An Improved Statistical Model of Appearance under Partial Occlusion

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Abstract: *The Appearance Models (AMs) are widely used in many applications related to face recognition, expression analysis and computer vision. Despite its popularity, the AMs are not much more accurate due to partial occlusion. Therefore, the authors have developed Robust Normalization Inverse Compositional Image Alignment (RNICIA) algorithm to solve partial occlusion problem. However, the RNICIA algorithm is not efficient due to high complexity and un-effective due to poor selection of Robust Error Function and scale parameter that depends on a particular training dataset. In this paper, an Improved Statistical Model of Appearance (ISMA) method is proposed by integration techniques of perceptual-oriented uniform Color Appearance Model (CAM) and Jensen-Shannon Divergence (JSD) to overcome these limitations. To reduce iteration steps which decrease computational complexity, the distribution of probability of each occluded and un-occluded image regions is measured. The ISMA method is tested by using convergence measure on 600 facial images by varying degree of occlusion from 10% to 50%. The experimental results indicate that the ISMA method is achieved more than 95% convergence compared to RNICIA algorithm thus the performance of appearance models have significantly improved in terms of partial occlusion.*

Keywords: *Computer vision, appearance model, partial occlusion, robust error functions, CIECAM02 appearance model.*

Received September 28, 2014; accepted March 2, 2015

1. Introduction

The Appearance Models (AMs) or Active Appearance Models (AAMs) [8] are built on a statistical approach to learn the shape and texture of the face varying across a range of images. In the Active Appearance (AM) framework, the model is constructed using automatic and semi-automatic landmark points on the input image and training set. These landmark points highlight the outline of the cutting-edge, such as the inside and outside of the eyes, mouth, and nose so on. The great significance of AMs is that these models are widely used in 2D or 3D Face Recognition, Expression Analysis, Computer Vision and Medical Imaging [5, 9, 10, 11, 12]. To achieve rapid and accurate matching of this model, they need an efficient fitting algorithm. By using this fitting algorithm, the error between instance of model and the real image is minimized so it is a non-linear problem. When there are other occluded objects in images then it will degrade the quality of model fitting. It is important to detect occlusion or measuring the robustness of model fitting to image.

In recent years, some researches were dedicated to investigate effective fitting algorithms. In the start, Edwards *et al*. [8] treated fitting algorithm as a least squares optimization problem, which is obviously sensitive to partial occlusion. After this, the Lucas-Kanade and the Inverse Compositional Alignment (ICA) algorithms attempt to minimize by gradient descent and assume that:

1) No occlusion
2) No pixel in background contains template image
3) The brightness constancy.

The robust ICA algorithm has solved these assumptions but it is not efficient due to define error mask and scale parameter still depends on training dataset. Later on Baker *et al*. [4] proposed many extensions to ICA algorithm. In fact, all the extensions are not effective due to partial occlusion, which can cause the AM fitting algorithm to fully divergence. Afterwards Gross *et al*. [12] has proposed efficient extensions to the AM fitting algorithm (robust inverse compositional).They have tested their extensions to the AM fitting algorithm in terms of synthetic occlusion with single subject dataset and assumed that all vertices are not marked in case of occlusion in every training images and this is not the case in real-life situations because it is very hard to determine the type of occluded image regions. This extension is very good on a single subject dataset like video frames because it is easy to choose robust error function to determine occlusion 40% because the distribution of outliers in images can differentiate by using previously see frames.

Theobald [20]was further proposed error measures to accommodate partial occlusion. He showed that if you know un-occluded data then one can use Gaussian distribution at each pixel to measure both occluded and un-occluded regions. He has expected that E7 [20] robust error function perform very well in case of known good data. However this technique is also un-effective because a scale parameter is required and the AM model is built on single subject, which restricts its applicability for general applications.

The same strategy was also adapted to a statistical framework by Yu *et al*. [23]. They have developed a model based on statistical Gaussian approach and Maximum A-Posteriori (MAP) algorithm to make the adaptive AM fitting algorithm with occlusion. They have tested their robust fitting algorithm in synthetic occlusions, which may not be a real case. Motivated by the robust AMs fitting algorithm with occlusion on single subject video sequences, Bagnato *et al*. [3] proposed stochastic approach to combine several dynamic models to account different occlusion. But due to adding additional model parameters and for detection of re-initialization in case of occlusion make it slow in some situations.

