A Compute-efficient Algorithm for Robust Eyebrow Detection

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***Abstract*—Detection of facial landmark features is an initial step in facial expression recognition. Detection of eyebrows can aid the detection of the remaining facial features as eyebrows are relatively more stable across changing facial expressions. Existing eyebrow detection algorithms in literature involve complex computations and are not suitable for direct porting on to embedded platforms. In this paper, a compute-efficient eyebrow detection algorithm has been proposed and tested on three standard databases with an average detection rate of 96%. The method has also been shown to be computationally less complex compared to the state of the art.**

***Keywords*-eyebrow detection; facial feature extraction; computational efficiency;**

I. Introduction

Detection of facial features is an important step in facial expression detection and face recognition [1], [6], [10], [4]. The facial expressions are analyzed by combining the individual facial muscle movements measured by a combination of action units (AUs) based on the FACS (facial action encoding system [13]). In facial expression recognition, an initial estimation of the facial features is first obtained for face alignment [10]. In geometric feature-based methods for extracting facial features for expression analysis, the shape and location of the landmark facial features are extracted [16]. In appearance-based methods, image filters are used to extract the facial features [16]. In both of these methods, the detection of landmark facial features is a basic step.

Among the facial landmark features, i.e. eyebrows, eyes, nose and mouth [3], [8], eyebrows are considered relatively more intransient [9], [7], [14]. For instance, eyes and mouth appear different when open and closed, but eyebrows remain relatively more stable in appearance. Even under changing expressions, eyebrows are observed to show lesser variation in appearance compared to eyes and mouth [9], [7]. In [7], eyebrows along with head gestures are used as promising indicators in the detection of emotional states. Apart from being distinctive features, eyebrows are also used as a frame of reference for obtaining the rest of the facial features [9]. It is observed that the algorithms proposed in literature for eyebrow detection [1], [14], [2], [7] are intended for achieving high precision and robustness, but involve complex computations. This can become a bottleneck in realization of the algorithms on an embedded platform, where resource constraints have to be met.

This motivates the need for a computationally efficient algorithm for eyebrow detection. A compute-efficient and robust method to detect the eyebrow has been proposed in this paper. The concept of gradient map and signed-edge map [15] are used to capture the distinct properties of eyebrows followed by a systematic evaluation of the other static and symmetry properties unique to eyebrows. The proposed method is evaluated on standard databases for robustness and is also shown to be computationally efficient compared to existing methods.

The following sections will elaborate on existing related work, the proposed method, test results and computational complexity analysis.

II. Related Work

Eyebrow detection algorithms have been proposed under various contexts such as face alignment, face recognition in biometrics, recognition of landmark facial features and facial expression recognition. In [1], a rough estimation of the eyebrows are first obtained using a spatial constrained sub-area K-means clustering algorithm, following which they are precisely traced using Snake method. In [7], active shape models are used to obtain the facial features including eyebrows. A skin color model and a Laplacian operator are used in [2], where the non-skin color regions above the eyes are detected as potential eyebrow candidates which are further processed. In [17], among the 22 fiducial facial points that are to be detected, 2 points are along the eyebrow. In [12], a template matching technique is used within a defined area relative to location of the eyes.

III. Proposed Method

The proposed algorithm is based some unique properties of the eyebrows that are retained in spite of changes in facial expressions, which are listed as follows: (a) on scanning the face from top, eyebrows are most often the features that show the first prominent transition from light $\rightarrow$ dark intensity at the upper edge of the eyebrow followed by a transition from dark $\rightarrow$ light intensity at the lower edge of the eyebrow, (b) the right and left eyebrows will be of similar length and thickness that are within a certain range defined with respect to the width and height of the face, (c) the separation between left and right eyebrows in the y-direction will be within specific bounds in spite of slight variation in roll of the face, (d) the difference in intensity between the region enclosed within the eyebrow and the region just above the eyebrow.

