution model to represent the variants of a geometrical shape as shown in (1).

$$X \approx \mu_E + w^\Phi b_E \tag{1}$$

where X is denoted as the distribution of facial shape. The parameters w^Φ is extracted from kernel PCA which can be found in Figure 1. The mean face, μ_E is calculated as shown in (2) and subtracted with the whole set of G_E to compute the Weighted Features, b_E of the test faces as shown in (3), that holds the test's expression features.

$$\mu_E = \frac{1}{n}\sum_{i=1}^{n} G_E \tag{2}$$

$$b_E = (G_E - \mu_E) \tag{3}$$

Kernel PCA is then executed for each set of group E to construct the basis of shape model called the Expression Features. We adopted kernel PCA method as in [17]. The Expression Features consists of eigenvalues and eigenvectors that are sorted in order of the highest eigenvalues to the lowest. As stated in [30], the highest eigenvalues carry the most informative characteristics of the trained set. Since eigenvectors represent the variation in the training set, the lower eigenvectors indicate less variation and more noise. Therefore, only the first eigenvector is selected in this study as it represents the most dominant features of the faces in the training set. Figure 1 presents the basic algorithm of kernel PCA to extract the kernel eigenvalues and eigenvectors. In [31], the extraction of nonlinear components cannot be done directly in the covariance matrix of PCA as the computation is prohibited when D is larger than 2. Thus, in this study, Gaussian kernel is introduced with the width σ of 100 corresponds to the dot product of Φ mappings as shown in Figure 1(1) before performing extraction of nonlinear principal components as shown in Figure 1(3).

Given a dataset M, with m = 54, and $D = 5090 \times 3$, dimensional vectors (where $M < D$), $M = [x_1, \dots, x_m]^T \in R^m$.
(1) Choose a kernel function to construct kernel matrix K: $K_{ij} = K(\Phi_i, \Phi_j) = \Phi(x_i).\Phi(x_j)$
using Gaussian kernel, $K(x, y) = \exp\left(-\frac{\|X-Y\|^2}{2\sigma^2}\right)$
(2) Centre K matrix: $\widetilde{K}_{ij} = K - 1_M K - K1_M + 1_M K1_M$, where $1_M = \frac{1}{m}$.
(3) Solve the eigenvalue problem $\lambda w^\# = C^\# w^\#$, with eigenvalue, $\lambda \neq 0 : M\lambda a = \widetilde{K}a$
where a denote a column vector with all entries of the projected samples $\Phi(x)$,
which in turn determines the eigenvectors, $w^\# = \sum_{i=1}^{m} a_i \Phi(x_i)$.
(4) Preserves the first P eigenvectors ($1 \leq P \leq m$), where P^{th} is the selected eigenvalues of $\widetilde{K}_{ij}$ in decreasing order, and $w_p w_p^T = 1$.
(5) $w^\#$, is the nonlinear principal components.

Figure 1. Kernel PCA algorithm

Ideally, to synthesize neutral expression, neutral mean face is substituted with the other expressional mean face in the point distribution model. Hence, we proposed to synthesize neutral expression by using Identity Features from the original neutral expression computed in (6) and Expression Features from Group E expression computed in (3), which then are fed into the Expression Model as shown in (7).

The synthesized neutral expression Z is generated when a test face G with E expression, is passed through the mKASM algorithm. We proposed to add another parameter i.e. the Identity Features to be added into the projected faces to increase the proportion distribution of neutral expression and to retain the subject's identity. The Identity Features, I_N is computed by subtracting G of neutral face, with its mean, μ_N calculated similar as in (2).

$$I_N = (G_N - \mu_N) \tag{6}$$

The newly synthesized neutral face model from a test face can be constructed by substituting the μ_E by μ_N, adding I_N and projecting the eigenvector w^Φ with the weight b_E.

$$Z \approx I_N + \mu_N + w^\Phi b_E \tag{7}$$

4. RESULTS AND ANALYSIS

The performance of the synthesized neutral face is evaluated using kPCA-based face recognition adopted from [32] with Gaussian kernel. The experiments are performed using the standard cross validation. The benchmark would be the original neutral facial expression of 54 subjects, which is used as training set, while the synthesized neutral expression faces are used as the testing set. All expressional faces (m =54), in the training set are projected to a reduced space using the w^{Φ} and the recognition is performed based on the nearest neighbor classifier. The number of principal components is set as 54, which equals to the number of subjects since the highest recognition is achieved with this value. The experimental results are presented below. To determine the effectiveness of the synthesized neutral face, the original expression is also tested using the same recognition method with the benchmark. The implementation of mKASM is developed using MATLAB.