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After the modification of original ICA fitting algorithm, George Papandreou *et al.* [16] have done improvement to this model based on multi-subject images. But they did not consider the AM robust fitting strategy to detect occlusions. In contrast, Storer *et al*. [19] developed a different strategy to detect occlusion by using fast robust principle component analysis. This approach is working fine for larger datasets but the efficiency of AM fitting algorithm is decreased due to reconstruction strategy. As a result, the partial occlusion [2] is very challenging tasks for every detection process using appearance models even though many authors have recently proposed different variations [6, 7, 13, 14, 21, 22] to this model. According to literature review, the authors have done lots of extension to inverse compositional algorithm in terms of robustness or occlusion detection. But the Robust Normalized Inverse Compositional Image Alignment (RNICIA) [12] algorithm is the best model fitting algorithm for synthetic occlusion in terms of speed and accuracy. But due to poor selection of Robust Error function and hard to determine scale parameter makes it is still depends on training data on single subject human faces.

To solve above mentioned problems, an Improved Statistical Model of Appearance (ISMA) under Partial Occlusion is proposed by integrating the techniques of perceptual-oriented CIECAM02 color space [11] and Jensen-Shannon Divergence (JSD). This ISMA method is developed based on RNICIA fitting algorithm [12, 20], which is further enhanced in terms of computational speed and accurately detection of occlusions both on testing and training multi-subject datasets. By using perceptual-oriented CIECAM02 color appearance model and JSD measure, the distribution probability of each occluded and un-occluded image regions are calculated.

In practice, the JSD statistical measure is developed by making an extension to Kullback-Leibler Divergence (KLD) [24]. In this study, the JSD measure is utilized because it has capability to measure the average pixels divergence. The experiments are performed on 600 2-dimensional images which are obtained from two [15, 17] online sources. To compare the performance between RNICIA and Improved Statistical Model of Appearance (ISAM) method, the convergence is measured by varying 10% to 50% occlusions.

The remainder of this paper is organized as follow. In section 2, a short description is presented about previous related work. In section 3, enhance ISMA algorithm by using RNICIA method is developed. The experiments and comparisons between ISMA and RNICIA methods can be found in section 4 on the AR face and IMM face databases which show the effectiveness of the proposed method. Conclusions and future works are presented in section 5.

2. Related Works

2.1. Appearance Models

The Appearance Model (AM) is a statistical model, which is build based on shape and appearance (texture) features. For this AM, the model fitting and training are two important steps. For AM model training, the PCA technique is utilized by using shape and appearance features from facial images. But for fitting AM model, the iterative improvement process is adopted, which is sequentially changes the model parameters by using update function. The robust extension to the AM model fitting is to detect occlusions and next section shows how to construct the robust AM model.

2.2. Model Construction

The manual 56 landmark points of shape information (2D vertices) are normalized to deal with global geometric transformations such as scale and rotation sing the procrustes analysis [18]. In case of occlusion, all vertices are assumed to visible in the training data set to differentiate with the approach [12] in which only a subset of the vertices may be visible in any given training image that may leads toward complex handling of Procrustes algorithm with occlusion for label data. In the following, the normalized Shape (s) and the appearance model can be expressed as Equations 1 and 2.

$$s = s_0 + \sum_{i}^{n} p_i s_i \tag{1}$$

and

$$A(x) = A_0(x) + \sum_{i=1}^{m} \lambda_i A_i(x) \forall x \in s_0 \tag{2}$$

2.3. Model Fitting with Occlusion

The central issue with AM is designing the fitting algorithm that minimizes Equation 3. To minimize this Equation 3, first RNICIA algorithm [12] is introduced, which has the same complexity as Lucase and Kanade algorithm but is much more robust in terms of occlusion.

$$Eq(x) = \sum_{x \in s_0} [A(x) - I(w(x;p))]^2 \tag{3}$$

2.4. Model Fitting with RNICIA Algorithm

A robust error function may be used with scale parameter to minimize Equation 3 which shows the effect of outliers or occluded pixels in image regions. This is particularly important to build a robust fitting model to minimize this equation: Eq(x).

$$E_x = \sum_{x \in s_0} [\varepsilon\{A_0(x) + \sum_{i=1}^{m} \lambda_i A_i(x) - I(w(x;p))\}^2; \sigma] \tag{4}$$

