INTRODUCTION

The detection of wrinkle positions is critical for applications like facial beauty within which the positions of wrinkle lines and regions must be detected before they are removed or trimmed.\(^1,2\) The quantitative evaluation of skin condition has been an area of quite an intense study. There is great interest in complementing the dermatologist’s diagnostic visual assessment of skin with objective measures. These methods are also valuable for the efficient development of effective treatments.\(^3\) Facial skin wrinkles are not only important features in terms of age estimation, skin texture classification, expression recognition, and simulation. Fat deposition in facial skin is also critical in the field of facial beauty and is associated with a decrease in skin elasticity.\(^4\) Wrinkle lines are negative characteristics; therefore, tasks such as wrinkle line detection are important in facial beauty applications. \(^5\) The wrinkle line is a curvilinear discontinuity, and wrinkles play an important role in face feature analysis. They have been widely used in applications, such as age estimation, skin texture classification, expression recognition, and simulation. Fat deposition in facial skin is also critical in the field of facial beauty and is associated with a decrease in skin elasticity.\(^4\) Wrinkle lines are negative characteristics; therefore, tasks such as wrinkle line detection are important in facial beauty applications.
of facial aging and beauty but also can also provide cues to a person's lifestyle and health condition. For example, facial wrinkles can recognize facial expression,\textsuperscript{6,7} or whether the person has been a smoker.\textsuperscript{6,7} Some of the factors influencing facial wrinkles are a person's lifestyle, genetic inheritance, ethnicity, overall health, skincare routines, and gender. Hence, computer-based analysis of facial wrinkles has great potential to exploit this underlying information for relevant applications. However, wrinkle regions continue to be manually located in various works, which could largely restrict their applicability. These wrinkle detection methods are limited to some simple wrinkles, and they are not enough accurate or general. To improve the efficiency of these methods, wrinkle detection should be automatic and general.

However, each method has its own strengths and weaknesses. Current wrinkle detection methods focused on detecting active wrinkle positions as forehead wrinkles,\textsuperscript{8-10} but detecting passive wrinkle position as cheek wrinkles is not effective with previous methods. The cheek wrinkles are more complicated and challenging. The above algorithms rely on a distinct boundary texture of the wrinkle region, and the information of texture around the wrinkle area is not sufficiently complete or effective for curve type wrinkle line detection.

To make nasolabial wrinkle detection method more efficient, this work is divided into two main parts:

1. Detecting initial position of wrinkle line by Hessian filter: To make wrinkle detection method more effective and common was detected candidate wrinkle position by applying a ridge detection algorithm.
2. Apply initial wrinkle line to Active Appearance Model as individual mean shape: Create an active shape model and localize the wrinkle line using initial shape of wrinkle line.

The main contribution of this work is summarized as follows: The information about related works on the wrinkle area was introduced in section 2. The proposed wrinkle detection method demonstrated in Section 3. Then, the experimental results and the corresponding figures are presented in Section 4. Finally, discussion and conclusion are in Section 5.

2 | RELATED WORK

In this section, we introduce related work based on wrinkle line detection. We divided the section into three parts rely on methods that were used in the wrinkle research area: texture based, filters based, and shape model-based.

2.1 | Texture based

The automated location of wrinkles from images is an important step in age estimation. Ng et al\textsuperscript{11} studied a different wrinkle region extractor for age estimation. This method works by applied a Canny operator to detect the wrinkles and represented it as a pattern of age estimation. The edge detector detects the boundaries of the pattern, and it could not be suitable for wrinkle localization. Batool and Chellappa\textsuperscript{12} proposed to detect wrinkles by marked point processes, and the Markov chain Monte Carlo method was used to detect the initial positions of wrinkles. In Ref.\textsuperscript{1} the authors proposed a method to detect forehead wrinkles, using a curve pattern as a soft biometric. The permanent wrinkles are often relatively simple with distinct shapes. Detection methods aiming at this type of wrinkle might not be useful for temporary wrinkles with nonlinear and blurry shapes.

