EFFECT OF FACIAL EXPRESSIONS ON FEATURE-BASED LANDMARK LOCALIZATION IN STATIC GREY SCALE IMAGES

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Abstract: The present aim was to examine the effect of facial expressions on the feature-based landmark localization in static grey scale images. In the method, local oriented edges were extracted and edge maps of the image were constructed at two levels of resolution. Regions of connected edges represented landmark candidates and were further verified by matching against the edge orientation model. The method was tested on a large database of expressive faces coded in terms of action units. Action units described single and conjoint facial muscle activations in upper and lower face. As results demonstrated, eye regions were located with high rates in both neutral and expressive datasets. Nose and mouth localization was more attenuated by variations in facial expressions. The present results specified some of the critical facial behaviours that should be taken into consideration while improving automatic landmark detectors which rely on the low-level edge and intensity information.

1 INTRODUCTION

Facial expressions result from contractions and/or relaxations of facial muscles. These non-rigid facial movements result in considerable changes of facial landmark shapes and their location on the face, presence/absence of teeth, out-of-plan changes (showing the tongue), and self-occlusions (bitted lips). The best known and most commonly referred linguistic description of facial expressions is the Facial Action Coding System (FACS) (Ekman and Friesen, 1978; Ekman, Friesen, and Hager, 2002). The FACS codes an expressive face in terms of action units (AUs). The numerical AU code describes single and conjoint facial muscle activations. It is anatomically-based and therefore represents facial expressions as a result of muscle activity without referring to emotional or otherwise cognitive state of a person on the image.

It was suggested that structural changes in the regions of facial landmarks (eyebrows, eyes, nose, and mouth) are important and in many cases sufficient for AU recognition. In automatic AU recognition, manual preprocessing is typically needed to select a set of fiducial points (for example, eye centres and mouth corners) in static image or initial frame of the video sequence. Fiducial points are further used to track changes in the face resulted from its expressive behaviour or to align an input image with a standard face model. Currently, there is a need for a system that can automatically locate facial landmarks in the image prior to the following steps of the automatic facial expression analysis.

In static facial image, there is no temporal information on facial movements available. Facial landmark localization in this case is generally addressed by modelling a local texture in the regions of landmarks and by modelling a spatial arrangement of the found landmark candidates (Hjelmas and Low, 2001; Pantic and Rothkrantz, 2000; Yang, Kriegman, and Ahuaja, 2002). The main challenge is to find a representation of the landmarks that efficiently characterizes a face and remains robust with respect to facial deformations brought about by facial expressions.

Addressing the problem of expression invariant localization of facial landmarks in static grey scale images, the feature-based method was introduced (Gizatdinova and Surakka, 2006). In the method,

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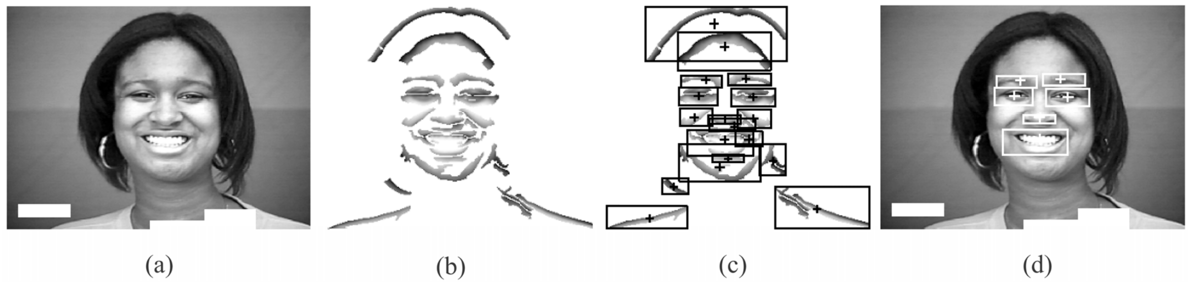


Figure 1: Facial landmark localization: (a) original image, (b) parts of the image located as regions of connected edges; (c) landmark candidates; (d) final localization result after edge orientation matching. Bounding boxes indicate locations and crosses define mass centres of the found regions. Image indexes are masked by white boxes. Images are courtesy of the Cohn-Kanade AU-Coded Facial Expression Database (Kanade, Cohn, and Tian, 2000). Reprinted with permission.

edge representation of the face was taken at ten edge orientations and two resolution levels to locate regions of eyes (including eyebrows), lower nose, and mouth. The resulted edge map of the image consisted of regions of connected local oriented edges presumed to contain facial landmarks. To verify the existence of a landmark on the image, the extracted landmark candidates were matched against the edge orientation model. Figure 1 illustrates the main steps of the method. The description of edge detection, edge grouping, and edge orientation matching steps is given in more detail in Appendixes A and B.

