Improvements on Human Skin Segmentation in Digital Images

Anderson Carlos Sousa e Santos[1], Helio Pedrini
Institute of Computing, University of Campinas
Campinas-SP, Brazil, 13083-852

***Abstract*—Human skin segmentation has several applications in computer vision and pattern recognition fields, whose main purpose is to distinguish skin and non-skin regions. Despite the large number of available methods, accurate skin segmentation is still a challenging task. Three main contributions toward this need are presented in this work. The first is a self-contained method for adaptive skin segmentation that adjusts the color model to a particular image. The second is the combination of saliency detection with color skin segmentation, which performs a background removal to eliminate non-skin regions. The third is a texture-based improvement employed to characterize non-skin regions and thus eliminates color ambiguity adding a second vote. Experimental results on public data sets demonstrate a significant improvement of the proposed methods for human skin segmentation over state-of-the-art approaches.**

***Keywords*-segmentation; saliency; texture; skin detection**

I. Motivation

Human skin segmentation serves as a key step in a diverse of applications in image analysis. Summarily, it aids human detection [1], [2], face detection [3], [4], nudity detection [5], [6], [7], gesture analysis [8], [9] and content-based image retrieval [10], [11] since it can benefit from any semantics extracted from the images.

However, the applications will still demand further processing and analysis, such that the skin detection configures as a preprocessing stage, which creates a requirement for speed and simplicity. The term simplicity here means that complex configuration, parameter selection and manual adaptation should be avoided. In other words, the method for skin segmentation should enable real-time applications and be adaptable to different purposes.

There are many challenges associated with skin segmentation in real-world images. First, the images acquired through different illumination conditions present different skin characteristics. Furthermore, shadows, light intensity variation, reflections and person's pose cause discrepancy between skin regions of the same image. Image resolution and size, as well as compression techniques, are also significant aspects. Moreover, some intrinsic difficulties implied by natural characteristics of human skin include: its color varies with ethnic diversity; its texture change with age — babies have a soft skin while elders have a more coarse skin; elasticity, which means that facial expressions and pose can change its aspect.

[1] M.Sc. Dissertation.

Although not robust to all these problems, color presents a meaningful evidence for skin detection. In fact, the vast majority of researches in the literature focus on color information to determine whether a pixel belongs to skin or not. Nevertheless, there is an intrinsic problem associated with the use of color. It does not provide a separability between the pixels belonging to skin and one portion of non skin, referred to as skin-like pixels. This transition is considerably large and can frequently occur in an image, causing more errors than later applications could normally afford.

II. Objectives and Contributions

The main purpose of this work is to improve the human skin segmentation process through increasing the separability between skin and skin-like pixels. This dissertation presents three major contributions on this matter:

- A *self-adaptive method* for generating a skin color model specific to each image, which reduces color ambiguity and, that way, decreases the skin-like pixels. This method presents the novelty to be self-contained, that is, differently from usual approaches that rely on face detection or previous knowledge, it uses spatial analysis to obtain true skin regions from which a specific color model is derived.
- A *saliency-based framework* for saliency detection to remove background skin-like regions. A saliency detector captures the regions that "catch the eye" on an image. Thus, they can be used to separate foreground from background. A framework that combines color skin detection with a saliency detector is proposed to remove false positives from the first process.
- A *texture-based method* for modeling texture energy in skin and non-skin regions. It aims to remove the ambiguity caused by color, providing a second vote for classification. Texture is captured by a convolution filter and an energy measure is derived from each region to characterize it. The skin and non-skin energies are learned through Gaussian models, which are then applied to the image to obtain a skin texture probability. Skin texture and skin color are combined in a way that the pixel is considered skin only if both information agree.

III. Background

Many approaches found in the literature have been proposed to address the problem of human skin segmentation [12], [13],

[14], [15]. The simplest and earlier strategies for classifying a pixel are based on static decision rules that restrict skin to some specific intervals on a chosen color space. Sobottka et al. [16] developed a skin detection method based on the HSV color space. A transformation of RGB color space into a single-channel was proposed by Cheddad et al. [17] for skin detection purpose. Hsu et al. [18] adopted various thresholds that partition the HSI color space into three zones that define the skin pixels. A rule based on two quadratic functions for the normalized RG space was proposed by Soriano et al. [19].