2.2 | Filters based

Localization wrinkle is a line or ridge detection problem. Only a few methods have been proposed in the previous. Ng et al\textsuperscript{9} introduced the detection of permanent wrinkles with a linear shape used a hybrid Hessian filter to locate the whole wrinkle line rather than the wrinkle edges. Forehead wrinkles were detected by growing and stitching wrinkle centerline parts extracted from filtered images of the maximum Gabor imitation with different thresholds.\textsuperscript{13} Cula et al\textsuperscript{14} proposed automatic detection of facial wrinkles, based on estimating the orientation and the frequency of elongated spatial features, captured via Gabor filtering of image. However, the above approaches are not efficient for blurry transient wrinkles, whose boundary edges might not be detected correctly by the edge detectors or filters.

2.3 | Shape model-based

Facial shape detection has received a lot of attention over the past decade and successfully applied in many research areas and have been topics of high interest using shape models to detect wrinkle line. The Active Shape Model (ASM) was used by training and locating 81 face feature points, including several points in the nasolabial region.\textsuperscript{15} In addition, wrinkles in some previously extracted fixed areas were detected using geometric elements such as a change in mean curvature. Wrinkle measurements are subsequently obtained using image gradient and surface curvature descriptors. Huang et al\textsuperscript{16} to detect wrinkles used active wavelet network with located feature points on relatively fixed positions and the deformable template model by replacing PCA-based texture model with wavelet networking.

Current algorithms leave many opportunities to improve wrinkle detection method and introduced by the following drawbacks:

- Current wrinkle detectors rely on a bold boundary pattern of the wrinkle line.
- Texture and geometrical information around the wrinkle line not used completely.
- Above methods mainly suitable for detecting forehead wrinkle lines, wherein nasolabial wrinkle lines remain unexplored.
3 | PROPOSED METHOD

The proposed detector Figure 1 largely consists of three steps: first, detecting wrinkle position area; second, the ridge detection method is applied; and third, creating a unique initial shape and finally apply AAM using created initial shape.

3.1 | Wrinkle edge detection

The first and most important step is to detect face and face feature points from the input image. In this step, using general AAM localized detect face and face features. The shape of the face represented as a sequence of 88 points (Figure 4), in which 68 points are face features, and 20 points are wrinkle line.

Chin region is initially extracted using points coordinates in Table 4. The extracted area covers the cheek, mouth, and nose regions, to remain only cheek part of the face, other regions overlay with the non-zero mask, which allows concentrating only to the cheek region. Because human skin has many noises that impede detecting wrinkle line correctly, the Gaussian filter with histogram equalization is employed to balance skin noise.

To extract the initial position of wrinkle lines in cheek area using edge detection operator is not effective, as edge detection operators detect borders between areas of high and low gray values, it could not detect wrinkle position. An edge detector is a first derivative operator, an edge detector measures the steepness of the slope at each point of the landscape. Our aim is thin lines are darker or the wrinkle line might be weak or strong, as the cheek region is a passive part of the face in some cases just using second-order derivatives is not enough to detect the whole line position. Detecting wrinkle with filters leads to losing some weak parts of the whole line, and an active appearance model (AAM) is applied to prevent such outcome and to find all of the candidate wrinkle lines. Active Appearance Model (AAM) introduced by Cootes et al.19 AAM is a statistics-based pattern matching method in which shape and texture variability are extracted from a representative training set. Principal component analysis (PCA) according to the shape and texture data allows to get a parameterized face model that fully describes both trained faces and invisible with photorealistic quality. Fitting the AAM model to the target face is a nonlinear optimization task, where the difference in texture between the current model estimate and the target image covered by the model is minimized. AAM studying the correlations between texture residues and model parameters allows you to build a fast and efficient algorithm of steepest descent.

\[
\text{Value} = \text{Last} \left[ \begin{bmatrix} H_{xx} & H_{xy} \\ H_{xy} & H_{yy} \end{bmatrix} \right] \tag{3.4}
\]

Then:

\[
\frac{1}{2} \left( H_{xx} + H_{yy} + \sqrt{H_{xx}^2 + 4H_{xy}^2 + 2H_{xx}H_{yy} + H_{yy}^2} \right) \tag{3.5}
\]

where \( H_{xx}, H_{xy} \), and \( H_{yy} \) are the second derivative.

