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ADAPTIVE SKIN DETECTION IN COLOUR IMAGES USING ERROR SIGNAL SPACE

Summary. In this paper we present a study on skin detection methods which operate in an *error signal*, obtained from the RGB colour space. Using this single-dimensional space, a global skin colour model was defined, as well as a facial region-based adaptation scheme was proposed recently. Our contribution lies in investigating the importance of how the facial regions are defined, and also we extend the existing methods that operate in the error space. Obtained experimental results indicate that the proposed improvements help better exploit the potential of the error space, and they reduce the skin detection errors.

Keywords: skin detection and segmentation, image processing, adaptive skin colour modelling

ADAPTACYJNA DETEKCYJA SKÓRY W OBRAZACH BARWNYCH Z WYKORZYSTANIEM PRZESTRZENI SYGNAŁU BŁĘDU

Streszczenie. Artykuł przedstawia badania dotyczące metod detekcji skóry na podstawie *sygnału błędu*, otrzymanego po przekształceniu przestrzeni barwnej RGB. We wcześniej opublikowanych pracach sygnał błędu posłużył do zdefiniowania globalnego modelu barwy skóry, a także modelu adaptacyjnego bazującego na wykrytych obszarach twarzy. Wkład autorów polega na zbadaniu istotności sposobu określania obszarów twarzy, a ponadto zaproponowane zostało rozwinięcie istniejących metod. Otrzymane wyniki eksperymentalne pokazują, że proponowane udoskonalenia umożliwiają bardziej efektywne wykorzystanie przestrzeni błędu oraz skutkują redukcją błędów detekcji skóry.

Słowa kluczowe: detekcja i segmentacja obszarów skóry, przetwarzanie obrazów, adaptacyjne modelowanie barwy skóry

1. Introduction

Skin detection is a process of identifying and classifying image pixels in order to decide whether they present the human skin. The detection is performed primarily on the basis of pixels' colour, however spatial and textural features were also reported to be beneficial here. Skin detection is often followed by skin segmentation that is aimed at exact determination of skin region boundaries based on the skin detection outcome. Both procedures are important tasks in numerous image processing applications, ranging from face detection and tracking, gesture analysis to human computer interaction (HCI) systems. Furthermore, skin detection may be used for image filtering and indexation purposes which are of a great importance in the case of multimedia databases.

There exist many difficulties that must be faced to solve the problem of skin detection. One of the most important is caused by the variations in the skin colour itself, due to age, ethnicity and other individual characteristics. Apart from how the person is represented, also the illumination conditions differ in terms of light distribution and colour (colour constancy problem). The third group of factors consists in varying image capturing device characteristics, due to different sensor types and internal processing algorithms used.

As the skin detection and segmentation is currently a fast-evolving domain, new techniques are being researched that may deliver better detection rates while decreasing the number of erroneously classified pixels. The motivation for the research reported in this paper was to assess the performance and quality of two existing methods of skin tone detection that operate in a recently introduced error signal space [3].

This paper presents a detailed experimental study focused on the adaptation proposed by Yogarajah et al. [22], which is based on a facial region obtained using automatic face detectors. In our research reported here, we investigated several possible extensions of the method which increase its effectiveness. First of all, we used a continuous rather than binary decision surface, which gave us a deeper insight into how the acceptance thresholds should be set. Then, we compared the results obtained using a facial region proposed in the original method with a trapezoidal region used in our earlier works. Finally, we learned the Bayesian classifier in the error space both in the case of the global and local models.

The paper is organized as follows. In Section 2 we present a short overview of existing skin modelling techniques. Section 3 is focused on the error signal space, and the skin model adaptation scheme is outlined there. Proposed improvements are described in Section 4, and the experimental study is reported in Section 5. The paper is concluded in Section 6.

2. Related work

Skin detection is an intensively explored field of computer vision and many different approaches have been proposed. In general, all of the existing methods take advantage of the observation that skin-tone colour has common properties which can be defined in various colour spaces. An interesting survey on skin colour modelling was published in 2007 by Kakumanu et al. [10]. The classification of existing algorithms was performed according to two main criteria: 1) the colour space being used (such as basic, perceptual, orthogonal or perceptually uniform) and 2) the type of the classifier applied (e.g. fixed thresholding [13], Gaussian mixture models [7], histogram model with the Bayesian classifier [9, 23] or neural networks [16]).