A more sophisticated scheme, proposed by Jones and Rehg [2], is based on modeling the statistical distribution of color. There are two main approaches: parametric and non-parametric techniques. Both approaches calculate the probability of a given color (c) to be skin ($P(skin|c)$), which generates a probability map such that the segmentation can be performed through a threshold. However, parametric approaches assume that the skin distribution fits some explicit model.

In order to have a more accurate model, it is possible to suppose that there is an overlap between skin and non-skin colors [13], such that many researchers have adapted the mentioned methods according to the context. For instance, Kovac et al. [20] defined different rules depending on lighting conditions, whereas Phung et al. [21] created an iterative method for determining an optimal threshold for the probability map of a particular image.

Nevertheless, the most significant results are obtained by content-based adaptation, more specifically for face detection. The first of such approaches [22] uses the region acquired by a face detector to update a unimodal Gaussian previously determined. Taylor and Morris [23] used only the facial skin in normalized RG to construct a Gaussian model, discarding any previous training. A more robust technique [24] uses the face region to build a local skin histogram and a $P_{face}(skin|c)$ is derived and combined with the general probability for the final map.

Another strategy, known as spatial analysis, considers the structural alignment in the neighborhood of pixels classified as skin, generally with a probability map, such that it refines the segmentation process by removing false positives. Most of these techniques perform an expansion of seeds found by a high threshold. This expansion can be performed through different criteria, such as energy accumulation [24], cost propagation [25] and threshold hysteresis [26]. Although cost propagation is complex, it usually provides superior results, where the Dijkstra's algorithm [27] is used to calculate the shortest routes in a combined domain composed of hue, luminance, and skin probability.

Wang et at. [28] used fixed rules for RGB and YCbCr color spaces, then combined the result of both and applied the gray-level co-occurrence matrix (GLCM) [29], [30] to extract texture features and classify the found skin regions. Although the false positive rate decreased, the true positive rate also decreased.

Ng and Chi-Man [31] combined both color and texture features for skin segmentation. The texture features were extracted through 2D Daubechies wavelets, whereas a Gaussian mixture model was used to classify the skin regions. Non-skin regions were discarded by using K-means. The method is dependent on the number of clusters and the improvement was not significant since the decrease in true skin detection is approximately the same as false skin detection.

Jiang et al. [32] employed a histogram-based skin probability map to find initial skin candidates. A lower threshold was used as a second stage to discard skin-like pixels. Gabor wavelets were used to extract texture features and combined to produce an untrained texture map. Therefore, a threshold on this map was required to eliminate non-skin texture. Similarly to other methods, this approach also compromises the true skin detection. Then, the authors used color and texture information to select markers of watershed segmentation [29] to grow skin regions.

IV. Adaptive Human Skin Segmentation Method Based on Seed Growing

We propose a skin segmentation method that combines spatial analysis and adaptive models for better skin probability estimation. The main steps of our method are presented in the diagram shown in Figure 1. First, seeds are extracted from a general skin probability map, then an edge restriction propagation is performed and the generated segment is used to build a local skin histogram. Local and global maps are combined to achieve the final segmentation.

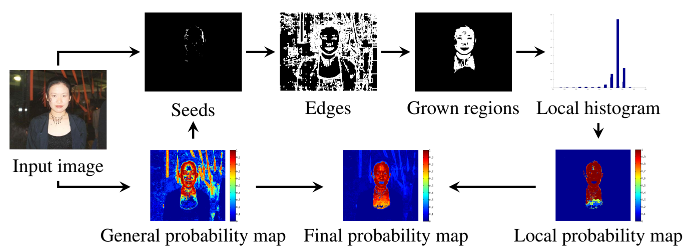

Fig. 1. Main stages of the skin detection process based on seed growing.

The global probability map is generated by Bayes' rule with the posterior probabilities defined through histograms of skin and non-skin colors collected from a training set. Contrary to the usual approach using a fixed high threshold to the map, we estimate the best high threshold for a particular image, by first applying a mean filter to the probability map and then take the maximum probability as seed threshold for the original probability map. To allow for images with no skin at all, if the maximum value is smaller than a minimum threshold ($T_{seed_{min}}$), it is discarded, otherwise it is assigned as the seed threshold for the original probability map. Therefore, we obtain seeds with high probability by considering the neighbors probability as well.