The first test is to evaluate the synthesized neutral expressions of an angry expression. In Table 1, it is shown that the recognition rate of the original angry expression decreases when the expression intensity increases. This is due to the extreme facial deformations that gave a large expression residue between the expressional face and the benchmark. The maximum recognition rate achieved by the original angry expression is at level 1 with 70.37%, followed by level 2 with 68.52% and level 3 with 42.6%, while the minimum rate is at the level 4 with 31.48%. After the angry expressions are synthesized to neutral expressions, the average recognition rate for all level of expression intensities has improved from 53.24% to 100%. This proves that the mKASM has successfully synthesized neutral expression and improves the face recognition rate.

Table 1. The recognition rate of synthesized neutral expression and original angry expression

Expression intensity	Recognition Rate (%)	
	Original Angry	Synthesized Neutral
Level 1	70.37	100
Level 2	68.52	100
Level 3	42.6	100
Level 4	31.48	100
Average	53.24	100

Table 2 presents experimental result when the neutral expression is synthesized from disgust expression. From the table, it can be observed that from the original disgust expression, there is a decline in recognition rate as the expression intensity increases from level 1 with 61.11%, followed by 33.33% at level 2, 27.78% at level 3 until level 4 with 22.22%. On the other hand, after all levels of the disgust expressions were synthesized into neutral expressions, the rate of recognition improves to 100%. This shows that all synthesized faces are correctly recognized. From the table, we can see that the average recognition rate of the original disgust expression is 36.11% and achieved 100% after the neutral expression synthesis. The 100% recognition shows that the mKASM has successfully synthesized neutral expression and is proven to be effective.

Table 2. The recognition rate of synthesized neutral expression and original disgust expression

Expression intensity	Recognition Rate (%)	
	Original Disgust	Synthesized Neutral
Level 1	61.11	100
Level 2	33.33	100
Level 3	27.78	100
Level 4	22.22	100
Average	36.11	100

Table 3 shows experimental result when the synthesized neutral from fear expressions are tested with the benchmark. To compare the effectiveness of the neutralized face, the original fear expression sample is also tested with the benchmark. The experiment is carried out for each intensity level of fear expression. Based on the result, we can see that the highest recognition achieved by testing fear expression with the benchmark is 37.04% at level 1 while the lowest is at level 4 with 29.63%. A significant observation from the table is that the recognition rate for synthesized neutral is 100% for all level of expression intensities. These results indicate that the synthesized faces are correctly recognized. The synthesis improvement can be seen from the average face recognition rate with the record of 100% whereas the original fear expression only achieved 31.02%.

Table 3. The recognition rate of synthesized neutral expression and original fear expression

Expression intensity	Recognition Rate (%)	
	Original Fear	Synthesized Neutral
Level 1	37.04	100
Level 2	31.48	100
Level 3	25.93	100
Level 4	29.63	100
Average	31.02	100

Table 4 shows the face recognition result when the synthesized neutral from happy expression is tested with the benchmark. As for comparison with the neutralized face, the original happy expression sample is also tested with the benchmark. The experiment is carried out for each level of expression intensities. From the result, we can see that the original happy expression records the highest recognition with 64.81% at level 1 but the recognition rate decreases as the expression intensity increases until level 4 with 31.48%. After the neutral expression synthesis, the 100% recognition rates achieved for all synthesized neutral expression faces from four level of expression intensities have shown that the synthesized faces are correctly recognized. The average recognition rate has also shown that the synthesized neutral is higher than the original happy expression.