3.2 | Active appearance model

The wrinkle line structure of different persons might appear different and the wrinkle line might be weak or strong, as the cheek region is a passive part of the face in some cases just using second-order derivatives is not enough to detect the whole line position. Detecting wrinkle with filters leads to losing some weak parts of the whole line, and an active appearance model (AAM) is applied to prevent such outcome and to find all of the candidate wrinkle lines. Active Appearance Model (AAM) introduced by Cootes et al.19 AAM is a statistics-based pattern matching method in which shape and texture variability are extracted from a representative training set. Principal component analysis (PCA) according to the shape and texture data allows to get a parameterized face model that fully describes both trained faces and invisible with photorealistic quality. Fitting the AAM model to the target face is a nonlinear optimization task, where the difference in texture between the current model estimate and the target image covered by the model is minimized. AAM studying the correlations between texture residues and model parameters allows you to build a fast and efficient algorithm of steepest descent.
(SD) based on a fixed Jacobi matrix. During this process, model parameters were periodically reevaluated to better describe the target. AAM was trained using the FACES dataset\(^\text{20}\) to face images with different emotional expressions. For detecting nasolabial wrinkles more accurately, have used local area features of the face, that labeled with a total of 88 points Figure 3, which 68 is present main face features (eyes, nose, mouth, jawline) and 20 points located in a wrinkle line. All labeled points represented as \(n_k\) vector.

\[
x = (X_1, Y_1, X_2, Y_2, \ldots, X_n, Y_n) \]

(3.6)

The vector of labeled points Equation (3.6) used to create the mean shape of the trained dataset by Procrustes:

\[
\bar{x} = \frac{1}{n} \sum_{i=1}^{n} x_i
\]

(3.7)

Procrustes transformation is applied to remove the difference between labeled shapes by the transformation of scaling translation and rotation Equation (3.7). Then, principal component analysis (PCA) is employed to keep the information about the identity of the pose and expression:

\[
S = \frac{1}{n-1} \sum_{i=1}^{n} (x_i - \bar{x}) (x_i - \bar{x})^T
\]

(3.8)

where \(S\) represents the eigenvectors of the shape, and \(\bar{x}\) is the mean shape of Equation (3.8). By calculating this calculation, we take the mean shape of the database.

The quality of the AAM model fitting is very dependent on the initial estimate location:

Algorithm 1. AAM Iteration.

\[
\text{Iteration} = 1
\]

\[
\text{while Iteration} < \text{MaxIteration or no improvement is made to error E}_0
\]

Sample image at \((x,y)\) \(\xrightarrow{\text{Image}} \mathbf{g}_{\text{image}}\)

Build an AAM instance AAM \((p) \xrightarrow{\text{Model}} (x_{\text{model}}, Y_{\text{model}}) \mathbf{g}_{\text{model}}\)

Compute residual \(\mathbf{g} = \mathbf{g}_{\text{image}} - \mathbf{g}_{\text{model}}\)

Evaluate Error \(E_0 = ||\mathbf{g}||^2 = \mathbf{g}^T \mathbf{g}\)

Predict model displacements \(\mathbf{d} = (J^TJ)^{-1} J^T \mathbf{g}\)

Set \(a = 1\)

Update model parameters \(p_k = p_{k-1} - a \mathbf{d}\)

Update sample control points from \((x_k, y_k) \xrightarrow{\text{Model}} (x_{\text{model}}, Y_{\text{model}})\) with similarity compositional pose correction

Sample image at \((x_k, y_k) \xrightarrow{\text{Image}} \mathbf{g}_{\text{image}}\)

Compute residual \(\mathbf{g}_k = \mathbf{g}_{\text{image}} - \mathbf{g}_{\text{model}}\)

Evaluate Error \(E_k = ||\mathbf{g}_k||^2 = \mathbf{g}_k^T \mathbf{g}_k\)

if \(E_k < E_0\)

Accept model parameters, \(p_k\)

Accept control points \((x, y) = (x_k, y_k)\)

Update current error \(E_k = E_0\)

else

Try \(a = 1, a = 0.5, a = 0.25, a = 0.125\)

end if

Iteration = Iteration + 1

end while

### Table 1

| Region       | Points    | Covering area                        |
|--------------|-----------|--------------------------------------|
| Cheek        | 2,5,11,14 | Cheek, nose, and mouth               |
| Left cheek   | 1,7,31,32,50,49 |                           |
| Right cheek  | 15:11,35,53,54,64 |                                 |

#### 3.3 Fitting active appearance model

The AAM requires an initial estimate to the location of the shape, the better is this estimate, and minor is a risk of being trap in a local minimum. The disadvantage of AAM using for every input image only one created an initial mean shape of the trained database that brings failings in detecting various shape position of wrinkle line. Thus, Hessian filter was applied to create a unique wrinkle initial line for each input image, by wrinkle structures constructed to utilize the local deformation for shape variance modeling Table 1. Based on the detected edge, wrinkle lines using second-order derivatives creating mean shape consist following steps:

Extract all detected wrinkle lines.