To prevent the occurrence of false positives, we exclude the choice of seeds located in edge regions, since skin is usually a smooth and homogeneous region. In order to avoid "leakages" we modified the cost propagation proposed in Kawulok [25] by adding a constraint in which the propagation cannot flow out the image edges. These edges are found by combining (through logical *or* operator) the results of Canny detector for each of the three channels in HSV color space. Following that, a morphological dilation operation is performed, such that small gaps can be closed. Besides preventing false positives, this also speeds up the algorithm, once the original approach calculates the costs from the seeds to every other pixel in the image.

The propagation process generates a cost for each pixel that can be reached and the final skin regions are obtained from a threshold in the cost map. Once we have generated these regions, we use them to build a local statistical model that adapts to the particular conditions of the image. From the histogram of these resulting skin regions, we obtain a $P_{local}(c|skin)$. As for non-skin, we assume that the local distribution follows the global one. The final probability is defined as

$$P(skin|c) = \gamma P_{local}(skin|c) + (1-\gamma) P_{global}(skin|c) \quad (1)$$

where $P_{local}(skin|c)$ and $P_{global}(skin|c)$ are calculated by using local and global data, respectively. The parameter γ controls the importance of the local model.

From Equation 1, we generate the final skin probability map, in which the detection can be performed through a fixed threshold.

V. Human Skin Segmentation Improved by Saliency Detection

We propose a method for reducing the false positive rate in skin segmentation with the use of a saliency detection method. This is based on the premise that, although, the skin is not always salient in the image, the background will be not salient. Therefore, saliency detection methods that operate by finding the background to achieve the salient region are preferable, for instance, methods with boundary priors. The main steps of our skin detection framework are illustrated in the diagram of Figure 2.

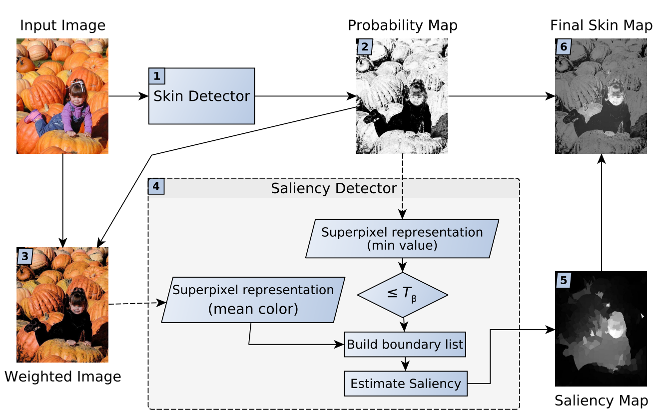

Fig. 2. Main stages of the proposed skin detection framework based on saliency.

First, the skin detector (Stage 1) is applied to the image, creating a probability map (P_{map}) (Stage 2), which is used to build a weighted image (Stage 3), expressed as

$$W_I(i,j,k) = P_{map}(i,j) \cdot I(i,j,k) \quad (2)$$

where $W_I(i,j,k)$ represents the weighted image pixel in channel k and $I(i,j,k)$ the original image pixel in channel k.

The weighted image serves as input for the saliency detector (Stage 4), whereas the probability map is also used to exclude probable skin from the boundary list. This is done with a threshold (T_β) applied to the map and aims to prevent skin pixels adjacent to the boundary from being discarded. Since many saliency implementations use superpixels, in that case the probability map needs to be modeled with the same superpixel structure, however the representative value of each superpixel will be the minimum value of the region instead of the usual mean value. This is done such that only regions containing all probability values larger than T_β will be excluded as background.

The output saliency map (S_{map}) (Stage 5) is again combined with P_{map}, expressed as

$$F_{map}(i) = \gamma P_{map}(i) + (1-\gamma) S_{map}(i) \quad (3)$$

where F_{map} is the final skin map (Stage 6) and γ defines the weight of the probability map in the mean combination in the range between 0 and 1.

VI. Skin Segmentation Improved by Texture Energy Under Superpixels

We propose a method for reducing the rate of false positives in skin detection caused by skin-like color. Law's texture energy measure [33] is employed in the process, which works on the response of the intensity image to a special filter mask. The main steps of our skin detection method are illustrated in the flowchart of Figure 3.