A degradation in the landmark localization rates was reported for expressive dataset as compared to neutral dataset. The further analysis (Guizatdinova and Surakka, 2005) suggested that there were certain AUs which significantly deteriorated the performance of the method. It was assumed that AUs activated during happiness (AU12), disgust (AU 9 and 10), and sadness (AU 1 and 4) would be such central AUs. Having such a ground, the main motivation for the present study was the fact that although a degradation in the landmark localization rates due to expression variations is generally appreciated in the computer vision society; however, a little attempt has been done to analyze what muscle activations cause the degradation. To estimate more accurately what facial muscular activity affects the feature-based landmark localization, a more detailed study was needed.

The present aim was to evaluate the developed method on a larger AU-coded database of expressive images and investigate the impact of single AUs and AU combinations on the facial landmark localization in static facial images.

2 DATABASE

The Cohn-Kanade AU-Coded Facial Expression Database (Kanade, Cohn, and Tian, 2000) was used to test the method. The database consists of image sequences taken from 97 subjects of both gender (65% female) with ages varying from 18 to 30 years. The database represents subjects with different ethnic background (81% Caucasian, 13% African-American, and 6% Asian or Latino). There were no images with eye glasses and strong facial hair.

Each image sequence starts with a neutral face that gradually transforms to an expressive one. Expressions from different sequences can differ in levels of intensity. Expressive images are labelled in terms of AUs, and AUs occur both alone and in combinations. The AU descriptors taken from the FACS manual (Ekman, Friesen, and Hager, 2002) are as follows. Upper face AUs: 1 - inner eyebrow raiser, 2 - outer eyebrow raiser, 4 - eyebrow lowerer, 5 - upper lid raiser, 6 - cheek raiser and lid compressor, 7 - lid tightener, 43 - eye closure, and 45 - blink. Lower face AUs: 9 - nose wrinkler, 10 - upper lip raiser, 11 - chin raiser, 12 - lip corner depressor, 14 - lips part, 15 - jaw drop, 16 - mouth stretch, 17 - lower lip depressor, 18 - lip pucker, 20 - lip tightener, 23 - lip presser, 24 - nasolabial furrow deepener, 25 - lip corner puller, 26 - lip stretcher, and 27 – dimpler.

From each image sequence, the first and the last frames were selected which corresponded to neutral and expressive faces, respectively. A total of 468 neutral and 468 expressive images were selected. All images were scaled to approximately 300 by 230 pixel arrays. No face alignment was performed. Image indexes were masked by white boxes.

(a) AU 4+7a+17e+23d+24d+31 (b) AU 1+2+5+16+20+25 (c) AU 1+2+5+25+27

(d) AU 15d+17e+B22 (e) AU 1+4+15c+17c (f) AU 4+7+17e+23e+24e

Figure 2: Examples of correctly located facial landmarks. Bounding boxes indicate locations and crosses define mass centres of the found regions. Image indexes are masked by white boxes. Images are courtesy of the Cohn-Kanade AU-Coded Facial Expression Database (Kanade, Cohn, and Tian, 2000). Reprinted with permission.

3 LANDMARK LOCALIZATION

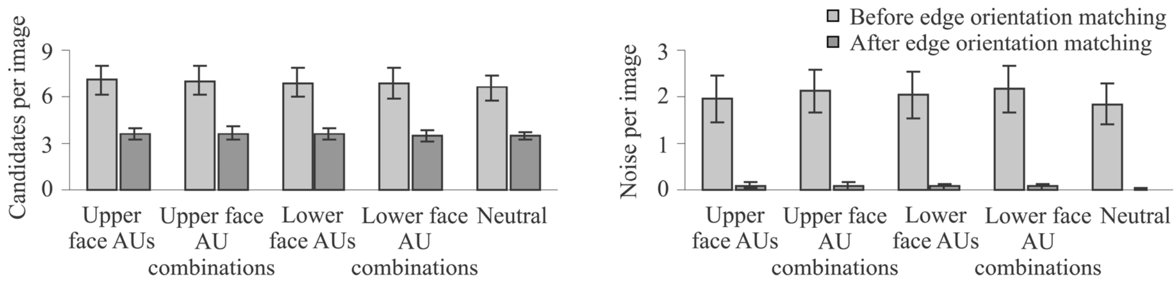
All the localization results were checked manually and classified into one of the following groups: correct, wrong, and false localization. Different from systems in which a point defines the localization result, in this study the localization result was defined as a rectangular bounding box placed over the located region. The mass centre of the located region indicated an estimate of the centre of the landmark.

