Facial features extraction using active shape model and constrained local model: a comprehensive analysis study

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ABSTRACT

Human facial feature extraction plays a critical role in various applications, including biorobotics, polygraph testing, and driver fatigue monitoring. However, many existing algorithms rely on end-to-end models that construct complex classifiers directly from face images, leading to poor interpretability. Additionally, these models often fail to capture dynamic information effectively due to insufficient consideration of respondents' personal characteristics. To address these limitations, this paper evaluates two prominent approaches: the constrained local model (CLM), which accurately extracts facial features depending on patch experts, and the active shape model (ASM), designed to simultaneously extract the appearance and shape of an object. We assess the performance of these models on the MORPH dataset using point to point error as evaluation metrics. Our experimental results demonstrate that the CLM achieves higher accuracy, while the ASM exhibits better efficiency. These findings provide valuable insights for selecting the appropriate model based on specific application requirements.

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1. INTRODUCTION

A face feature is defined as the recognition of specific facial characteristic points [1]. Kumar *et al.* [2] characterize the facial feature as anchor points also known as facial features have a big impact on further analysis and are crucial for precise face registration. The points show the essential information required to categorize an individual through the creation of a model [3]. The model's predetermined number of landmark points is determined by the object's design complexity and desired level of detail. Other terms for face landmarks in the literature include facial points of characteristic, points of anchor, identical points, and significant points [4].

Oh *et al.* [5] computed local random features directly using partial facial image matrices. Reduced face data from the architectural representation of the original facial shot, both horizontally, and vertically, is a vital component of the random characteristics that were recovered. A cancellable face template is then created by adjusting and averaging the recovered features at the feature level in each direction. Many approaches consider the general shape formed by the collection of facial feature points as well as the picture of the face. These techniques employ pre-existing knowledge (from labeled training photographs) on the face position and restrict the landmark search using heuristic criteria like as areas, angles, and distances. Consequently, the techniques give an unnamed face the appropriate shape [6]. Examples of such techniques are active shape model (ASM) [7], active appearance model (AAM) [8], and constrained local models (CLM) [9]. Srivastava *et al.* [10] creates a feature extraction technique with a simple Gabor filter and the discrete cosine transform (DCT). Prior to the transition, the images were first reduced using an image optimizer and then transformed using the Gabor filter. Sivakavi and Minu [11] illustrated deep learning techniques for eliciting facial traits using convolutional neural network (CNN). Unlike earlier CNN-based models, they made use of characteristic maps obtained in several layers.

Many methods have recently been presented to extract face points or features from the photos in order to enhance feature extraction [12]. Tan *et al.* [13] insufficient repair method to correct their misaligned faces. In place of a straightforward regression using the center of those characteristics in form space, the reconstruction concept for shape augment is offered. Additionally, the local appearance is regressively dependent by specific deep qualities known as those form rise in a position of paired throughout entire investigation [14]. Depending on the information source used to support the methodology, facial landmark recognition techniques can be classified as either model-based or non-model-based [15].

Model-based technique: this method views the grouping of points related to facial characteristics as a whole form and takes into account the picture of the faceNext, it attempts to fit a face that isn't known to it with the right form [16]. The ASM, AAM, and CLM are a few instances of these methods. Non-model-based technique: without the use of a model, this method seeks to independently identify each face feature or small clusters of landmarks [17].

The ASM is a statistical depiction of the shape of an item composed of a collection of predefined points. The ASM was initially presented in [7], the forms are controlled using a point distribution model (PDM). To model and limit the variance of the points that comprise the template, statistical analysis is employed. The eigenvectors describing the variance in the models for each face are then extracted using the average template and principal component analysis (PCA). The constraints of ASM [18] are as follows, the findings struggled to match an image's bounds because of the parametric definition of shapes. It was not very good at processing new photos. As a result, issues arose during the picture analysis [19]. A lot of landmark points and training tests are required for the model to represent shape and its variations, which increases the cost and duration of the training process. The local scan area surrounding landmarks determines the model division's outcomes.