Every group of methods mentioned above carries its own advantages and drawbacks related to the computational complexity and efficiency in terms of false positives (non-skin pixels being marked as skin) and false negatives (skin pixels marked as non-skin values).

There exist many solutions exploiting fixed thresholds and rules in different colour spaces. The thresholds, which allow for discriminating skin and non-skin pixels, were, among others, determined in the YIQ [5], YCbCr [8], HSV [20] and normalized rgb [21] spaces. Cheddad et al. [3] used a transformed $e(x)$ channel calculated on the basis of the RGB space.

There is a group of skin detection methods which adapt the model to specific illumination conditions and individuals' characteristics. This allows for achieving much higher detection scores and lower error rates. These methods are based on tracking the skin-coloured objects in series of video frames [4, 17, 18], or a skin colour model is adapted based on whole-image analysis [1, 14, 19]. Also, the adaptation may be proceeded using a skin sample acquired from hand [2] or face detectors [6, 11, 22]. Yogarajah et al. [22] extended the fixed threshold-based method which operates in the error space [3] by dynamic threshold adaptation using a facial region. This method is described later in Section 3.

3. Skin detection in the error signal space

Cheddad et al. [3] developed a skin detection method relying on fixed thresholding in a proposed error space $e(x)$, being a transformation of the original RGB colour space to a single-dimensional signal.

3.1. Error signal space

First of all, the input RGB images are normalized, so as the pixel values fall into the $[0,1]$ interval. The 3D space is transformed to the $I(x)$ channel:

$$\delta(\mathbf{u}) = \sum_k (\mathbf{g}_k \cdot \mathbf{u})^2 I(x) = \Psi(r(x), g(x), b(x)) \otimes \bar{a}, \quad (1)$$

where the \otimes operator denotes matrix multiplication and

$$\delta(\mathbf{u}) = \sum_k (\mathbf{g}_k \cdot \mathbf{u})^2 \bar{a} = \begin{bmatrix} 0.29893602129377539 \\ 0.58704307445112136 \\ 0.1402090425510325 \end{bmatrix}. \quad (2)$$

As it follows from (1) and (2), every RGB channel is multiplied by an appropriate coefficient from the \bar{a} vector and then they are summed up to form the $I(x)$ channel.

The $\hat{I}(x)$ channel is a modified luminance channel with the R vector not taken into account. The channel is defined by the maximal value chosen from green and blue channels for every pixel:

$$\delta(\mathbf{u}) = \sum_k (\mathbf{g}_k \cdot \mathbf{u})^2 \hat{I}(x) = \arg \max_{x \in \{1, \dots, n\}} (G(x), B(x)). \quad (3)$$

Finally, both obtained channels are subtracted in order to obtain the error signal:

$$\delta(\mathbf{u}) = \sum_k (\mathbf{g}_k \cdot \mathbf{u})^2 e(x) = I(x) - \hat{I}(x). \quad (4)$$

This constitutes a single-dimensional space, in which the further processing is applied.

3.2. Global skin model

The skin detection method discussed in [3] consists in applying fixed thresholds that were obtained after statistical analysis of 147 852 pixel samples representing skin regions of people with different ethnicity, captured under extremely varying lighting conditions. The resulting data distribution bears similarity to a Gaussian and was easily fit into a bell curve. After choosing the lower and upper thresholds to be positioned 1 and 3 sigmas away from the mean μ , respectively, the following skin segmentation condition is obtained:

$$\delta(\mathbf{u}) = \sum_k (\mathbf{g}_k \cdot \mathbf{u})^2 f_{skin}(x) = \begin{cases} 1, & \text{if } 0.02511 \leq e(x) \leq 0.1177 \\ 0, & \text{otherwise} \end{cases}. \quad (5)$$

The obtained empirical rule for the skin segmentation is claimed by the authors to be optimal. In fact, such a general binary decision rule cannot deliver satisfactory results in case of specific lighting conditions. This was confirmed during our experiments which demonstrate that when the thresholds are adapted to a particular image, the detection accuracy may be increased.

3.3. Adaptive skin model

Yogarajah et al. reported [22] that the Cheddad's approach does not provide sufficient robustness to separate skin regions from non-skin areas, if the latter contains colours similar to the human skin.