Where $\varepsilon(...;\sigma)$ is a symmetric robust error function [15] and is a scale parameter which is a known constant. Let us denote robust error function which can be selected from literature [20] (Probability density function assumes the distribution of the residual at each pixel is Gaussian is best robust error function among them see Equation 5 and drop scale parameter which is known constant. In practice, one approach is that the estimate of σ parameter can be derived from the median of the absolute residuals from Gaussian distribution from Equation 5. This has been claimed to have excellent resistance towards outliers, tolerating almost 50% of them as given by Equation 5.

$$\delta(E_x) = (\sigma_x \sqrt{2\pi}.e^{[\frac{|E_x|}{2\sigma^2 x}]})^{-1}, \sigma = 1.4 \times med(E_x) \tag{5}$$

And the error image can be calculated as:

$$E_x = A_0(x) + \sum_{i=1}^{m} \lambda_i A_i(x) - I(w(x;p)) \tag{6}$$

Then error image in the direction of A_i is 0, while computing λ_i at the same times that minimize this equation as:

$$\sum_{x} \varepsilon(E_x)^2 [E_x + \sum_{i=1}^{m} \Delta\lambda_i A_i(x)]^2 \tag{7}$$

The least squares minimum of this expression is:

$$\Delta\lambda = -H_A^{-1} \sum_{x} \varepsilon'(E_x)^2 A^T(x) E(x) \tag{8}$$

Where

$$H_A = \sum_{x} \varepsilon'(E_x)^2 A^T(x) E(x) \tag{9}$$

The steepest descent parameter updates are computed using:

$$\Delta p = -H_p^{-1} \sum_{x \in s_0} \varepsilon'(E_x)^2 [\nabla A_0(x) \partial w / \partial p] E_x \tag{10}$$

Where $\nabla A_0(x)$ is the gradient and $\partial w / \partial p$ is the Jacobian of the warp [22].Then the Hessian H_p is computed as follows:

$$H_p = \sum_{x \in s_0} \varepsilon'(E_x)^2 SD_{IC}^T(x) SD_{IC}(x) \tag{11}$$

Where

$$SD_{IC}(x) = [\nabla A_0(x) \partial w / \partial p] \tag{12}$$

After that Hessian is divided into two parts as:

$$H = H_A + \sum_{i=1}^{k} \varepsilon'.H_p^i \tag{13}$$

If we assume that outliers are spatially coherent then to make these assumptions true, A_0 should be subdivided into set of triangles (T_i) of the base mesh S_0 so the Equation 11 can be re-written as:

$$H_p = \sum_{x \in s_0} \varepsilon'(E_x)^2 \sum_{x \in T_i} SD_{IC}^T(x) SD_{IC}(x) \tag{14}$$

Assume that $\varepsilon'(E_x)^2$ is constant in each triangle; e.g., say, $\varepsilon'(E_x)^2 = \varepsilon_i'$ for all $x \in T_i$ .If ε_i' is constant for each triangle then it can be estimated from $\varepsilon'(E_x)^2$. For example, by setting mean value computed over the triangles see Equation 15 and for further detail refers to [16].

$$\varepsilon_i' = \frac{1}{N} \sum_{x \in T_i} \varepsilon'(E_x)^2 \tag{15}$$

Now in General H_A and H_p for each T can be pre-computed:

$$H_p^i = \sum_{x \in T_i} SD_{IC}^T(x) SD_{IC}(x) \tag{16}$$

And

$$H_p^i = \sum_{x \in T_i} \varepsilon'(E_x)^2 A^T(x) A(x) \tag{17}$$

The Equation 11 for triangle T_i can be simplified as:

$$H_p = \sum_{i=1}^{k} \varepsilon'(H_p)^2 \tag{18}$$

Note that this Hessian does vary from iteration to iteration but the cost of computing is negligible [16] for real time video tracking, the efficiency of RNICIA would run at 48.8 frames per second. This efficiency can be increased as has been suggested by Shum and SZelsiki who use spatial coherence of Hessian itself (rather than robust weighting function). In this approach, the Hessian is estimated from a single sample for each triangle using Equation 19 and it might leads to poorer convergence because it requires more iteration to the parameter estimation algorithm.