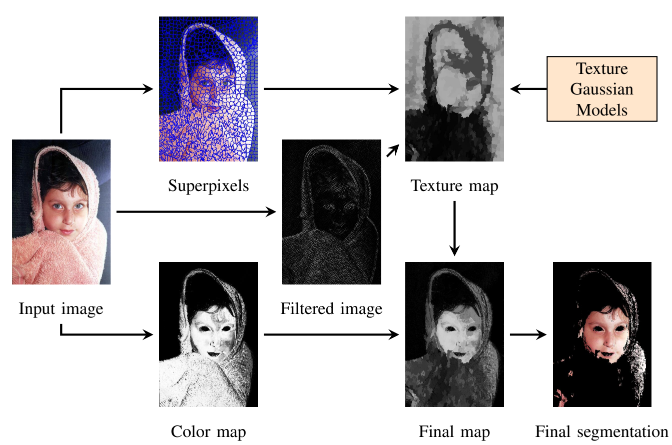

Fig. 3. Main stages of the proposed skin detection method improved by energy under superpixels.

The filters defined by Law are build by the product of two vectors obtained from a fixed set of 1-D masks designed to detect edges, spots, ripple, among others. A filter is named according the purpose of the vectors from which it was produced and it's size. For example, an E5S5 mask is a 5×5 mask produced by the product of a 1-D edge mask and a 1-D spot mask.

To allow the calculation of energy over a region and prevent that the same region covers both skin and non-skin, we use the Simple Linear Iterative Clustering (SLIC) [34] technique for segmenting the image into superpixels. Thus, we calculate the mean energy of each superpixel in the training and test sets.

The goal of the training stage is to obtain two Gaussian models, one for skin and another for non-skin texture energy measures. The images are submitted to superpixels over segmentation and convoluted with a spatial filter. The texture energy is computed for each superpixel, such that mean and standard deviation are extracted for each class (skin and non-skin), forming the two Gaussian models.

In the test stage, once the energies of an image have been computed through the same pipeline as in the training step, the skin and non-skin probability densities for each superpixel are obtained. The skin probability given the texture energy is computed as

$$P(skin|E_{\Phi}) = \frac{f(E_{\Phi}, \mu_{skin}, \sigma_{skin})}{f(E_{\Phi}, \mu_{skin}, \sigma_{skin}) + f(E_{\Phi}, \mu_{\neg skin}, \sigma_{\neg skin})} \quad (4)$$

where E_{Φ} is the energy measure and $f(E_{\Phi}, \mu_{class}, \sigma_{class})$ is the Gaussian probability density function for the texture energy.

As texture in a face can vary from the rest of the body, the skin probability in the region close to the nose, around the eyes and mouth will be very low. Thus, it is necessary to apply a heuristic to avoid this type of problem. In our work, we perform a postprocessing mechanism, where areas with low probabilities, surrounded by high probabilities, are filled with the mean of these surroundings high probabilities. Finally, the result of this process constitutes the skin texture probability map.

The texture probability map (T_{map}) is combined with a color probability map (C_{map}) through an AND operation to generate the final skin probability map F_{map}, expressed as

$$F_{map} = \sqrt{C_{map} \cdot T_{map}} \quad (5)$$

which means that high probability values will be assign to regions where both color and texture agree as skin region.

VII. Experiments

The experiments were evaluated on two different data sets. To train the Bayes classifier, we used 8,963 non-skin images and 4,666 skin images from the Compaq database [2]. For evaluation and comparison purposes, we used the ECU database [14] divided into 1,000 images for validation and 3,000 images for testing. The metrics employed to assess the performance of the methods were true positives rate (η_{tp}), false positive rate (δ_{fp}), F_{score} and detection error δ_{min}.

For comparison with our self-adaptive method, we selected some state-of-the art methods available in the literature: Cheddad's decision rule [17], statistical model [2], face-based adaptation [24] built with Viola-Jones face-detector [35] and cost propagation [25].

Figure 4 presents a comparison of the ROC curves. The points in the curves were obtained with different thresholds, except for Cheddad's rule, whose output is binary.

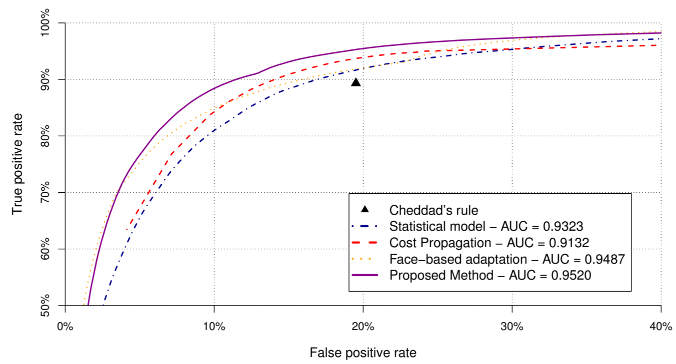

Fig. 4. ROC curves for comparison of the tested methods.