The proposed method comprises of two main steps. The first step involves extraction of possible eyebrow edge candidates by taking advantage of property (a) listed above. The next step is a filtering step that uses the properties (b) to (d) to detect the correct eyebrow candidates from the pool obtained from the first step. The two steps are performed in an iterative fashion so that the algorithm is robust to varying surrounding conditions, features on faces and facial expressions.

A. Signed Edge Maps for Eyebrow Candidate Extraction

The first step of the proposed algorithm involves generation of signed edge maps [15], which will be analyzed further to detect the edges of eyebrows. In the proposed method, it is assumed that we have the cropped faces from a face detection algorithm such as [18]. The upper half of the face region I (as shown in Fig. 1.(b))will be considered and processed in the further steps of the algorithm. The gradient

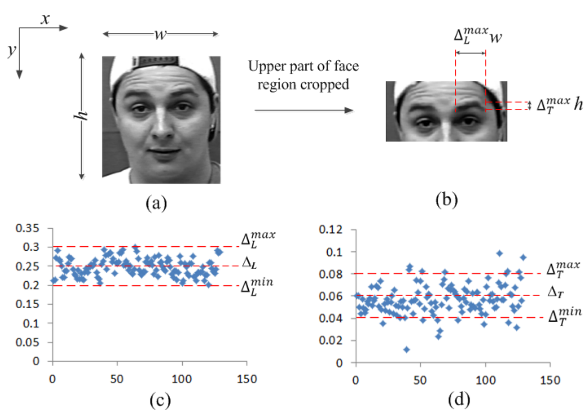

Figure 1. (a) Width and height of face w and h respectively (b) Maximum length and thickness of eyebrow relative to w and h respectively (c) Plot showing ratio of eyebrow length to width of face over 140 images (d) Plot of ratio of eyebrow thickness to height of face over 140 images

map of I in the y-direction G_y is computed and the two signed edge maps as per equations 1 are obtained in order to extract the upper and lower edges of the eyebrow in the two signed edge maps E_{y-} and E_{y+} respectively.

$$\begin{aligned} E_{y-}(x,y) &= 1 \; if \; G_y(x,y) \geq T_u \wedge E_y(x,y) = 1 \quad (1) \\ E_{y+}(x,y) &= 1 \; if \; G_y(x,y) < T_l \wedge E_y(x,y) = 1 \\ E_y &= E_{y+} \cup E_{y-} \end{aligned}$$

The thresholds T_u and T_l represent the fraction of the highest gradients in E_{y-} and E_{y+} that will be set as thresholds while obtaining the signed edge maps. T_u is initialized to a certain value at the start of the algorithm. T_l is set to a value lesser than T_u, since the transition across the lower edge of the eyebrow, which is the transition from dark $\rightarrow$ light intensity is not as distinct as the light $\rightarrow$ dark transition across the upper edge of the eyebrow. In the proposed algorithm, the value of T_l has been set to be 30% of T_u. The algorithm is iterative and in each iteration of the algorithm, the values of T_u and T_l are reduced and the signed edge maps are computed again if the eyebrow edges are not extracted.

The signed edge maps E_{y-} and E_{y+} are divided into 2 parts - E^R_{y-} and E^L_{y-}, and E^R_{y+} and E^L_{y+} respectively. These denote the signed edge maps for the right and left halves of the face respectively. The following paragraphs explain the further steps performed using the signed edge maps for the right half of the face, and the same steps are carried out for the left half of the face as well.

E^R_{y-} and E^R_{y+} are divided into overlapping horizontal bands b_1, b_2,... b_n with a bandwidth $\Delta_T^{max} \times h$. $\Delta_T^{max} \times h$ is the maximum thickness of eyebrow expected as shown in Fig. 1.(b), and Δ_T^{max} and Δ_T^{min} are percentages of face height h derived heuristically as shown in Fig. 1.(d). Edge pixels in E^R_{y-} and E^R_{y+} are accumulated in each band to find out the most prominent edges. Since the bands are overlapping, a non-maximal suppression function is applied.