$$H_p = \sum_{x \in T_i} SD_{IC}^T(x) SD_{IC}(x) \tag{19}$$

3. Enhanced ISMA Model Fitting

The proposed ISMA method is based on the analysis of distribution of pixels across occluded and un-occluded regions present in both training data and input images. This approach can also work in synthetic or real type of occlusion with the different approach as presented in literature. In the training set, annotated landmark points on both AleixMartinez and RobertBenavente (AR) facesand Informatics and Mathematical Modelling (IMM) datasets [15, 17] are utilized. All RGB images in the training datasets are transferred into perceptual-oriented JCh (J: Luminance, C: Chroma and h: hue) color space, which is obtained from CIECAM02 appearance model. In the literature, many methods were transformed the RGB color image to other spaces such as HSV, HIS and CIEL*a*b*. However, these color spaces are non-uniform or provide approximate uniformity as compared to JCh uniform color space of CIECAM02 color appearance model. The CIECAM02 color appearance model provides JCh uniform color space and may be represented in Equation 20.The readers are advised to study ref. [1, 11] for detail help about CIECAM02 color appearance model.

First, JChcolor space is used to calculate JCh component of each triangle T in every image. For each color distribution in training data which does not have any occlusion, the JChcolor histogram is computed and the height of a bin in the histogram represents the maximum histograms values for the J, C and h components.

$$Input\ [RGB] \rightarrow M_{CAT02}[X \quad Y \quad Z] = JCh \tag{20}$$

Let us calculate color histogram of each triangle T and denote by H_{JCh} and compute mean color histogram denoted by H'_{JCh} for the "normal" color distribution of the specific color histogram that can be calculated by Equation 21:

$$H'_{JCh} = \frac{1}{N}\sum_{i=1}^{N} H_{JCh}{}^{i} \tag{21}$$

Then through mean histogram H'_{JCh}, its occlusion probability H^{Φ}_{JCh} is calculated by computing its deviation from the mean color histogram by JSD (Jensen-Shannon divergence) for this purpose as follows:

$$Jsd = \sum_{i=1}^{m} min(H^{\varphi}{}_{JChi}\, log(2H^{\varphi}{}_{JChi}) / (H^{\varphi}{}_{JChi} + H'_{JCh}) + M \tag{22}$$

Where $M = H'_{JCh}\, log(2H'_{JCh}) / (H^{\varphi}_{JCh_i} + H'_{JCh})$

This Jsd indicates the degree of apart from $H^{\phi}{}_{JCh}$ and H'_{JCh} these histograms have m bins. Therefore; the occlusion probability is measured as follows:

$$P = \begin{cases} K & if\ Jsd < T_{JCh} \\ K + Jsd & otherwise \end{cases} \tag{23}$$

Where K is constant and T_{JCh} is a threshold for local color JCh histogram which can be learned independent of the training and input datasets. If the triangular part of the image is occluded completely, then a zero value is assigned, if it is partial occluded then (*K*+*Jsd*) weighted value will assign that decreases its significance for model fitting, otherwise, if it is not occluded then assign one weighted value. Furthermore, this probabilistic factor is used to decide occluded regions in each region present in the training dataset and input image. So, this probability factor with error image is calculated to create robust weighted error function which is independent from the training data set. Now, further added a refine step as:

$$w(x) = 1/n \times \sum_{i=1}^{k} min(H_{JCh}{}^{1}(A(x), H_{JCh}{}^{2}) I(w(x;p))) \tag{24}$$

$$\varepsilon'(E(x)^2) = (1-p) \cap \omega(x) \tag{25}$$

Where *P* denotes the occlusion probability of the color histogram and can be calculated from equation (23) and *w*(*x*) denotes that how to compute a normalized similarity measure, based on the intersection [5] between two color histograms. To compute robust error function as a distance measure, first the inverse and intersection operations are converted using Equation 25. The estimation of this occlusion probability is the key step for the solution of occlusion. Apparently the distribution of the normal regions (without occlusion) of JChcolor scale is similar while the distribution of the occluded region of the JChcolor scale is different from the normal regions. To calculate HSV Histogram with JSD for input image and warp appearance model, the cost of computing is negligible. The pre-computations overhead cost is $O(n+n\log_2 n)$ added for calculation of color histogram JCh and JSD while the post-computation cost is for intersection of two histograms compares it with RNICIA[12, 20] which requires to determine median of N pixels. An improved ISMA algorithm is summarized next.