Table I shows the obtained results for each method considering the point closer to coordinate $(0, 1)$ in the ROC curve.

TABLE I
DETECTION RESULTS FOR DIFFERENT METHODS.

Method	η_{tp} (%)	δ_{fp} (%)	F_{score} (%)	δ_{min} (%)
Cheddad	89.33	19.51	64.78	30.18
Statistical model	87.90	14.51	69.71	26.61
Face-based adaptation	86.83	11.79	72.63	24.96
Cost propagation	**90.40**	14.46	71.05	24.06
Proposed method	89.78	**11.24**	**74.95**	**21.46**

Considering the statistical model as a baseline, the face-based approach shows a decrease in the false positive rate and the cost-propagation an increase in the true positive rate, whereas our method presents enhancement for both metrics, giving a significant upgrade to F_{score}.

In order to evaluate the improvement for adding texture and saliency according our framework, we selected the three widely used skin detectors with different approaches: Cheddad's rule [17] (rule based), Gaussian Mixture Model (GMM) [2] (parametric) and Histogram Model [2] (non-parametric).

Figures 5 and 6 show comparative ROC curves between original skin detectors and our combination with saliency detector and texture, respectively.

Tables II and III show the results for the best points. A noticeable aspect in Table II is that the Gaussian Mixture Model method, which holds the worst results individually, when submitted to the our improvement, achieves superior results when compared to the best method (Histogram) without improvement.

For the texture (Table III), although the improvement has not been so high, it is still noticeable. This is because the

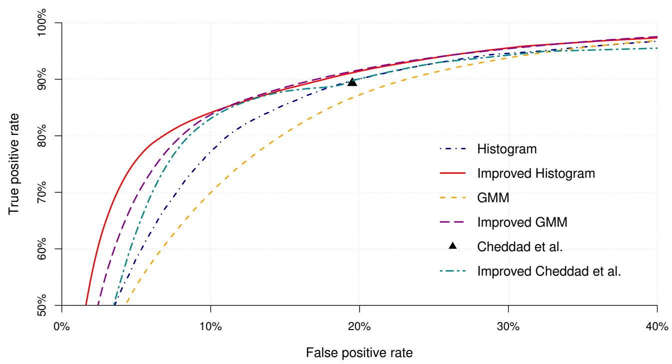

Fig. 5. ROC curves for the results of the improvement through our saliency method.

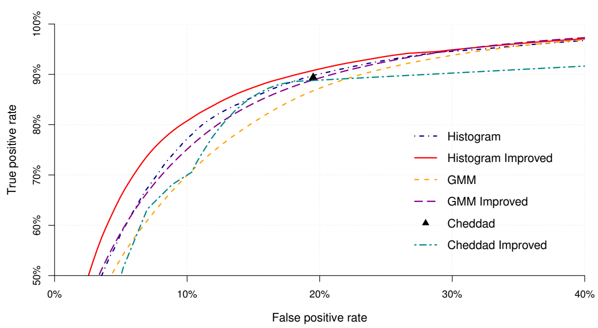

Fig. 6. ROC curve for the results of the improvement through our texture method.

TABLE II
DETECTION RESULTS FOR DIFFERENT METHODS WITH SALIENCY.

Method	Original		+ Saliency	
	F_{score} (%)	δ_{min} (%)	F_{score} (%)	δ_{min} (%)
Cheddad	64.78	30.18	71.67	26.29
Gaussian Mixture	63.09	32.76	72.08	25.93
Histogram Model	66.95	29.33	**73.63**	**25.91**

TABLE III
DETECTION RESULTS FOR DIFFERENT METHODS WITH TEXTURE.

Method	Original		+ Texture	
	F_{score} (%)	δ_{min} (%)	F_{score} (%)	δ_{min} (%)
Cheddad	64.78	30.18	67.38	28.90
Gaussian Mixture	63.09	32.76	65.64	30.41
Histogram Model	66.95	29.33	**69.17**	**27.59**

texture analysis acts well in heterogeneous ambiguous regions, whereas the saliency works better in person centered images, which is more common.

VIII. CONCLUSIONS

In this work, three main contributions are achieved to improve the separability between skin and skin-like regions for human skin segmentation: a self-adaptive skin color model, a method that uses saliency for non-skin background removal, as well as a combination of skin texture and color.