Instead of an off-line determination of thresholds by the analysis of a sufficiently large amount of skin pixels, the authors proposed a new skin detection technique. It relies on the on-line adaptation by analysis of the skin colour from a facial region.

The facial region is found via an eye detection algorithm and generating an elliptical face region around the eyes. The centre of the ellipse is the eyes symmetric point. Minor and major axes are estimated to be equal $1.6D$ and $1.8D$ respectively, where D is the distance between the eyes. Once the facial region of interest (ROI) is defined, it is necessary to filter out non-smooth areas that may obstruct the threshold value, such as eyes, hair, lips, nose edges. For this purpose, the Sobel edge detector is used, as it is computationally simple, while sufficient. To further assure that the non-smooth areas will not be taken into account, a dilation operation is performed on the detected edge pixels. An example of a facial region determined based on the detected eye positions is presented in Fig. 1 (c, f).

For the threshold calculation, only these $e(x)$ values that correspond to smooth face region pixels are taken into account. On this basis, a histogram showing the frequency distribution is built and a Gaussian distribution is fit to the data. The thresholds for skin detection are obtained as 95% confidence interval boundaries on the frequency distribution of face region in the $e(x)$ channel.

Then, given the dynamically determined thresholds, all pixels in the image are examined and classified as skin or non-skin values. The authors claim that the developed method [22] possesses better error rates when compared to Cheddad et al. However, no quantitative results were published there.

It is worth noting that both Cheddad's and Yogarajah's approaches construct a binary map representing the skin segmentation results – every pixel belongs to one of two classes, i.e. the skin or non-skin class.

4. Proposed improvements

First of all, we extended the methods, so that their response is continuous rather than binary. For the Cheddad's method, the skin probability is inversely proportional to a distance from the middle value of the skin interval in the signal $e(x)$, and it is normalized, so as the probability of 0.5 is achieved at the threshold values. In the case of the Yogarajah's adapta-

tion, $e(x)$ signal distribution in the facial region was approximated using a single Gaussian, and the skin probability was computed as:

$$\delta(\mathbf{u}) = \sum_k (\mathbf{g}_k \cdot \mathbf{u})^2 P(x) = \frac{1}{\sqrt{2\pi\sigma}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right). \quad (6)$$

Subsequently, we compared the results obtained using the Yogarajah's adaptation scheme [22] with two different facial region generation procedures, namely the original *elliptical* region proposed in [22], and based on a *trapezoidal* shape excluding the eyes' area. The latter was used during our earlier research [11], focused on the adaptation in the RGB space. Examples of the facial regions obtained using these two techniques are presented in Fig. 1. It can be seen that the *trapezoidal* region covers the mouth area, while the *elliptical* region takes into account the forehead region. Results obtained using these methods are presented and discussed later in Section 5.



Fig. 1. Facial regions: trapezoidal [11] (b, e) and elliptical [22] (c, f)

Rys. 1. Obszar twarzy wyznaczony dwiema różnymi metodami: [22] (c, f) i [11] (b, e)

Finally, we intended to avoid setting fixed thresholds in the error space, and we learned the Bayesian classifier instead. This classification scheme is often used for skin detection using two [23] or three [9] dimensions of a colour space. It works based on the colour histograms for the skin (C_S) and non-skin (C_{NS}) classes. The probability that a pixel of a colour v appears in the x -th class is computed as:

$$\delta(\mathbf{u}) = \sum_k (\mathbf{g}_k \cdot \mathbf{u})^2 P(v|C_x) = C_x(v)/N_x, \quad (7)$$

where $C_x(v)$ is the number of v -coloured pixels in the x -th class and N_x indicates the total number of pixels in that class. These numbers depend on the size of a training set. The probability that a pixel presents the skin given a colour v is obtained using the Bayes rule:

$$\delta(\mathbf{u}) = \sum_k (\mathbf{g}_k \cdot \mathbf{u})^2 P(C_S | v) = \frac{P(v|C_S)P(C_S)}{P(v|C_S)P(C_S) + P(v|C_{NS})P(C_{NS})}, \quad (8)$$

where it is usually assumed that the *a priori* probabilities $P(C_S) = P(C_{NS}) = 0.5$. Here, we learned the Bayesian classifier using a single-dimensional $e(x)$ signal. While the signal is continuous and the Bayesian classifier is defined based on the histogram bins, the signal was quantised into 256 intervals for a range of $-0.0675 \leq e(x) \leq 0.21$ that was determined experimentally.