The algorithm enhanced RNICIA describe in Algorithm 1 is similar to the RNICIA fitting algorithm [5] of Raphl Gross *et al.* (2004) and details are presented in [20] but there are two main differences exist. Firstly, main difference is that our modified approach will restrict the degree of freedom in the model parameters, and increases the accuracy and speed of fitting. Secondly, it uses robust weights (JSD-JCh) that are being updated from image to image. Granted that this robust weighted function can be sufficiently improved the fitting performance and efficiency.

4. Experimental Results and Discussions

To motivate approach, the performance of ISMA method is computed against the RNICIA fitting algorithm in terms of synthetic and real occlusion. By the introduction of fastest and accurate robust weighting function, the computational efficiency of ISMA approach is shown in Table 1.

Table 1. The computation cost of basic aam model fitting and our enhanced model.

Method	Computational Efficiency Comparisons	
	Pre-computation	Post-computation
RNICIA	$O(n.N + n.n)$	$O((n^2 + m^2).k + (n+m)N + n^3)$
ISMA	$O(n.N + n + n.n)$	$O(n^2 + m + n + (n+m)N + n^3)$

The comparisons between these two methods were performed on total 600 facial images, which are obtained from two databases such as the IMM Face database and AR Face database.

Algorithm 1: An algorithm for improved statistical model of appearance to solve partial occlusion problem Pre-compute

1) *Evaluate the gradient of base appearance* $\nabla \mathrm{A}$ and $\nabla \mathrm{A}_i$
2) *Evaluate the Jacobian* $\partial w / \partial p$ *at* $(x;0)$
3) *Compute the steepest descent images using Equation 12.*
4) *Compute Hessian* H_p^i *for each triangle using Equation 16 and Compute appearance Hessian* H_i^i *using Equation 17.*
5) *Compute* H'_{JCh}, *Jsd and P for each triangle using proposed Equations 21, 22 and 23 respectively Iterate*
7) *Warp I with W(x;p) to compute I(W(x;p))*
8) *Compute the error image* $\Delta\alpha_1 = E_x$ *using Equation 6 and Compute Robust Error function* $\varepsilon'(E_x)^2$ *using Equation 25.*
9) *if ((iter> 0) and (abs*$(\Delta\alpha_1 - \Delta\alpha_2) > Jsd$*)) then Compute* $H_A = \sum_{i=1} \varepsilon'(i)(H_A^i)$
10) *Compute* $\Delta\lambda$ *and* λ *update and E(x) using Equation 8 End if*
11) *Compute the Hessian* H_p *and invert it using Equation 18*
12) *Compute* $\Delta\theta = \sum_x \varepsilon'(E_x)^2 \sum_{x \in T_i} (E_x)^2 SD_{IC}^T E_x$
13) *Compute* $\Delta p = -H_\varepsilon^1 \sum_x \varepsilon'(E_x)^2 SD_{IC}^T E_x$
14) *Update* $w(x;p) \leftarrow w(x;p) \circ w(x;\Delta p)$
15) $\Delta\alpha_2 = \Delta\alpha_1$ *and Iter = iter + 1, Until* Convergent

To test the effects of occlusion to ISMA algorithm, a number of experiments are performed on images taken from two online sources such as IMM and AR Face Databases. In total, 600 face images are used in training and testing process in which 260 images from IMM database and 360 face images from AR database. The 58 landmark points are fully manually labelled on both of the databases. By using random strategy, the regions are selected for artificial occlusion in the training stage. The other occlusion isalso added such as sun glasses and scarf. The occlusions are varied 10% and 50% degree on the testing images. Using occluded data in this way enables us to systematic training appearance models containing occlusion with different degrees and types. Also, in training stage, the JChcolor histogram is already stored that measure data for occluded probability and un-occluded regions data in ASF file by using the Equation 23 see the detail format of ASF file [9].

Initially, experiments were conducted by dividing the images into two groups, occluded and un-occluded face images. These two groups contain face images under varying illumination, different head pose, facial expression and occlusions. In first step, compute the JCh histogram of each triangular mash present in each image when the height of the bin of the histogram is determine by maximum J, C and h values. For making it normalizes, the range of (40*255) is defined to reduce to the size of histograms. Then the mean JChcolor histogram is calculated of un-occluded face images having fixed value N=470 of each face images. After that, how much the each occluded images from mean histogram deviate is defined by using JSD where m is equal to the height the bin in color histogram. Afterwards, the occlusion probability is measured to make divergence among histograms to make it final decision. Where for experiments, the value of *T*parameter is determined by calculating the maximum value of intensity of un-occluded images and *k* value is 1 which means no occlusion part detected , 0 means occlusion in the triangle part of the image and assign weighted value to decrease its significance for fitting algorithm which does not discuss in previous literature [12, 20, 23]. The final step is to now measure the similarity between input images and warp appearance model through histogram intersection.