CLM [9] is the methodology for detecting and aligning features that fuses the advantages of a local appearance model with a statistical shape model for precisely locating object landmarks, as it is highly employed in the application of facial landmark detection and shape fitting. The following are the limitations of CLM [20], landmark position estimation requires an initial estimate in CLM; hence, poor convergence, affecting alignments, might result if this initial estimate is poor. Poor initial guesses far from the true locations may never arrive at the correct solution [21]. Limited robustness to occlusions, CLM relies on the response of local features. Partial occlusions, like hands occluding parts of the face or sunglasses occluding the eyes, can destroy its performance. If some of the landmarks are invisible, the model does not perform well, especially when large portions of the object are invisible [22]. Local patch quality dependence, local appearance models employed in CLM, like scale-invariant feature transform (SIFT), histogram of oriented gradients (HOG), or local binary patterns (LBP), work great in controlled scenarios, but under significant lighting variations, facial expressions, or non-frontal poses, their performances decrease. This results in feature extraction that leads to misalignment. The following succinctly describes our primary contribution. We compare two new ordinal models that are often used, CLM and ASM, which are able to model the ordinal landmarks of various face hierarchical levels. Using real-use case MORPH datasets, we evaluate the two model methods' efficacy and accuracy.

The remainder of the research is organized as follows: section 2 describes the steps involved in the suggested technique. Section 3 displays the findings and discussions. Section 4 concludes the suggested model.

2. METHOD

This section contains a discussion of the methodology and approaches employed in this work. The CLM technique is explained in section 2.1. Section 2.2 discusses the ASM model, and section 2.3 displays the database that was used.

2.1. Constraint local model

Since our method uses the CLM [9] structure, as Figure 1 shows, it is investigated in depth as follows. The three main components of CLM are the PDM, patch expert, and fitting procedure. Patch experts can be employed to model the appearance of neighborhood patches surrounding troublesome monuments. The non-uniform regularized landmark mean shift (NU-RLMS) approach is the appropriate one for CLM. In (1) illustrates how to apply a suitable method to the labeled samples of these models to get the stiff and non-rigid parameters (p) that best fit the underlying picture.

$$P^* = \log \min_{P}[\mathcal{R}(P) + \textstyle\sum_{i=1}^{n} D_i(x_i, \mathrm{I})] \quad (1)$$

Where R is the regularization expression that penalizes too complex or unrealistic forms, and D is the measure of the misalignment the i^{th} point of interest is experiencing toward the xi area in picture I, the region of the i^{th} feature, $x_i=[x_i, y_i, z_i]$ T (the i^{th} feature's area) is controlled toward the parameters P.

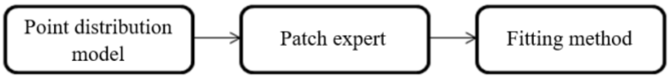

Figure 1. Flow chart of CLM model

2.1.1. Point distribution model

PDM [5] are employed for both managing the landmark regions and regularizing the form to the convolutional experts constrained local model (CE-CLM) schema. The word $\mathcal{R}(P)$ is used in (1) to punish surprising designs that become into famous monuments. The landmark areas $x_i=[x_i, y_i]$ T are parameterized using p=[s, t, w, q] in the PDM (2).

$$x_i = s.R_{2D}.(\overline{x_i} + \Phi_i q) + t \quad (2)$$

$\overline{x_i}$ in this case $[\overline{x_i}, \overline{y_i}, \overline{z_i}]^T$ is the i^{th} feature's average quality feature; Φ_i is the three-by-m primary component matrix; and q is the m-dimensional vector obtained from the non-rigid form's regulating parameters. Six scalars can be used to parameterize the rigid form parameters: the scaling term, orientation: $w=[w_x, w_y, w_z]^T$. s, and $t=[t_x, t_y]^T$. Rotation parameters w regulate the rotation grid R_{2D}, which begins with two rows of a 3×3 rotation grid R since it is easier to linearize. Moreover, it would enter axis-angle form. The whole form might be represented by p=[s, t, w, q].