Discard some short and distorted lines less than Line Length Threshold (LLT) LLT = 100.

Remain wrinkle line with Line Angle Threshold (LAT) less than LAT = \(\pi\).

\[
\text{msh} = \begin{cases} 
\text{if extracted edges} < \text{LLT} \\
\text{if edge angel} < \text{LAT}
\end{cases}
\]

\[
(3.10)
\]

AAM consists of shape and texture models\(^\text{19}\) Figure 2. Before creating the initial shape, the Procrustes transformation is applied to remove the shape differences of the training wrinkle structures using affine transformation. To retain the principal information of identity, pose, and expression, principal component analysis (PCA) is employed on the shape variations. For the new AAM model, the wrinkle detection structure \(n = (x_1, y_1, \ldots, x_n, y_n)^T\) represented as:

\[
s = msh_0 + E_p, p = E (n - msh_0)
\]

(3.11)

where \(E\) represents the Eigen vectors of shape, and \(msh\) represents new unique mean shape.

To apply the AAM algorithm for sets of points with unique initial shape under Procrustes transformation and reduce the error between input image and model using the relationship between the shape and texture model was applied:

\[
\mathbf{w} = \frac{1}{2} ||\mathbf{w} - \mathbf{W}||^2 + \lambda ||s||^2
\]

(3.12)

where \(W\) is a vectorization of wrinkle structure after Procrustes transformation, \(s\) is the spars coefficient corresponding to the wrinkle structure database, \(\mathbf{vec}\) is the vectorization of the input shape, and \(\lambda\) is the regularization parameter \(1e^{-6}\).
The idea of the Hessian filter centers on the utilization of second-order partial derivatives for edge detection. Eigenvalues of the Hessian filter were applied to extract principal directions into which the local second-order structure of the image can be analyzed Figure 6.

Despite the fact that the Hessian filter benefits from the presence of the curve and valley extraction, a significant drawback is its omnidirectional nature. The vertical and horizontal discontinuities are detected as wrinkles; however, some of them are actually non-wrinkles. To remain only wrinkle lines, the Equation (3.10) was implemented.

### 4.4 Wrinkle initial position result

In this research, for detecting the cheek wrinkle position was used for each input image unique initial shape based on edges of wrinkle line and AAM. Figure 7 illustrates two results: the first one (a) mean shape created by the appearance model and the second one (b) the mean shape created using second-order derivatives. Since for every input image applied unique initial shape based on wrinkle shape characteristics, the curve lines detected more accurately than AAM.

### 4.5 Quantitative results

To compare the proposed method with state-of-the-art algorithms, ASM-based and general AAM-based edge-based wrinkle detectors are implemented for comparison in which the same environment wrinkle initialization strategy Figure 8. In contrast, these two algorithms, the proposed method not only learns from the part deformation by constructing a wrinkle structure enclosing but also utilizes the texture information learned by the intrinsic function of AAM. The competitive ability of the proposed method can be proved by the observation that Jaccard Similarity Index (JSI) index values of the proposed method are better than those of the other two methods (Table 2). The proposed method not only estimates the positions of wrinkles but also created a new mean shape for every input that illustrated a better result on detecting wrinkle line position.

The ASM-based method detects cheek wrinkle line depending on other feature points geometrical features, and this method could not detect whether wrinkle lines have curves shape or sharp changings. The AAM method does not suitable to detect the different structures of shapes and does not sufficiently make use of local deformation around the wrinkle line. The competitiveness of the proposed algorithm can be proved by observation Figure 8 that is more accurate than those of the two methods. Moreover, the proposed algorithm estimated wrinkle line by modified AAM using the unique initial shape for each input image gave results more accurate than other methods, showing the effectiveness of this method.