Table 4. The recognition rate of synthesized neutral expression and original Happy expression

Expression intensity	Recognition Rate (%)	
	Original Happy	Synthesized Neutral
Level 1	64.81	100
Level 2	53.7	100
Level 3	46.3	100
Level 4	31.48	100
Average	49.01	100

Table 5 compares the face recognition result of synthesized neutral from sad expression and the original sad expression. From the table, we can see that the highest recognition is achieved by testing original happy expression with neutral is 61.11% at level 1, followed by 46.3% at level 2, 42.6% at level 3 and the lowest with 31.48% at level 4. Apparently, the recognition rate decreases as the expression intensity increases. This might also be due to shape deformations in the face dataset. After the neutral expression synthesis, the recognition rate of the synthesized neutral face sample has increased to 100% on all four level of happy expression intensities. This shows that the synthesized faces are correctly recognized by the facial recognition system. The average recognition rate difference between the synthesized neutral and original sad expression shown by the figures are significant, where the original sad achieved average of 45.37% as compared to synthesized neutral with 100%.

Table 5. The recognition rate of synthesized neutral expression and original sad expression

Expression intensity	Recognition Rate (%)	
	Original Sad	Synthesized Neutral
Level 1	61.11	100
Level 2	46.3	100
Level 3	42.6	100
Level 4	31.48	100
Average	45.37	100

Table 6 shows the experimental result of testing synthesized neutral from surprise expression sample on trained benchmark. The original surprise expression sample is also tested with the benchmark for comparison with the synthesized neutral sample. The experiment is carried out for each level of expression intensity. Based on the result, we can see that the maximum recognition is achieved by testing the original surprised expression with the benchmark is 50.00% at level 1, followed by 37.04% at level 2 and 12.96% at level 4 while the lowest rate is achieved at level 3 expression with 1.85%. Through visualizing the 3D faces, we have found that there is an incomplete face data, see Figure 2(a), that has affected the whole data. However, with the proposed method, we were able to reconstruct new neutral expression from the deformed facial shape. The reconstructed neutral expression can be found in Figure 2(b). Note that the synthesized neutral and the ground truth neutral expression presented in Figure 2(c) are almost alike. The rate of

recognition for synthesized neutral from original sad expression in level 3 has improved tremendously from 1.85% to 100%. Moreover, after the neutral expression synthesis, all level of expression intensities achieved 100% recognition rate. This proves that the synthesized faces are correctly recognized. Furthermore, the average recognition rate achieved after the neutral expression synthesis has increased from 25.46% to 100%.

Table 6. The recognition rate of synthesized neutral expression and original surprise expression

Expression intensity	Recognition Rate (%)	
	Original Surprise	Synthesized Neutral
Level 1	50	100
Level 2	37.04	100
Level 3	1.85	100
Level 4	12.96	100
Average	25.46	100

(a) Original surprise expression   (b) Synthesized neutral from surprise   (c) The ground truth of neutral expression

Figure 2. Improvement made on an incomplete surprise face sample of surprised expression

Overall, it is interesting to note that the synthesized neutral faces in all six expressions records 100% rate of facial recognition which shows that there is a good potential of using the proposed mKASM. The synthesized neutral faces are also rendered in 3D environment using Microsoft Visual Studio to observe the impact of the expression synthesis. Figure 3 presents an example of a neutral face synthesized from fear expression sample. The figure shows visual comparison of the synthesized neutral face with the original fear expression and the benchmark. The mouth and cheeks from the original expression became more relaxed after the neutral expression synthesis. Interestingly, the synthesized neutral face turns out almost similar to the ground truth.
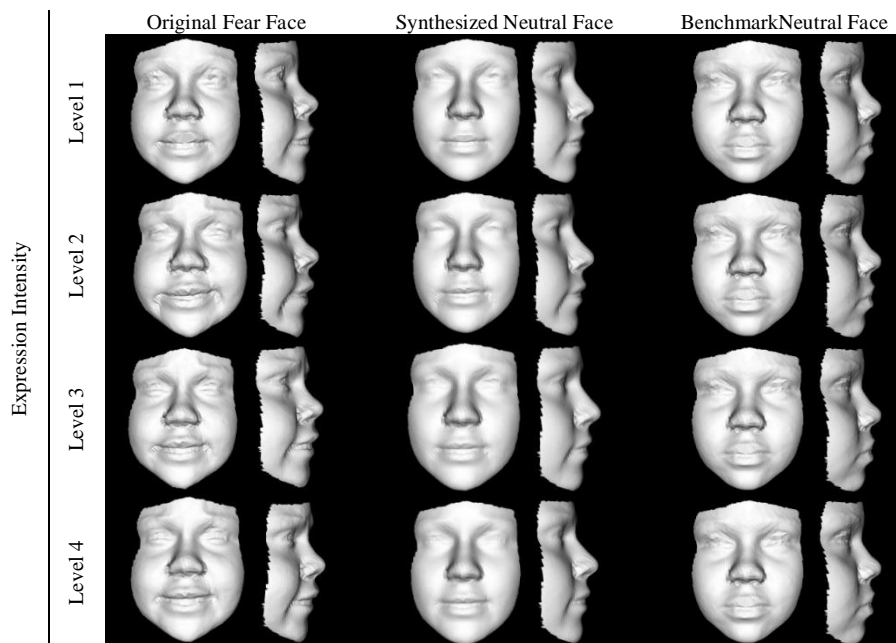