A correct landmark localization was considered if the bounding box overlapped approximately more than a half of the visible landmark and enclosed the area surrounding a landmark less than the actual area of the landmark (Figure 2). Eye localization was counted correct if the bounding box included both eye and eyebrow, or eye and eyebrow were located separately. In case if eyebrow was located as a separate region, it was obligatory that a corresponding eye was also found.

A wrong landmark localization was considered if the bounding box covered several neighbouring facial landmarks. Wrong landmark localization was observed in 0.54 cases per image. For this type of localization error, the failure in nose and mouth localization was mainly due to the effect of lower face AUs 9, 10 and 12. These AUs, occurring alone or in combinations, produced the erroneous grouping of nose and mouth into one region. AUs 4, 6, 7, and their combinations with other AUs sometimes caused the merging of the eye regions.

A false landmark localization was considered if the bounding box included some non-landmark regions as, for example, elements of clothing, hair or face parts like wrinkles, shadows, ears, and eyebrows located without a corresponding eye. The procedure of orientation matching reduced the average number of candidates per image into almost a half for neutral (from 6.57 to 3.49) and expressive (from 6.97 to 3.60) images, see Figure 3,a. Accordingly, the average number of false localizations per image was reduced from 1.84 to 0.01 for neutral and from 2.07 to 0.08 expressive images, see Figure 3,b. Figure 4 shows some examples of the localization errors.

Table 1 summarizes the performance of the method. For each landmark, a rate of its localization was defined as a ratio between the total number of correctly located landmarks and the total number of images used in testing (as there was one landmark per image). A false positive was defined as a number of false localizations.



(a) (b)

Figure 3: Average number of landmark candidates per image before and after the procedure of orientation matching. The error bars show plus/minus one standard deviation from the mean values.

(a) AU 6+12+16+25 (b) AU 4+6+7+9d+17d+25 (c) AU 12c

Figure 4: Examples of errors in facial landmark localization: (a) nose and mouth wrong localization; (b) eye region wrong localization and nose and mouth wrong localization; (c) false localization. Bounding boxes indicate locations and crosses define mass centres of the found regions. Image indexes are masked by white boxes. Images are courtesy of the Cohn-Kanade AU-Coded Facial Expression Database (Kanade, Cohn, and Tian, 2000). Reprinted with permission.

Table 1: Performance of the method on neutral and expressive datasets.

Dataset	Rates of landmark localization				Total	False positive
	R eye region	L eye region	Nose	Mouth		
Neutral	98%	99%	93%	91%	95%	9
Expressive	93%	93%	55%	55%	74%	55

The method achieved average localization rate of 84% in finding all facial landmarks. On the whole, localization rates were better for neutral than for expressive images. Thus, eye regions were located with high rates in both neutral and expressive datasets. However, nose and mouth localization rates were considerably better for neutral than for expressive images. In the next sections, the effect of single AUs and AU combinations on the landmark localization rates will be considered.

3.1 Effect of Facial Expressions on Landmark Localization Rates

The results of the previous section demonstrated the degradation of the landmark localization rates in case of expressive dataset. The same results can be interpreted in a way that specifies what facial behaviours caused the degradation. At this point we aimed to analyze the effect of upper and lower face AUs on the landmark localization rates. To do that the localization results were classified systematically using the following approach. The results were combined into four AU groups according to AUs presented in the test image, see Table 2. Thus, if image label included single AU, the localization result was classified into group I or II. If image label included a combination of two AUs, the localization result was classified into group III or IV. AU43 (eye closure) and AU45 (blink) were combined together because they both have the same visual effect on the facial appearance and different durations of these AUs can not be measured from the static images.