2.1.2. Patch experts

Patch specialists, also known as local detectors, are crucial parts of the CLM. They evaluate the probability of a feature point being moved to a specific pixel area. The response from the i^{th} patch expert π_{xi} at the image point x_i is described as (3). Taking into account the supporting district circumstances:

$$\pi_i = C_i(x_i; I) \quad (3)$$

Where C_i is the regressor result for the i^{th} feature. Next, a regressor with values ranging from 0 (no alignment) to 1 (perfect alignment) may be used to indicate the misalignment. Patch experts have developed a number of novel strategies, such as logistic regressors and support vector regression (SVR) models, or extremely basic format matching algorithms. An illustration of a patch expert response map is provided in Figure 2. Patch experts SVR is utilized in this study.

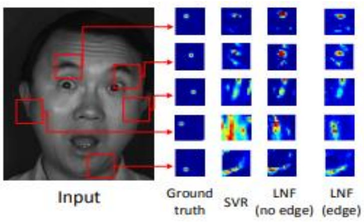

Figure 2. A patch expert response map

In Figure 2, the ideal answer is displayed above the ground truth column. The term "typical patch expert" SVR [23] describes the person used by CLM procedures. We give two instances of the constrained local neural fields (CLNF) model: one in which the spatial qualities (gk and lk) are stopped being provided, and another in which they are not.

2.2. Active shape model

First, the ASM is trained using a collection of manually landmarked images. Manually landmarking an image means that the system developer must manually place key points on each image to define the shape of interest. These landmarks help the model learn shape variations, allowing it to accurately detect and adjust to similar structures in new images.

2.2.1. Shape model

The common application of the PCA concerning the forms of the object might provide the shape model, also known as the PDM. This makes it clearer how the shape S may be described using a basic shape S_0 plus a linear combination of k shape vectors [10]. The process for the shape modeling of the photos is shown in Algorithm 1.

Algorithm 1. Shape model for images
Input: database D. The base shape S_0. Number of images N
Output: labelled shape (S_1, S_2, …, S_N)
Begin
    // Main iteration loop
    for t=1 to N
    // For each parameter
        for j=1 to P parameters
        Select 80 from D
        $S(P) = S_0 + \sum_{i=1}^{k} p_i S_i$
        end for
    end for
End

In Algorithm 1, p=(pk, p1, p2, ...)^T will be the shape parameter. The S_0 and the k [10] are determined from the training shapes using T. (PCA). The shape vectors [10] are the k eigenvectors connecting the k largest eigenvalues {λi}, and the base shape S_0 is the mean shape. A set of parameters of a deformable model is characterized by the shape parameter, p. To vary the components around p, we can modify the shape S(p). The disparity between the i-th. For λi, parameter pi may be given crosswise across the training group. In order to ensure that the shapes generated are comparable to each person's training set, the following constraint is placed on p_i as in (4).

$$|p_i| \leq 3\sqrt{\lambda_i} \tag{4}$$

The synthetic form is kept from warping by this farthest point.

2.2.2. Appearance model

Iterative search methods are used in the process. Every iteration of the process examines a portion of the image surrounding each point of interest with the intention of uprooting it to a desired location. The process for the appearance modeling of the photos is outlined in the Algorithm 2 that is discussed.

Algorithm 2. Appearance model for images
Input: database D. The landmarks number I. Number of images J
Output: labelled appearance (S_1,S_2,….,S_N)
Begin
    // Main iteration loop
    for j=1 to N
    // For each landmark
        for i=1 to I landmark
        Select j from D
            // Mean normalized derivative profile
            $\overline{g_i} = \frac{1}{N}\sum_{J=1}^{N} g_{ij}$
            //Covariance matrix
            $S_{gi} = \frac{1}{N-1}\sum_{J=1}^{N}(g_{ij} - \overline{g_i})\,(g_{ij} - \overline{g_i})^T$
        end for
    end for
End

2.3. Dataset: MORPH database

This dataset consists of 600 face pictures in datasets, each confirmed with 68 landmark points. The information set experiments were analyzed, the point relocation precision was calculated, and the processing time and texture correspondence were assessed. The training set consisted of 400 images, while the testing set included 200 images from the MORPH database [24].