For the Bayesian classifier, we used two adaptation schemes derived from [11], namely *local* and *adaptive*. First of all, the skin colour distribution is obtained from the pixels in the facial region. It is assumed that the non-skin colour distribution is complementary to the skin colour distribution, and hence a local Bayesian model is built. Here, the number of skin pixels depends on the size of the facial region in the input image. Afterwards, the local model can be used for skin detection, or it can be used to adapt the global model. The adaptation consists in taking an average mean of the probabilities obtained using the global and local models:

$$\delta(\mathbf{u}) = \sum_k (\mathbf{g}_k \cdot \mathbf{u})^2 P(C_S | v) = \omega P_{local}(C_S | v) + (1 - \omega) P_{global}(C_S | v), \quad (9)$$

where ω is the weight of the local model. Such an approach was also used in [6, 18]. The adaptive model is more stable, which was also confirmed in our experimental study.

5. Experimental validation

The experiments were carried out using 4000 images from the ECU database [15], which contains colour images associated with ground-truth skin binary masks indicating skin regions. These images were acquired in uncontrolled lighting conditions, and skin-colour objects often appear in the background, which altogether complicates the skin detection task. Face and eye detection was performed using our method developed during our earlier research [12]. The data set was split into two equinumerous subsets, i.e. a train set used for learning the global Bayesian model in the $e(x)$ signal space, and a validation set.

We measured the skin segmentation performance based on two errors determined for the image in the validation set, namely: a) *false positive* rate (δ_{FP}), obtained as a percentage of background pixels classified as skin, and b) *false negative* rate (δ_{FN}), i.e. a percentage of skin pixels misclassified as background. If the detector's response is continuous, then the false positive and false negative rate both depend on the acceptance threshold, and their mutual relation is commonly presented using *receiver operating characteristic* (ROC).

ROC curves obtained for the investigated methods are presented in Figs. 2 and 3. For the Cheddad's [3] and Yogarajah's [22] methods, a continuous response was considered to render the curves, and the results obtained based on the binary decision are indicated with an asterisk. It can be observed that the choice of a facial region shape used for the adaptation has a significant influence on the obtained results. Using the trapezoidal shape, the errors were reduced, which was not achieved with the original elliptical shape proposed by Yogarajah. From the graphs, it can be observed that the original method reduces the false positives, but the false negatives grow, and the sum of these two errors is larger than in the case of the

Cheddad's method (i.e. the former ROC curve is positioned above the latter). The difference resulting from the facial region shape may be explained by the fact that the elliptical region includes the forehead which is often covered with the hair. Also, including the colour of the lips in the case of the trapezoidal region may be beneficial for the overall score. In general, it is worth further investigation which facial parts should be included into the region used for building a local model, as the differences between these two schemes are significant.