Due to the fact that some AUs were not presented in the database or the number of images was too few (less than 6), only a limited number of AUs and AU combinations was used. The classification allowed the results to belong to more than one group. On the next step, average landmark localization rates were calculated for each AU subgroup. Tables 3 and 4 illustrate the effect of chosen AU groups on the landmark localization rates. In the tables, AUs and AU combinations were defined as having no or slight effect if average localization rates were in the range of 90-100%, as medium if localization rates were in the range of 80-89%, and strong if localization rates were below 79%. Table 3 demonstrates that eye region localization was consistently good in the context of the presented AU groups. Among all the facial behaviours, upper face AU9 and AU combinations 4+6, 9+25, and 10+17 had the most deteriorating effect on the eye region localization. Lower face AU 9 and AU combinations 4+6, 9+17, 12+20, 12+16 had the most deteriorating effect on the nose and mouth localization in Table 4. In the tables, bold font defines AUs and AU combinations which had the strongest effect on both upper and lower face landmark localization.

4 DISCUSSION

The effect of facial expressions on the feature-based localization of facial landmarks in static facial images was evaluated. In this section, the impact of upper and lower face AUs and AU combinations on the landmark localization rates will be analyzed and discussed.

4.1 Effect of Upper Face AUs on Eye Region Localization Rates

On the average, the results demonstrated that eye region localization was robust in some extent with

Table 2: AU groups for analysis of the effect of upper and lower face AUs on the method performance.

AU groups	AU subgroups
I. Upper face AUs	1, 2, 4, 5, 6, 7, 43&45
II. Lower face AUs	9, 10, 11, 12, 14, 15, 16, 17, 18, 20, 23, 24, 25, 26, 27
III. Upper face AU combinations	1+2, 1+4, 1+5, 1+6, 1+7, 2+4, 2+5,4+5, 4+6, 4+7, 4+45, 6+7
IV. Lower face AU combinations	9+17, 9+23, 9+25, 10+17, 10+20, 10+25 11+20, 11+25, 12+16, 12+20, 12+25, 15+17, 15+24, 16+20, 16+25, 17+23, 17+24, 17+25, 18+23, 20+25, 23+24, 25+26

Table 3: Effect of upper and lower face AUs and AU combinations on the eye region localization rates.

Effect	I. Upper face AUs	II. Lower face AUs	III. Upper face AU combinations	IV. Lower face AU combinations
No or Slight	1, 2, 5	11, 12, 14, 15, 16, 20, 25, 26, 27	1+2, 1+4, 1+5, 1+6, 1+7, 2+4, 2+5, 4+5	10+20, 10+25, 11+20, 11+25, 12+16, 12+20, 12+25, 15+17, 15+24, 20+25, 25+26, 25+27
Medium	4, 6, 43&45	17, 18, 23, 24	-	9+23, 16+20, 16+25, 17+24, 17+25, 18+23
Strong	**7**	**9, 10,**	**4+6, 4+7, 4+45, 6+7**	**9+17, 9+25, 10+17, 17+23, 23+24**

Table 4: Effect of upper and lower face AUs and AU combinations on the nose and mouth localization rates.

Effect	I. Upper face AUs	II. Lower face AUs	III. Upper face AU combinations	IV. Lower face AU combinations
No or Slight	-	-	-	-
Medium	2m	27	(1+2)m, (1+5)m, (2+5)m	15+24, 25+27
Strong	1, 2n, 4, 5, 6, **7**, 43&45	**9**, **10**, 11, 12, 14, 15, 16, 17, 18, 20, 23, 24, 25, 26	(1+2)n, 1+4, (1+5)n, 1+6, 1+7, 2+4, (2+5)n, 4+5, **4+6**, **4+7**, **4+45**, **6+7**	**9+17**, 9+23, **9+25**, **10+17**, 10+20, 10+25, 11+20, 11+25, 12+16, 12+20, 12+25, 15+17, 16+20, 16+25, **17+23**, 17+24, 17+25, 18+23, 20+25, **23+24**, 25+26

Note: Letters n and m indicate different localization results for nose and mouth localization.

respect to facial expressions. Thus, upper face AUs (1, 2 and 5) and AU combinations (1+2, 1+4, 1+5, 1+6, 1+7, 2+4, 2+5, 4+5) which result in raising of eyebrows and widening of eyelids had a slight or no effect on the eye region localization. The degradation in the eye region localization rates was mainly caused by activation of upper face AUs (4, 6, 7, and 43/45) and AU combinations (4+6, 4+7, 4+45, and 6+7) which typically narrow down a space between the eyelids and/or cause the eyebrows to draw down together. These facial behaviours were the main reasons for wrong eye region localization error.