Figure 3. An example of synthesized neutral face from fear expression of a subject

5. CONCLUSION

The aim of this study was to explore the potentials of kernel approach in neutralizing facial expression synthesis to improve the recognition rates given the expression variants. We have introduced the modified kernel-based Active Shape Model (mKASM) that is used on the experiment. The results have shown a better recognition rate on the synthesized neutral faces as compared to the original expressional faces. These promising results confirm the effectiveness of the mKASM approach. Future works will include further analysis to measure the effectiveness of the kernel method and experiment the recognition results with the existing linear ASM approach.

ACKNOWLEDGEMENTS

REFERENCES

[1] J. L. Minoi, C. E. Thomaz and D. F. Gillies, "Tensor-based multivariate statistical discriminant methods for face applications," *2012 International Conference on Statistics in Science, Business and Engineering (ICSSBE)*, Langkawi, 2012, pp. 1-6.
[2] A. Z. Kouzani, "Facial expression synthesis," *Proceedings 1999 International Conference on Image Processing (Cat. 99CH36348)*, Kobe, vol. 1, pp. 643-647, 1999.
[3] N. A. B. M. Kasim, N. H. B. A. Rahman, Z. Ibrahim, and N. N. A. Mangshor, "Celebrity face recognition using deep learning," *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 12, no. 2, pp. 476-481, 2018.
[4] N. A. A. Rahim, N. A. M. Ghani, N. Mohamed, H. Hashim, and I. Musirin, "The application of modified least trimmed squares with genetic algorithms method in face recognition," *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 8, no. 1, pp. 154–158, 2017.
[5] J. Ueda and K. Okajima, "Face morphing using average face for subtle expression recognition," *2019 11th International Symposium on Image and Signal Processing and Analysis (ISPA)*, pp. 187-192, 2019.
[6] A. S. Agianpuye and J. Minoi, "Synthesizing neutral facial expression on 3D faces using Active Shape Models," *2014 IEEE REGION 10 SYMPOSIUM*, Kuala Lumpur, pp. 600-605, 2014.
[7] G. Pan, S. Han, Z. Wu and Y. Zhang, "Removal of 3D facial expressions: A learning-based approach," *2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, San Francisco, pp. 2614-2621, 2010.
[8] Y. Chen, R. Bai and C. Hua, "Personalised face neutralisation based on subspace bilinear regression," in *IET Computer Vision*, vol. 8, no. 4, pp. 329-337, 2014.
[9] S. Riaz, Z. Ali, U. Park, J. Choi, I. Masi, and P. Natarajan, "Age-invariant face recognition using gender specific 3D aging modeling," *Multimedia Tools and Applications*, vol. 78, no. 17, pp. 25163–25183, 2019.
[10] X. Wang and R. Yang, "Learning 3D shape from a single facial image via non-linear manifold embedding and alignment," *2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, San Francisco, pp. 414-421, 2010.
[11] V. Blanz, "Face recognition based on a 3D morphable model," *7th International Conference on Automatic Face and Gesture Recognition (FGR06)*, Southampton, pp. 617-624, 2006.
[12] B. Yang, X. Chen, R. Hong, Z. Chen, Y. Li, and Z.-J. Zha, "Joint sketch-attribute learning for fine-grained face synthesis," *International Conference on Multimedia Modeling*, pp. 790–801, 2019.
[13] M. He, J. Zhang, S. Shan, M. Kan, and X. Chen, "Deformable face net for pose invariant face recognition," *Pattern Recognition*, vol. 100, 2020.
[14] T. F. Cootes, C. J. Taylor, D. H. Cooper, and J. Graham, "Active shape models-their training and application," *Computer Vision and Image Understanding*, vol. 61, no. 1, pp. 38–59, 1995.
[15] T.F. Cootes, "Chapter 24 - Linear statistical shape models and landmark location," S. Kevin Zhou, D. Rueckert, and Gabor Fichtinger, Eds. *Handbook of Medical Image Computing and Computer Assisted Intervention*, Academic Press, pp. 575–598, 2020.
[16] I. T. Jolliffe, "Principal component analysis and factor analysis," *Principal Component Analysis*, pp. 115-128, 1986.
[17] B. Schölkopf, A. Smola, and K. R. Müller, "Kernel principal component analysis," *International conference on artificial neural networks*, pp. 583–588, 1997.
[18] M. M. Hussein*, et al.,* "Developed artificial neural network based human face recognition," *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 16, no. 3, pp. 1279-1285, 2019.
[19] L. Li, S. Liu, Y. Peng, and Z. Sun, "Overview of principal component analysis algorithm," *Optik*, vol. 127, no. 9, pp. 3935–3944, 2016.
[20] M. Esmaeilbeigi, A. Daneshkhah, and O. Chatrabgoun, "Some computational considerations for Kernel-Based Support Vector Machine," In *Digital Twin Technologies and Smart Cities*, Springer, Cham, pp. 177-189, 2020.
[21] H. M., Huang, and C. Lin, "A kernel-based image denoising method for improving parametric image generation," *Medical image analysis*, vol. 55, pp. 41-48, 2019.