In order to obtain upper edge of eyebrow, bands in E^R_{y-} with the summation of edge pixels greater than the eyebrow length threshold $\Delta_L \times w$ are computed as shown below.

$$\Sigma E^R_{y-}(b_j) \geq \Delta_L w \quad (2)$$

, where Δ_L is set to 50% of the difference between Δ_L^{max} and Δ_L^{min}, which are derived as shown in Fig. 1.(c). Let B such bands be obtained. In the event that at least one such band is not obtained, then the gradient threshold T_u is reduced by 25% and such that $T_u \geq 0.25$. So, if a prominent edge representing the upper edge of the eyebrow is not obtained, it is deciphered that the eyebrow is either occluded or has a very low contrast compared to the forehead.

Among the B bands in E^R_{y-} are found, the topmost band b_j is considered first. Then, the signed edge map E^R_{y+} is scanned to look for a prominent lower edge of the eyebrow. A band $b_{j'}$ which satisfies the condition in 3 as shown below possibly contains the lower edge of the eyebrow:

$$\Sigma E^R_{y+}(b_{j'}) \geq \Delta_L w \quad (3)$$

The band $b_{j'}$ is obtained such that $b_{j'}$ is located within a distance ranging from the minimum eyebrow thickness Δ_T^{min} to the maximum eyebrow thickness Δ_T^{max}. (d). If the lower edge of the eyebrow is not found, T_l is reduced by 25% and such that $T_l \geq 0.1$. If the lower edge is not found, the next among the B bands is considered and the above steps are repeated.

The above steps of obtaining the upper and lower edges of the eyebrow are carried out for the left half of the face as well.

B. Eyebrow Verification Process

The edge pixels captured in bands b_j and $b_{j'}$ are paired columnwise along the x-axis, i.e an edge pixel $E^R_{y-}(x, j)$

above an edge pixel $E^R_{y+}(x, j')$ along the same x co-ordinate are grouped as a pair (as shown in figure 2.(b)).

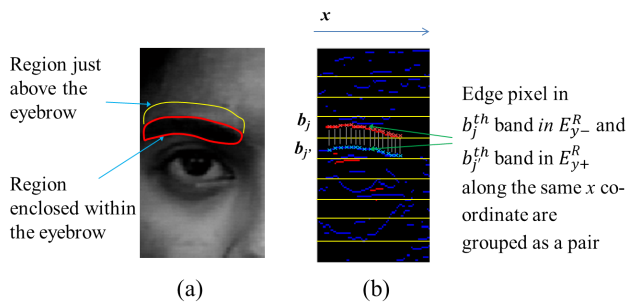

Figure 2. (a) grayscale image of eye region showing region enclosed within the eyebrow and region just above the eyebrow (b) edge pixels in $E^R_{y-}(b_j)$ and an edge pixels in $E^R_{y+}(b_{j'})$ grouped as pairs columnwise

Once the pairs of edge pixels along the upper and lower edge of the eyebrow are obtained, a continuity check is done in order to check if they represent a continuous segment of the eyebrow. If the length of the continuous eyebrow segment crosses the length threshold $\Delta_L^{min} \times w$, it is passed to the next step.

The position of the eyebrow with respect to the face is examined next. The (x,y) co-ordinates of the center of the eyebrow segment on both the right and left sides is computed and the (x,y) co-ordinates are checked if the right and left eyebrow segments are symmetrically positioned on the face and within specified horizontal and vertical limits. Also, the separation along y-direction between the segments obtained on the right and left halves of the face must be within the limits set considering a variation in roll of +/- 10^o. Then, the right and left eyebrow segments are compared to check if they are of similar thickness. The average thickness of the eyebrow segment along the length of the segment is computed on both the right and left sides and the difference in their average thickness α is checked for the condition $\alpha \leq 0.3\Delta_T^{max} h$.