Recently, studies on the feature-based AU recognition, which performance depends on the features used, reported similar results. In (Lien, Kanade, Cohn, and Li, 2000), first-order derivative filters of different orientations (horizontal, vertical, and diagonal) were utilized to detect transient facial features (wrinkles and furrows) for the purpose of AU recognition. They reported AU recognition rate of 86% for AU 1+2, 80% for AU1+4, and 96% for AU4. In (Tian, Kanade, and Cohn, 2002), the authors reported a decrease in performance of the feature-based AU recognition for nearly all the same AUs (AU 4, 5, 6, 7, 41, 43, 45, and 46) which created difficulties in landmark localization in the present study. Among all the upper face AUs, they found AUs 5, 6, 7, 41, and 43 as the most difficult to process with feature-based AU recognition method.

4.2 Effect of Lower Face AUs on Nose and Mouth Localization Rates

The results demonstrated that nose and mouth localization was significantly affected by facial expressions in both upper and lower face. As it was suggested in (Guizatdinova and Surakka, 2005), AUs 9, 10, 11, and 12 were found to cause a poor localization performance of the method.

There are certain changes in the face when the listed AUs are activated. In particular, when AU12 is activated, it pulls the lips back and obliquely upwards. Further, the activation of AUs 9 and 10 lift the centre of the upper lip upwards making the shape of the mouth resemble an upside down curve. AUs 9, 10, 11, and 12 all result in deepening of the nasolabial furrow and pulling it laterally upwards. Although, there are marked differences in the shape of the nasolabial deepening and mouth shaping for these AUs, it can be summed up that these AUs generally make the gap between nose and mouth smaller. These changes in the facial appearance typically caused wrong nose and mouth localization errors.

Especially, lower face AU 9 and AU combinations 4+6, 9+17, 12+20, 12+16 caused strong degradation in nose and mouth localization rates. Similarly, in (Lien, Kanade, Cohn, and Li, 2000), degradation in the feature-based recognition of the lower face AU combinations 12+25 and 9+17 was observed (84% and 77%, respectively). However, regardless of considerable deterioration of nose and mouth localization by the listed AUs, mouth could be found regardless of whether the mouth was open or closed and whether the teeth or tongue were visible or not (Figure 2).

4.3 General Discussion

So far we discussed the effect of upper face AUs on the eye region localization and the effect of lower face AUs on the nose and mouth localization. However, the results also revealed that expressions in the upper face noticeably deteriorated nose and mouth localization and some changes in the lower face affected eye region localization. It is due to the fact that occurring singly or in combinations, AUs may produce strong skin deformations to be in a far neighbourhood from those AUs. In the current database, upper face AUs were usually represented in conjunction with lower face AUs, and their joint activation caused changes in both upper and lower parts of the face. Because of this, the effect of single AU or AU combinations was difficult to bring into the light. The present study investigated only the indirect effect of AUs and AU combinations on the landmark localization.

The overall performance of the method can be improved in several respects. First, the results demonstrated that a majority of the errors was caused by those facial behaviours which resulted in the decrease of space between neighbouring landmarks. Thus, wrong localization errors occurred already on the stage of edge map construction. The reason for that was that a distance between edges extracted from neighbouring landmarks became less than a fixed threshold and edges belonging to different landmarks were erroneously grouped together. To fix this problem, adaptive thresholds are needed for edge grouping. To facilitate landmark localization further, the merged landmarks can be analyzed according to edge density inside the merged regions. The results showed that the regions of merged landmarks have non-uniform edge density. Such regions can be processed subsequently and separated into several regions of strong edge concentration. Second, it is widely accepted that analysis of spatial semantics among neighbouring facial features helps in detecting and inferring missed or occluded facial landmarks. To improve the performance of the method, a constellation of landmark candidates can be analyzed according to face geometry at the stage of orientation matching. As the results showed, eye regions were localized robustly regardless of facial expression. It gives a possibility to use eye region locations and overall face geometry as a guide for localization of other landmarks which were missed (occluded). It can also decrease a false localization rate.

In summary, the method was effective in localization of facial landmarks in neutral images. In this case, the localization rates were higher than 90% for all facial landmarks. In case of expressive faces, the present results specified some of the critical facial behaviours that caused the degradation of the landmark localization rates. We believe that these results can be generalized in some extent to other methods of landmark detection which rely on the low-level edge and intensity information. Further, using only grey level information contained in the image, the method was invariant with respect to different skin colour. The edge orientation model appeared to be effective in noise reduction. Thus the method was able to locate landmarks in images with hair and shoulders. Emphasizing simplicity and low computation cost of the method, we conclude that it can be used in the preliminary localization of regions of facial landmarks for their subsequent processing where coarse landmark localization is following by fine feature detection.