---

Algorithm 2. AAM Iteration with created unique mean shape.

\[
\text{Iteration} = 1 \\
\text{while} \quad \text{Iteration} < \text{MaxIteration or no improvement is made to error} \ E_0 \\
do \\
\text{Sample image at} \ (x,y) \rightarrow S_{\text{image}} \\
\text{Update model parameters} \ p_k = \text{New}p_{k-1} - \alpha dp \\
\text{Update sample control points from} \ \text{New}x_{\text{model}}, \ \text{New}y_{\text{model}} \text{with similarity} \\
s\text{compositional pose correction} \rightarrow (x_k, y_k) \\
\text{Evaluate Error} \ E_k = \partial g_x, \partial g_y \text{if} \\
\text{if} \ E_k < E_0 \text{then} \\
\text{Accept model parameters,} \ \text{New} p_k \\
\text{Accept control points} \ (x,y) = (x_k, y_k) \\
\text{else} \\
\text{Try} \ a = 1, \ a = 0.5, \ a = 0.25, \ a = 0.125 \\
\text{end if} \\
\text{Iteration} = \text{Iteration} + 1 \\
\text{end while}
\]
In this paper, JSI was applied to calculate the error metric of detected wrinkle lines by calculating the similarity between manually labeled and detected wrinkle lines. An expansion of 20 points is applied to the assumed line when calculating the JSI. The Jaccard index:

$$J(A, B) = \frac{|A \cap B|}{|A \cup B|}$$  \hspace{1cm} (4.1)$$

where $A$ the number of pixels on manually labeled wrinkle line, and $B$ the number of pixels on detected wrinkle line. To validate the accuracy of the similarity between ground truth and the detected shape is defined as:

$$\text{Accuracy} = \frac{\sum_{i=1}^{N} J_{\text{output}}}{N}, J_{\text{output}} = \begin{cases} \text{True} & \text{if } J_{\text{output}} > 80\% \\ \text{False} & \text{else} \end{cases}$$  \hspace{1cm} (4.2)$$

where $N$ is the total number of images 100, and $J$ is output from Equation (4.1). If A ground truth and B output shape alignment, more than 80% decided as correct detection.
FIGURE 3 Illustration FACES dataset with different facial expressions [Colour figure can be viewed at wileyonlinelibrary.com]

FIGURE 4 The 88 landmarks. 68 landmarks express face features illustrate as red points, and 20 landmarks illustrated as green line express nasolabial wrinkle positions [Colour figure can be viewed at wileyonlinelibrary.com]
Table 2 illustrates the JSI statistics between ASM, AAM, and the proposed method. Overall, the accuracy of the proposed method got better results than the other two algorithms. Thus, the proposed algorithm illustrated that it was prone to localize wrinkle curves near the mouth tip and can be trained with the small dataset.
5 | DISCUSSION AND CONCLUSION

The structure of wrinkles varies greatly in width, length, and pattern in different images, making it difficult to develop automatic wrinkle detection. Related works on the area of wrinkle line detection are mainly focused on detecting forehead and another part of the face based on filter and operators. Therefore, an efficient active appearance model has been proposed. This method is based on effective active appearance nasolabial wrinkle detection model, which apply the unique initial shape based on the wrinkle line structure.

In our study, was introduced the effectiveness of changing the structure of AAM and successfully applied in wrinkle line localizing. Although competitive results are achieved by the proposed wrinkle detection method, in the future, we planned to pay attention to skin texture information that can be used to achieve to create a wrinkle mapping model. In addition to wrinkle line structure, the effects of variation of color, face alignment, and illumination shall be studied in the future works.

ACKNOWLEDGEMENTS

This research was supported by the Bio & Medical Technology Development Program of The National Research Foundation (NRF) funded by the Ministry of Science & ICT (2017M3A9E207268921).