Then, the difference in intensity between region enclosed within the edges (region within the eyebrow segment) and the region above the eyebrow segment is computed (as shown in Fig. 2.(a)). The average intensity of the pixels in the gray scale image I enclosed within these edges is computed and is denoted by I_e. Then, the average intensity of the pixels enclosed within a region just above the upper edge of the eyebrow is computed and is denoted by I_a. The difference between $I_e - I_a = I_d$ is checked for the condition $I_d > I_t$, where I_t is the intensity difference threshold that is set. This step is performed for both the eyebrows.

The above properties are checked and if the right and left segments (also referred to as a candidate segment pair) satisfy all the conditions, then the algorithm is terminated and the eyebrows are marked on the face image. If any of the properties are not satisfied, the respective threshold values are reduced and the properties are checked again. If the termination condition is reached and the segment pair violates at least one of the properties, the next set of candidate segment pair is considered and the above steps in this subsection are repeated. If none of the candidate segment pair candidates qualify as eyebrows, T_u is reduced and all of the above steps are repeated.

C. The Overall Algorithm

In sections III-A and III-B, the eyebrow candidates are extracted in an iterative manner and the candidate pair that satisfies the properties of eyebrows are marked as eyebrows. In this subsection, the overall flow of the algorithm is presented. Referring to Fig. 3, following the face detection step, the upper half of the face is cropped. In step 1, the potential eyebrow candidates are extracted in an iterative manner. In step 2, the candidates are tested for the properties of eyebrows, which is also performed in an iterative manner so that the actual eyebrow candidates are not missed out due to slight variations in thickness, length or lighting conditions. If none of the eyebrow segment candidates satisfy the properties of eyebrows, then step 1 is repeated with a lower gradient threshold followed by step 2 until the eyebrows are found or a stopping condition is reached.

IV. Performance Evaluation

The proposed algorithm was tested on 126 images of the Cohn-Kanade face database(3 frontal face images each of 42 subjects from various ethnicities with different facial expressions) [5], 213 images of the Jaffe database (21 images of 10 Japanese subjects with different facial expressions) [19] and 310 images of the AR database (10 images each of 31 subjects with variations in expressions and lighting conditions) [11]. The ground truth data is generated by manually going through each image and marking a bounding box around each eyebrow. A true positive (TP) is defined as a correct detection of the eyebrow if the output bounding box fully overlaps the bounding box marked during ground truth generation. If the algorithm is unable to detect the eyebrow, it is defined as a false negative (FN) and a mis-detection is defined as False positive (FP).

Fig. 4 show the eyebrows detected in the images of the three databases respectively. The databases contain facial images of subjects with variations in facial expressions, where the eyebrows are lowered, raised, contracted in different measures and the proposed algorithm is able to robustly detect the eyebrows as shown. The detected eyebrows are marked with a red and green bounding box respectively on the right and left eyebrows. The proposed algorithm is intended to detect the eyebrows and not to exactly trace them. As seen in Fig. 4, the proposed algorithm successfully detects eyebrows in challenging cases such as partial occlusion of eyebrows, poor contrast between eyebrows and