[22] A. Z. A. Zainuddin, W. Mansor, K. Y. Lee, and Z. Mahmoodin, "Performance of Support Vector Machine in Classifying EEG Signal of Dyslexic Children using RBF Kernel," *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 9, no. 2, pp. 403–409, 2018.

[23] R. Fezai, M. Mansouri, O. Taouali, M. F. Harkat, and N. Bouguila, "Online reduced kernel principal component analysis for process monitoring," *Journal of Process Control*, vol. 61, pp. 1–11, 2018

[24] K. Arora, P. Garg, and V. P. Vishwakarma, "Face Recognition across Pose using ELM Framework," *European Journal of Electrical Engineering and Computer Science*, vol. 2, no. 3, pp. 7-12, 2018.

[25] J. Fan and T. W. S. Chow, "Exactly robust Kernel principal component analysis," in *IEEE Transactions on Neural Networks and Learning Systems,* pp. 1-13, 2019.

[26] S. Romdhani, S. Gong, and A. Psarrou, "A Multi-View Nonlinear Active Shape Model Using Kernel PCA," *BMVC*, vol. 10, pp. 483-492, 1999.

[27] M. Kirschner, M. Becker, and S. Wesarg, "3D Active Shape Model Segmentation with Nonlinear Shape Priors," *International Conference on Medical Image Computing and Computer-Assisted Intervention*, pp. 492–499, 2011.

[28] C. Twining and C. Taylor, "Kernel principal component analysis and the construction of non-linear active shape models," *BMVC,* vol. 1, pp. 23-32, 2001.

[29] L. Yin, X. Wei, Y. Sun, J. Wang and M. J. Rosato, "A 3D facial expression database for facial behavior research," *7th International Conference on Automatic Face and Gesture Recognition (FGR06)*, Southampton, pp. 211-216, 2006.

[30] W. S. Yambor, B. A. Draper, and J. R. Beveridge, "Analyzing PCA-based Face Recognition Algorithms: Eigenvector Selection and Distance Measures," *Empirical evaluation methods in computer vision*, pp. 39–60, 2002.

[31] K. I. Kim, K. Jung and H. J. Kim, "Face recognition using kernel principal component analysis," in *IEEE Signal Processing Letters*, vol. 9, no. 2, pp. 40-42, 2002.

[32] M. H. Yang. "Face recognition using kernel methods," *Advances in neural information processing systems*, pp. 1457-1464, 2002.