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REFERENCES

1. Batool N, Chellappa R. Detection and inpainting of facial wrinkles using texture orientation fields and Markov random field modeling. *IEEE Trans Image Process*. 2014;23(9):3773-3788.
2. Scherbaum K, Ritschel T, Hullin M, Thormahlen T, Blanz V, Seidel MH. Computer-suggested facial makeup. *Comput Graph Forum*. 2011;30(2):485-492.
3. Mizukoshi K, Takahashi K. Analysis of the skin surface and inner structure around pores on the face. *Skin Res Technol*. 2014;20(1):23-29.
4. Azazi SL, Lutfi IV, Fernández-Martínez F. Towards a robust affect recognition: automatic facial expression recognition in 3D faces. *Expert Syst Appl*. 2015;42(6):3056-3066.
5. Huang Y, Li Y, Fan N. Robust symbolic dual-view facial expression recognition with skin wrinkles: Local versus global approach. *IEEE Trans. Multimedia*. 2010;12(6):536-543.
6. Okada HC, Alleyne B, Varghese K, Kinder K, Guyuron B. Facial changes caused by smoking: a comparison between smoking and nonsmoking identical twins. *Plast Reconstr Surg*. 2013;132:1085-1092.
7. Osman OFE, Elbashir RMI, Abass IE, Kendrick C, Goyal M, Yap MH. Automated assessment of facial wrinkling: a case study on the effect of smoking. 2017 IEEE international conference on systems, man, and cybernetics (SMC). Banff, AB, Canada. 2017.
8. Batool N, Chellappa R. Fast detection of facial wrinkles based on Gabor features using image morphology and geometric constraints. *Pattern Recogn*. 2015;48:642-658.
9. Ng ChCh, Yap MH, Costen N, Li B. Wrinkle detection using hessian line tracking. *IEEE Access*. 2015;3:10179-11088.
10. Rangan J, Datta D, Saha R. Age estimation from face image using wrinkle features. *Procedia Comput Sci*. 2015;46:1754-1761.
11. Ng C-C, Yap MH, Costen N, Li B. An investigation on local wrinkle-based extractor of age estimation, in Proc. 9th Int. Joint Conf. Comput. Vis., Imag. Comput. Graph. Theory Appl., 2014;1:675-681.
12. Batool N, Chellappa R. Modeling and detection of wrinkles in aging human faces using marked point processes, in Proc. 12th Int. Conf. Comput. Vis., 2012:178-188.
13. Batool N, Chellappa R. Fast detection of facial wrinkles based on Gabor features using image morphology and geometric constraints. *Pattern Recog*. 2015;48(3):642-658.
14. Cula GO, Bargo PR, Nkengne A, Kollias N. Assessing facial wrinkles: Automatic detection and quantification. *Skin Res Technol*. 2013;19(1):e243-e251.
15. Tsalakanidou F, Malassiotis S. Real – time 2D+3D facial action and expression recognition. *Pattern Recog*. 2010;43:1763-1775.
16. Huang Y, Li Y, Fan N. Robust symbolic dual-view facial expression recognition with skin wrinkles: local versus global approach. *IEEE Trans Multimedia*. 2010;12:536-543.
17. Flusser J, Faroksi S, Hosch C, Suk T. Recognition of images degraded by gaussian blur. *IEEE Trans Image Process*. 2016;25:790-806.
18. Zhu Y, Huang CH. An adaptive histogram equalization algorithm on the image gray mapping, *Sci Direct*. 2012;25:601-608.
19. Cootes TF, Edwards GJ, Taylor CJ. Active appearance model – their training and application. *Pattern Recogn*.
20. Holland AC, Ebner NC, Lin T, Larkin RS. Emotion identification across adulthood using the dynamic FACES database of emotional expressions in younger, middle aged, and older adults. *Cogn Emot*. 2018;33:245-257.
21. Sagonas C, Antonakos E, Tzimiropoulos G, Zafeiriou S, Pantic M. 300 faces in-the-wild challenge: the first facial landmark localization challenge, 2013 IEEE international conference on computer vision workshops. Sydney, NSW, Australia. 2013.
22. Sagonas CH, Tzimiropoulos G, Zaferiou S, Pantic M. 300 faces in-the-wild challenge: the first facial landmark localization challenge, 2013 IEEE Conference on Computer Vision and Pattern Recognition Workshops. Portland, OR, USA. 2013.
23. Sagonas CH, Tzimiropoulos G, Zaferiou S, Pantic M. A semi-automatic methodology for facial landmark annotation, 2013 IEEE Conference on Computer Vision and Pattern Recognition Workshops. Portland, OR, USA. 2013.
24. Real R. Tables of significant values of Jaccard’s index of similarity. *Miscel Lania Zoologica*. 1999;22:29-40.
25. Cootes TF, Taylor CJ, Cooper DH, Graham J. Active shape model – their training and application. *Comput Vis Image Underst*. 1995;61:38-59.

How to cite this article: Sabina U, Whangbo TK. Edge-based effective active appearance model for real-time wrinkle detection. *Skin Res Technol*. 2021;27:444–452. https://doi.org/10.1111/srt.12977