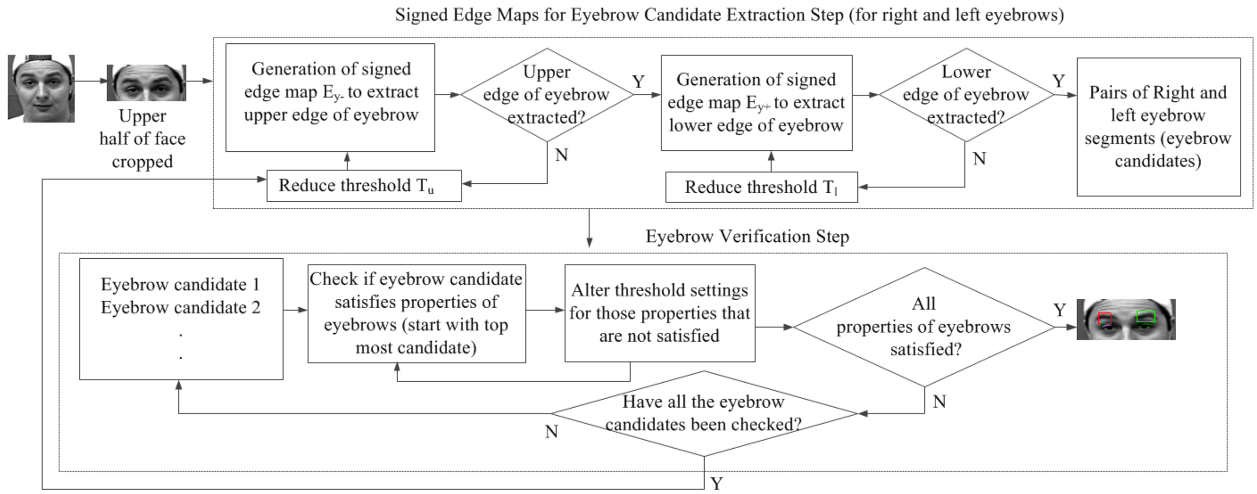

Figure 3. The proposed eyebrow detection algorithm

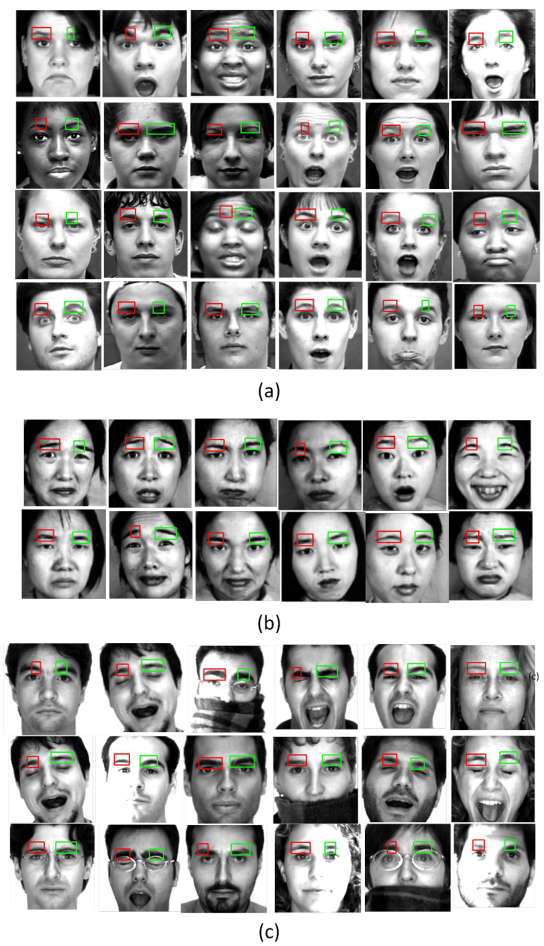

Figure 4. Eyebrow detection results for (a) Cohn-Kanade database (b) Jaffe database (c) AR database

skin color, variation in distance between eyebrow and eye, variation in yaw and roll of +/- 10^o and variation in facial expressions. The detection rate (TP/(TP+FN)) for the three databases is tabulated in Table I.

Figure 5. Cases of missed detections due to occlusions

Table I
DETECTION RATES FOR THE COHN-KANADE, JAFFE AND AR DATABASES

	Cohn-Kanade	*Jaffe*	*AR*
Number of images	126	213	310
Detection Rate	97.7	99.5	92

The mis-detections were analyzed and it was found that the proposed method failed to detect the eyebrows when the eyebrows were barely visible due to lighting conditions or when the eyebrows were occluded by hair or spectacles, examples of such cases are shown in figure 5.