For AM fitting on static images, the convergence rate is measured among consecutive iterations get less than 1 pixel. The performance is tested for both algorithms in the same person present in both testing and training data without occlusion in IMM face database. It has been observedfrom experiments that both algorithms perform well in case of artificial occlusion or without occlusion when 98% total appearance variations are retained. The fitting accuracy is measured based on 10 iterations to fit the model and in some steps the enhanced ISMA is faster than the RNICIA fitting algorithm.

The convergence is also measured by varying degree of occlusion from 10% to 50% using IMM and AR Face databases. In which some of the images having synthetic occlusion and others are having real occlusion. Then measure the convergence frequency, the convergent is plotted by counting the number of times each algorithm has converged. In total 600 images are consider for experiment. For measuring, synthetic occlusion was imposed by varying from 10% to 20% degree and real occlusion from 10% to 50% degree. To evaluate the robust fitting algorithm (for improved ISMA) with basic RNICIA, point-to-point distances are plotted between the input face image and the manually image. The input image is calculated by using the basic fitting and enhanced robust fitting algorithm. The Figure 1 plots the frequency of convergence for these two different fitting algorithms for different levels of occlusion on IMM and AR databases. As shown in this figure, the improved ISMA methodis significantly improve performance as compared to RNICIA algorithm in terms of fitting accuracy.

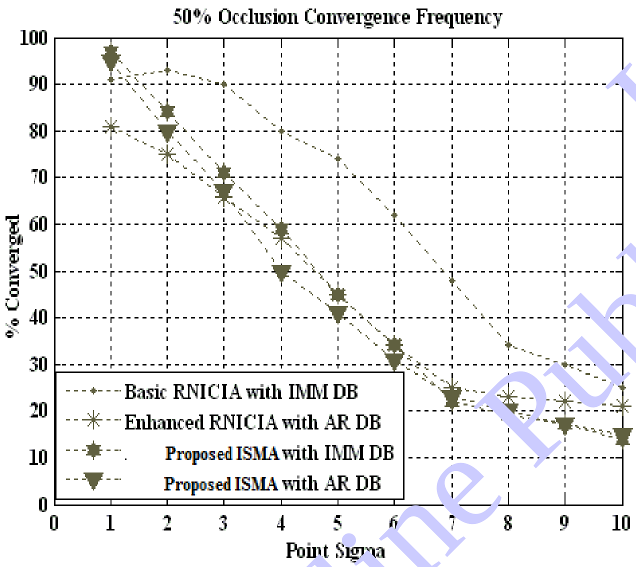

Figure 1. The average frequency of convergence of the basic fitting algorithm and imporved ISMAtechnique by maximum 50% degree of occlusion.

It should be noted that when two algorithms basic RNICIA and improved ISMA methods are tested by using Intel Core i7 system with 8 GB RAM and developed in VC++ using AAM API [17]. The average execution speed per second of both robust fitting algorithms is calculated. Due to restrict the change in parameters, it is reasonable to assume that the proposed ISMA fitting algorithm would run at the speed of 8.3 faster even faster than the speed of 18.8 which one purposed in [14, 20, 23] when both having single person images. It has been noticed through experiments that total theoretical complexity of the RNICIA is high in post-computation steps while the proposed robust fitting algorithm has high in pre-computation steps as shown in Table 1.

5. Conclusions

The obtained experimental results indicate that a new way is determined to solve the problem of partial occlusion by integrating the techniques of JSD statistical measure, JCh perceptual-oriented color space and color histogram of image regions. To design efficient training data set by considering this histogram as a probability mass function with RNICIA algorithm that significantly improves the performance in terms of computational speed and robustness. This algorithm can be extended to 3D images by just introducing 3D color histogram. This algorithm is tested on multi-person dataset in which all images are presented in testing and training datasets but when unseen images are coming then this model will requires too much iteration for fitting the model due to large variations in appearance model. For the future prospective, the other parameters of this algorithm will modify and then compare its performance with robust simulate inverse compositional algorithm for occluded facial expression video tracking for unseen frames.

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