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APPENDIX A: EDGE DETECTION AND GROUPPING

The grey scale image representation was considered as a two dimensional array $I = \{b_{ij}\}$ of the $X \times Y$ size. Each b_{ij} element of the array represented b intensity of the $\{i, j\}$ image pixel. If there was a colour image, it was first transformed into the grey scale representation by averaging of the three RGB components. This allowed the method to be robust with respect to small illumination variations and skin colour. The high frequencies were removed by convolving the image with a Gaussian filter to eliminate noise and small details (Equation 1).

$$b_{ij}^{(l)} = \sum_{p,q} a_{pq} b_{ij}^{l-1}, \quad b_{ij}^{(1)} = b_{ij} \tag{1}$$

where a_{pq} is a coefficient of the Gaussian convolution; p and q define the size of a filter, $p,q = -2 \div 2$; $i = 0 \div X-1$; $j = 0 \div Y-1$; $l = 1,2$ define the level of image resolution.

The smoothed images were further used to detect regions of image which were more likely to contain facial landmarks. The original, high resolution images were used to analyse the candidates for facial landmarks in more detail. In that way, the amount of information that was processed at high resolution level was significantly reduced.

Further, local oriented edges were extracted by convolving the image with a set of ten convolution kernels resulting from differences of two oriented Gaussians (Equations 2-5).

$$G_{\varphi_k}^{-} = \frac{1}{2\pi\sigma^2} e^{-\frac{(p-\sigma\cos\varphi_k)^2+(q-\sigma\sin\varphi_k)^2}{2\sigma^2}} \tag{2}$$

$$G_{\varphi_k}^{+} = \frac{1}{2\pi\sigma^2} \mathrm{e}^{-\frac{(p+\sigma\cos\varphi_k)^2+(q+\sigma\sin\varphi_k)^2}{2\sigma^2}} \tag{3}$$

$$G_{\varphi_k} = \frac{1}{Z}(G_{\varphi_k}^{-} - G_{\varphi_k}^{+}) \tag{4}$$

$$Z = \sum (G_{\varphi_k}^{-} - G_{\varphi_k}^{+}), \; G_{\varphi_k}^{-} - G_{\varphi_k}^{+} > 0 \tag{5}$$

where $\sigma = 1.2$ is a root mean square deviation of the Gaussian distribution; φ_k was an angle of the Gaussian rotation, $\varphi_k = k \cdot 22.5°$; $k = 2 \div 6, 10 \div 14$; $p,q = -3 \div 3$.

The maximum response of all 10 kernels defined the contrast magnitude of a local edge at its pixel location (Equation 6). The orientation of a local edge was estimated with orientation of a kernel that gave the maximum response.

$$g_{ij\varphi_k} = \sum_{p,q} b_{i-p,j-q}^{(l)} G_{\varphi_k} \tag{6}$$

After the local oriented edges were extracted, they were thresholded, and then grouped into the regions of interest representing candidates for facial landmarks. The threshold for contrast filtering of the extracted edges was defined as an average contrast of the smoothed image. Edge grouping was based on the neighbourhood distances between edge points and was limited by a number of possible neighbours for each edge point. Regions with small number of edge points were removed. The optimal thresholds for edge grouping were determined using a small image set randomly selected from the database.

To get more detailed description of the extracted edge regions, the steps of edge extraction and edge grouping were applied to high resolution image ($l = 1$) within the limits of these regions. In this case, the threshold for contrast filtering was determined as a double average contrast of the high resolution image.

APPENDIX B: EDGE ORIENTATION MATCHING

The procedure of edge orientation matching was applied to verify the existence of a landmark on the image. To do that, the detected regions were matched against the edge orientation model. The orientation model defined a specific distribution of the local oriented edges inside the detected regions.

The following rules defined the edge orientation model: 1) horizontal orientations are represented by the greatest number of the extracted edges; 2) a number of edges corresponding to each of horizontal orientations is more than 50% greater than a number of edges corresponding to any other orientations; and 3) orientations cannot be represented by zero number of edges.

The regions of facial landmarks had the specific distribution of the oriented edges. On the other hand, non-landmark regions like, for example, elements of clothing and hair, usually had an arbitrary distribution of the oriented edges and were discarded by the orientation model.