A. *Computational Complexity Analysis*

In this subsection, the computational complexity of the proposed eyebrow detection algorithm has been evaluated and compared against an existing eyebrow detection algorithm [1].

Given the grayscale input image of the upper part of the face $M \times N$ the sobel kernel is applied to every pixel of the image. The computation cost for computing the gradient G_y for all pixels in the image is summarized in equation 4.

$$C_{ADD} = 5MN \tag{4}$$

The computations involved in extracting the upper edge of the eyebrow are summarized in 5, where n_l is the number of iterations needed, with the gradient threshold reduced in every iteration and w is the window size for the non-maximal suppression.

$$\begin{aligned} C_{COMP} &= 2n_l(N/3(1/w+1)) + MN + n_l MN \\ C_{ADD} &= n_l(MN/2 + 4N/3) \\ C_{MUL} &= n_l \end{aligned} \tag{5}$$

The cost of finding the lower edge of the eyebrow is computed next. Considering a window size of w for the non-maximal suppression and the eyebrow thickness to be Δ, and n_d is the number of iterations needed for the lower edge of the eyebrow to be extracted, the computations can be summarized as follows:

$$\begin{aligned} C_{COMP} &= MN + n_d n_l MB\Delta + 2n_l n_d B\Delta(1+w)/(3w) \\ C_{ADD} &= n_l n_d BM\Delta/2 + 4B\Delta/3 \\ C_{MUL} &= n_l n_d \end{aligned} \tag{6}$$

The cost of performing a continuity check is computed. Then, the cost of computing the average intensity of the eyebrow segments and their difference with the region just above the eyebrow segments are computed considering thickness is equal to the maximum thickness of eyebrow expected. The computational cost for computing thickness, separation between the eyebrows along y-direction and position of eyebrows with respect to the face are found out next. If B is the average number of right and left candidate eyebrow segment pairs that need to be considered till the segment pair that satisfies the properties of eyebrows is found in each iteration, the above computations will have to be repeated B number of times. The equations in 6 will also have the factor B. The thresholds while checking whether the segment pair satisfies the properties are reduced by a small fixed amount in each of the n_e iterations until a stopping condition is reached.

$$\begin{aligned} C_{COMP} &= 13 n_l n_e B \\ C_{ADD} &= 2n_l B(M\Delta + 1) + 2n_l BM \\ C_{MUL} &= 6(n_l B + 1) \end{aligned} \tag{7}$$

The computational cost efficiency of the proposed method is compared with [1]. In the eyebrow contour extraction method in [1], the rough estimate of the eyebrow region is first obtained and then the exact eyebrow contour is extracted. First, the face contour is estimated by the Snake method, following which the eye corners are detected. With the eye corners as reference, the eyebrow position is estimated. Let $w \times h$ be the size of the window in which the eye corners will be detected (for each eye). Multi-binarization of the image within this window is performed, to extract the eye boundary. In the $w \times h$ window, intersecting lines forming a corner are detected within a 7×7 window through the 48 line combinations that are defined within the 7×7 window. Then, once the corners are detected, they are grouped into clusters (n_{cl} clusters) if the distance between every 2 points of the cluster is less than a threshold. Computational cost is computed assuming n_c corners are detected. Region dissimilarity is computed for every corner point, the cost of which is computed. The corner with the largest region dissimilarity D for every cluster is found out. Then, pairs of corners from among the n_1 corner points are formed based on a distance measure. Cost function for the resulting n_p such pairs is computed and the pair of points which gives minimum cost is found to be two of the eye corners. The next two corners are detected by evaluating a cost function for the potential corner candidates n_2 in the window of a certain size located relative to the two eye corners detected. All of the above computational cost will have to be multiplied by a factor of 2, since the above computational cost analysis was for finding corners of one eye. Summarizing the cost of all of the above computations in the following equations:

$$\begin{aligned} C_{COMP} &= 3wh + 2 *^{nc/4} C_2 + 5 *^{n_1} C_2 + 4 *^{n_2/2} C_2 +^{n_2} C_2 +^{2n_1} C_2 \\ C_{ADD} &= 6 *^{nc/4} C_2 + 3 *^{n_1} C_2 + 8 *^{n_2/2} C_2 \\ C_{MUL} &= 4 *^{n_1} C_2 + 8 *^{n_2/2} C_2 \end{aligned} \tag{8}$$