3. RESULTS AND DISCUSSION

The performance measurements are used to choose the best facial feature extraction model based on the results. The precision of the fitting is evaluated using the point-to-point error. Based on the discrepancy between the estimated landmarks and the hand labels, in (5) generates the point-to-point error.

$$E(S,\grave{S}) = \frac{1}{n}\sum_{i=1}^{n}\sqrt{(x_i - \grave{x}_i)^2 + (y_i - \grave{y}_i)^2} \quad (5)$$

Where S is the expected shape and $\grave{S}$ is the actual form. A successful fitting is defined as one where the point-to-point error is less than three pixels. Table 1 shows the average point-to-point inaccuracy of the AAM and CLM models in locating 68 landmarks out of 200 test images taken from the MORPH collection. The result shows that the lowest error rate was produced by the CLM.

Table 1. Analysis of the average point-to-point error and average detection time of ASM and CLM

Model	Point-to-point error	Avg. time (seconds)	No. of test samples
CLM	2.6607	365.67998	200
ASM	2.9574	231.35789	200

Figure 3 shows the point-to-point errors of the models' landmark identification performance in pictures from the MORPH database. Point-to-point is defined as the difference between the model's points and the similar points depicted in the images. The average time for ASM and CLM to identify landmarks from 200 photos in the MORPH database is shown in Table 1. The amount of time it takes the model to identify a face and fit it using its characteristics is called the average detection time. The outcome is presented in relation to the ASM and CLM models, two distinct models. The findings indicate that ASM is less efficient than CLM.

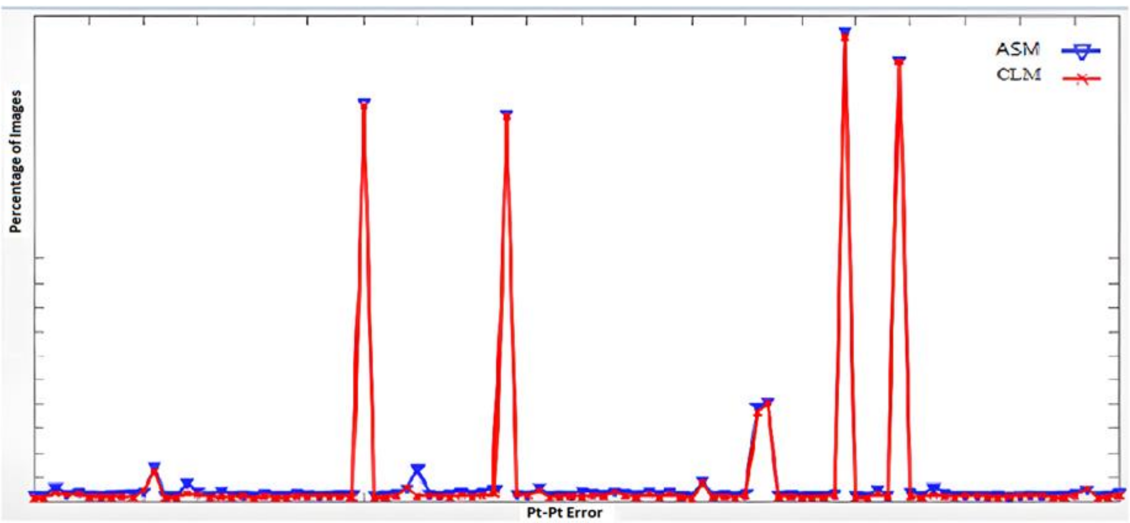

Figure 3. Point-to-point error for both ASM and CLM

3.1. Comparison with current work

Table 2 presents a comparison of the CLM and ASM model for feature extraction with the current research. It shows the comparison results based on point-to-point inaccuracy among the ASM and CLM models, as well as several state-of-the-art feature extraction approaches. As illustrated in Figure 4, the results confirm the effectiveness of the ASM and CLM models.