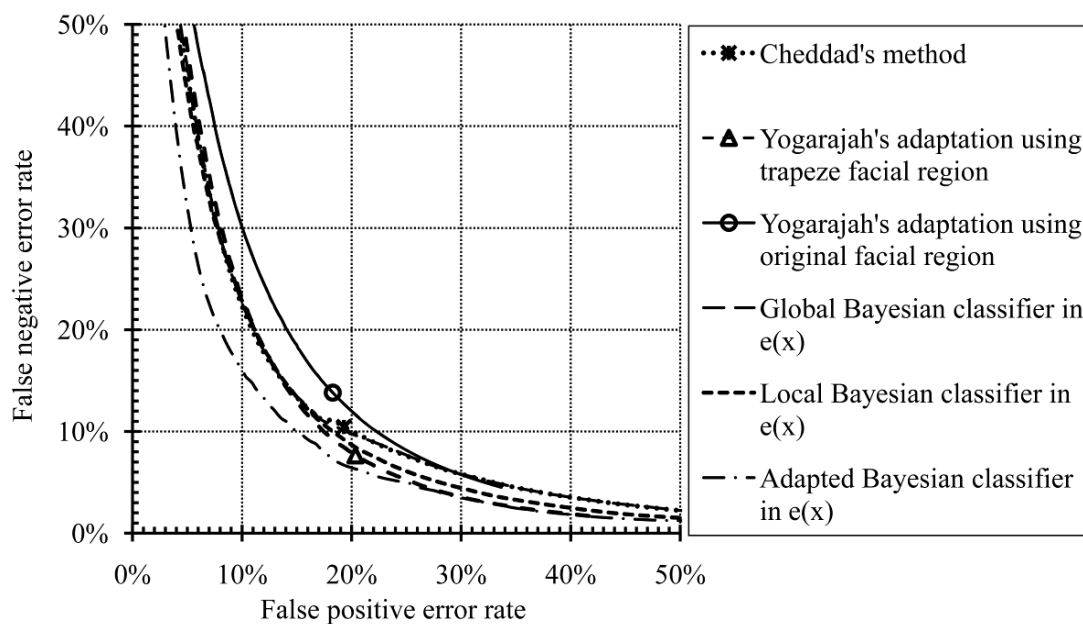


Fig. 2. ROC curves obtained for the investigated methods

Rys. 2. Krzywe ROC uzyskane dla przeanalizowanych metod

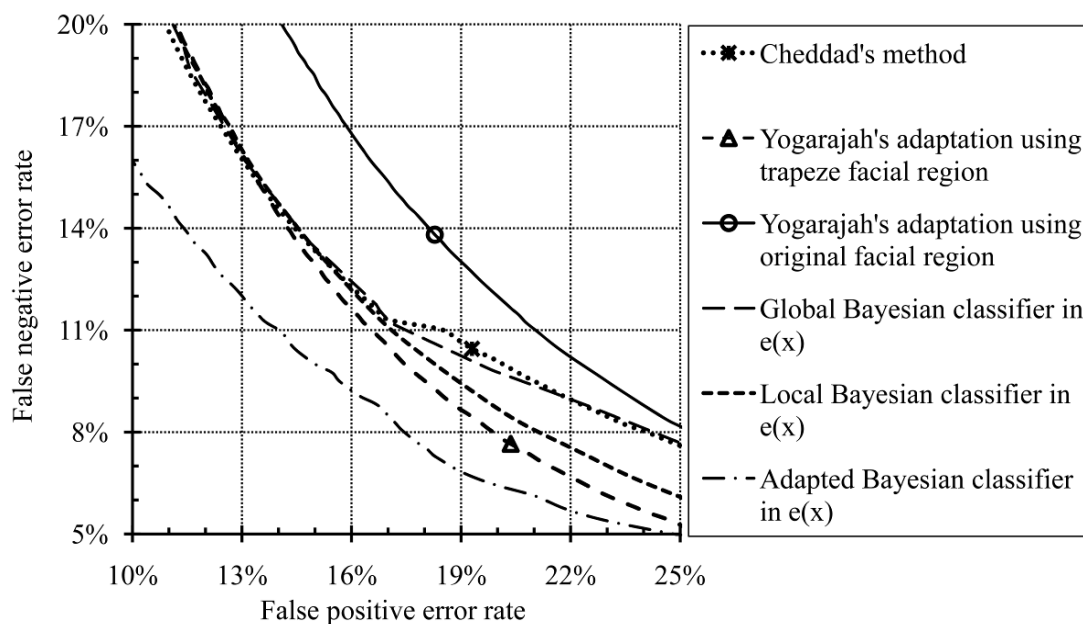


Fig. 3. ROC curves obtained for the investigated methods (magnified)

Rys. 3. Krzywe ROC uzyskane dla przeanalizowanych metod (powiększenie)

Furthermore, the curves obtained using the Bayesian classifier trained in the $e(x)$ space are also presented in Figs. 2 and 3. Using a global model, the results are fairly similar to the Cheddad's method. A local Bayesian model performs slightly better than the global one, however it is still slightly worse than the Yogarajah's adaptation. Finally, the adaptation scheme for the Bayesian classifier with $\omega=0.5$ outperformed all of the aforementioned techniques.



Fig. 4. Skin segmentation results: a) input images, b) facial regions, c) segmentation results obtained using Cheddad's method and d) using proposed adaptation

Rys. 4. Segmentacja obszarów skóry: a) obrazy wejściowe, b) obszar twarzy, c) wynik segmentacji za pomocą metody Cheddada i d) za pomocą zaproponowanej metody adaptacyjnej

Some qualitative results are presented in Figs. 4 and 5. Facial regions detected in the input images (a) are marked in (b), and the results obtained using the Cheddad's method (c) are compared with those delivered by the adapted Bayesian classifier (d). The false positives are indicated with a red tone, the false negatives – with the blue, and true negatives are faded. From Fig. 4 it can be seen that the adaptation reduces the errors in all of the presented cases, even when only some faces are properly detected (IV.) or when an eye is detected with low precision (V.). Fig. 5 presents the cases, in which the adapted model was outperformed by the global classifier. This may be due to the face detection errors as in VI., where a false positive face was detected over the hand region, taking some background pixels for the adaptation.