Based on the eye corners are obtained, the eyebrow location is approximately found. Then, a spatial constrained sub-area K-means clustering is performed in the region $M \times N$ just above the eye based on the estimated eye corner positions. The computations for the spatial constrained sub-area K-means clustering is summarized as follows (m is the number of iterations in the spatial constrained sub-area K-means clustering).

$$\begin{aligned} C_{ADD} &= 5MNm \\ C_{MUL} &= m(15 + 2MN) \\ C_{COMP} &= m - 1 \end{aligned} \tag{9}$$

The equations summarizing the computations in the proposed method and [1] are given in Table II.

Considering the image patch with the upper half of the face of size 100×200 for the sake of comparison of computational costs of the proposed method and [1]. In the proposed method, the number of iterations, number of candidates in each iteration have been set to reasonable values as follows: n_l = 3, n_d = 3, n_e = 1, B = 4, w = 3, Δ = 8. With respect to [1], 50×70 is the area considered each eye region for eye corner detection and 30×50 is the estimated eyebrow region for K-means clustering and the value of m, the number of iterations for K-means clustering is set to three different values and the computations are tabulated in Table III. An n-bit comparison and an n-bit × n-bit multiplication is considered equivalent to one n-bit addition and n n-bit additions respectively. We observe that the total number of computations in the proposed method is 37% lesser when compared to [1], even when m is set to a reasonably low value of 5.

V. Conclusions

A compute-efficient technique to detect eyebrows in faces of front facing humans has been proposed and evaluated

Table II
SUMMARY OF COMPUTATIONS IN PROPOSED METHOD AND [1]

Operations	[1]	Proposed
Comparisons	$2(3wh + 2 *^{n_c/4} C_2 + 5 *^{n_1} C_2 +$ $4 *^{n_2/2} C_2 +^{n_2} C_2 +^{2n_1} C_2 + m - 1)$	$2n_l(N/3(1/w+1)) + 2MN + n_lMN$ $+ n_dn_lMB\Delta + 2n_ln_dB\Delta(1+w)/(3w) + 13n_ln_eB$
Additions	$2(6 *^{n_c/4} C_2 + 3 *^{n_1} C_2 +$ $8 *^{n_2/2} C_2 + 5MNm)$	$5MN + n_l(MN/2 + 4N/3) + n_ln_dBM\Delta/2$ $+4B\Delta/3 + 2n_lB(M\Delta+1) + 2n_lBM$
Multiplications	$2(4 *^{n_1} C_2 + 8 *^{n_2/2} C_2$ $+m(15+2MN))$	$n_l + n_ln_d$ $+6(n_lB+1)$

Table III
COMPARISON OF COMPUTATIONAL COMPLEXITY BETWEEN PROPOSED METHOD AND [1]

Operations	Proposed Method	[1]		
		m=4	m=5	m=10
Additions	202466	60210	75210	150210
Multiplications	90	24288	30318	60468
Comparisons	158278	21366	21368	21378
Total computations (Equivalent additions)	362185	470184	581666	1139076
% Savings	-	22.96	37.73	68.20

on three standard databases - Cohn Kanade, Jaffe and AR database. The computational complexity analysis shows that the proposed method achieves a computational savings of 37% compared to [1], while the detection rate is comparable to existing methods in literature. An average detection rate of 96% was achieved upon evaluation.

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