Table 2. Comparing the proposed models with current research

Method	Database	Point-to-point error
End-to-end deep model [24]	FER2013	3.8
FER [25]	FACES	5.87
Deep learning model [26]	MobileNetV2	8.00
Dynamic attention-controlled cascaded shape regression (DAC-CSR) [27]	AFLW	2.27
ASM	MORPH	2.95
CLM	MORPH	2.66

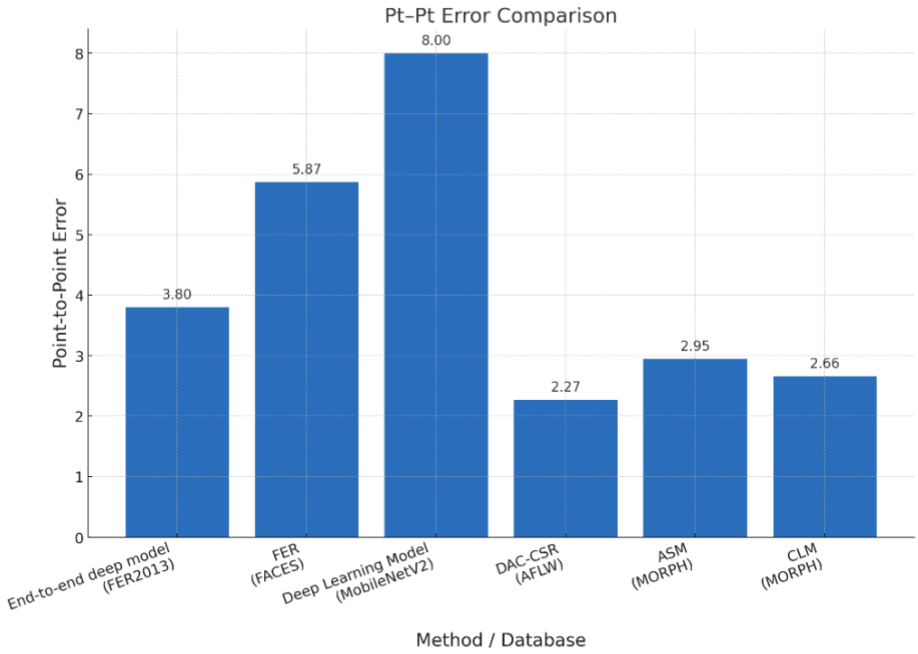

Figure 4. Comparison between current researches and ASM, CLM models

3.2. Limitations and potential failure scenarios

Although this work's proposed facial landmark detection approach is obviously effective, there are still several problems and limitations that require more research. To increase forecast accuracy, these models may use sophisticated or hybrid classification and regression techniques. Several possible failure situations might affect the models' applicability in tasks like object tracking, facial expression identification, or other relevant applications:

– Limited generalization to unfamiliar faces: the proposed model could perform worse on unfamiliar faces if it was developed using a dataset that lacks changes in age, ethnicity, lighting, or facial expressions.
– Occlusion and partial faces: if a face is partially obscured (for example, by hands, hats, glasses, or masks), the proposed model may have problems.
– Differences in lighting and head position: the proposed model may encounter issues due to notable differences in illumination or abrupt head angles.

4. CONCLUSION

This study compares ASM and CLM, two sophisticated algorithms for automated landmark recognition on a set of dense face landmarks. The effectiveness of each algorithm is evaluated in terms of actual mistakes in landmark detection. One of the key benefits of the CLM approach is its low mistake rate. Future assessments will determine how well these registration techniques perform in the presence of noise and occlusions. This study finds that CLM algorithms outperform other methods for autonomous landmarking on a dense landmarking scheme in terms of model training time, accuracy, and landmark identification, based on the tests conducted. This research may be extended to include gender recognition, face expression analysis, head posture estimation, and gaze estimation. Additionally, using a variety of datasets to test the suggested model can improve prediction accuracy by utilizing hybrid regression and classification methods.

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AUTHOR CONTRIBUTIONS STATEMENT
This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration. The authors confirm their contribution to the paper as follows:

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Musab Iqtait	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Marwan Harb Alqaryouti		✓				✓		✓	✓	✓	✓	✓		
Ala Eddin Sadeq	✓		✓	✓			✓			✓	✓		✓	✓
Suhaila Abuowaida	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	
Abedalhakeem Issa					✓		✓			✓		✓		✓
Sattam Almatarneh	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓			

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT
Authors state no conflict of interest.

INFORMED CONSENT
We have obtained informed consent from all individuals included in this study.

DATA AVAILABILITY
The data that support the findings of this study are openly available in the MORPH Database, a publicly accessible resource for facial aging research.

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