Also, in X. the true face was not detected, while a false face was found on the arm, which obviously caused a complete failure of the skin detector. For VII. and VIII., the errors were caused by some objects which partially occluded the facial region. This did not affect the face detector, but introduced some non-skin pixels into the adaptation process, which overall decreased the efficacy of the face detector. In the case of the image IX., the increase in the errors is due to specific image content. Basically, the facial colour is similar to the background, which makes the local classifier less discriminating than the global one. However, taking all of these cases into account it may be concluded that the face-based adaptation offers a significant reduction of the detection errors.



Fig. 5. Skin segmentation results: a) input images, b) facial regions, c) segmentation results obtained using Cheddad's method and d) using proposed adaptation

Rys. 5. Segmentacja obszarów skóry: a) obrazy wejściowe, b) obszar twarzy, c) wynik segmentacji za pomocą metody Cheddada i d) za pomocą zaproponowanej metody adaptacyjnej

6. Conclusions and future work

In the work reported in this paper, we have analysed the skin detection methods which operate using the error signal, obtained from the RGB colour space. The results indicate that the face-based adaptation allows for substantial error reduction, and the Bayesian classifier offers better adaptation than the method proposed by Yogarajah et al. [22]. Although the ob-

tained scores may be higher, if the classifier operates in the RGB space using all three dimensions, the advantage of using a single-dimensional space consists in reducing the memory and time requirements, which may be important in some applications.

It may be worth to investigate alternative procedures for determining the facial regions which are used for the adaptation. The differences between two simple techniques were significant, and none of them seems to be more error-prone. Possibly, employing a global skin colour model, as well as a sort of spatial analysis may help improve the selection process of the pixels used for building the local model.

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Omówienie

Detekcja i segmentacja obszarów skóry stanowią istotną grupę algorytmów przetwarzania obrazów. Będąc składnikiem wielu systemów wizyjnych, są one podstawowym źródłem informacji o lokalizacji dłoni, twarzy czy też całej sylwetki człowieka w analizowanym obrazie. Ponadto metadane dotyczące liczby obszarów skóry oraz ich cech, indeksowane w bazach danych, mogą stanowić podstawę do definiowania kryteriów wyszukiwania opartych na treści obrazów, a nie tylko na ich cechach globalnych.

Każda z metod segmentacji obszarów skóry w obrazach barwnych musi stawić czoła takim wyzwaniom, jak odmienność odcieni skóry wśród populacji, różniące się warunki oświetleniowe i cechy urządzeń rejestrujących obrazy (aparaty, kamery). W związku z tym opracowano wiele rozwiązań wykorzystujących rozmaite przestrzenie barwne i opartych na różnych typach klasyfikatorów. Niniejszy artykuł przedstawia ocenę jakości i efektywności dwóch rozwiązań wykorzystujących niedawno zaproponowaną przestrzeń sygnału błędu, wyprowadzaną z przestrzeni RGB. Obie metody pomimo użycia tego samego kanału reprezentują odmienne kategorie – metod stałoprogowych oraz metod adaptacyjnych. Oprócz porównania powyższych algorytmów opracowano ich rozwinięcia w celu zwiększenia dokładności detekcji obszarów skóry. W pierwszej kolejności wyniki segmentacji obu metod zostały przetransformowane do postaci ciągłej, przedstawiającej mapę prawdopodobieństwa zamiast binarnych wyników klasyfikacji. Ponadto zaproponowany przez twórców metody elipsoidalny obszar twarzy służący do adaptacji modelu został zamieniony na trapezoidalny. W celach porównawczych zostały użyte wytrenowane globalne i lokalne klasyfikatory Bayesa, operujące w tym samym kanale błędu.

Walidacja eksperymentalna została przeprowadzona na zbiorze 4000 obrazów z bazy ECU, a jej wyniki są przedstawione w niniejszym artykule.

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