The self-adaptive proposed method fits a skin color model to particular conditions of the images, addressing the problem of lighting variation and natural differences that occur in skin colors among people.

The improvement by saliency detection is a novelty since it has not been well explored in the skin segmentation problem, with many advantages: no training is necessary, it is fast and there are many different methods that can be employed.

The use of texture for skin detection is a complex task. Image quality, person's pose, age and amount of hair represent major obstacles to define a skin pattern. Thus, our method focuses on simple features, such as coarseness and homogeneity. Nonetheless, they are not explicitly defined but learned from a training set.

Experiments demonstrated that the self-adaptive approach overcomes not only non-adaptive methods but also an adaptive method based on faces. This is explained due to the inevitable errors brought by the face detector and because faces contain more than just skin. Moreover, it was possible to observe from the experiments that any type of color-based detector can be combined with saliency or texture, providing an overall improvement. The weaker the detector is, the larger is the improvement.

IX. PUBLICATIONS

The following four publications resulted from this dissertation:

- a self-adaptation method for human skin segmentation based on seed growing, described in Section IV, was presented in the 10th International Conference on Computer Vision Theory and Applications (VISAPP) [36].
- an extension of the previous work [36] using genetic algorithms for online parameter optimization and a fuzzy fusion operation for combining global and local color maps and a texture map has been accepted for publication as a book chapter in the special issue Hybrid Soft Computing for Image Segmentation [37].
- a human skin segmentation method improved by saliency detection, described in Section V, was presented in the 16th International Conference on Computer Analysis of Images and Patterns (CAIP) [38].
- a human skin segmentation method improved by texture energy under superpixels, described in Section VI, was presented in the 20th Iberoamerican Congress on Pattern Recognition (CIARP) [39].

REFERENCES

[1] T. Darrell, G. Gordon, M. Harville, and J. Woodfill, "Integrated Person Tracking using Stereo, Color, and Pattern Detection," *International Journal of Computer Vision*, vol. 37, no. 2, pp. 175–185, 2000.

[2] M. J. Jones and J. M. Rehg, "Statistical Color Models with Application to Skin Detection," *International Journal of Computer Vision*, vol. 46, no. 1, pp. 81–96, 2002.

[3] X. Hu, S. Peng, J. Yan, and N. Zhang, "Fast Face Detection based on Skin Color Segmentation using Single Chrominance Cr," in *7th International Congress on Image and Signal Processing*. IEEE, 2014, pp. 687–692.

[4] S. Ji, X. Lu, and Q. Xu, "A Fast Face Detection Method Combining Skin Color Feature and AdaBoost," in *International Conference on Multisensor Fusion and Information Integration for Intelligent Systems*. IEEE, 2014, pp. 1–5.

[5] C. Platzer, M. Stuetz, and M. Lindorfer, "Skin Sheriff: A Machine Learning Solution for Detecting Explicit Images," in *2nd International Workshop on Security and Forensics in Communication Systems*. New York, NY, USA: ACM, 2014, pp. 45–56.

[6] P. M. Silva and M. C. Polastro, "An Overview of NuDetective Forensic Tool and its Usage to Combat Child Pornography in Brazil," in *XLIII Jornadas Argentinas de Informática e Investigación Operativa - VI Workshop de Seguridad Informática*, 2014.

[7] H. Sevimli, E. Esen, T. K. Ateş, E. C. Ozan, M. Tekin, K. B. Loğoğlu, A. M. Sevinç, A. Saracoğlu, A. Yazici, and A. A. Alatan, "Adult Image Content Classification using Global Features and Skin Region Detection," in *Computer and Information Sciences*. Springer, 2010, pp. 253–258.

[8] L. Bretzner, I. Laptev, and T. Lindeberg, "Hand Gesture Recognition using Multi-scale Colour Features, Hierarchical Models and Particle Filtering," in *Fifth IEEE International Conference on Automatic Face and Gesture Recognition*. IEEE, 2002, pp. 423–428.

[9] J. P. Wachs, M. Kölsch, H. Stern, and Y. Edan, "Vision-based Hand-Gesture Applications," *Communications of the ACM*, vol. 54, no. 2, pp. 60–71, Feb. 2011.

[10] R. S. Choraś, "CBIR System for Detecting and Blocking Adult Images," in *9th WSEAS International Conference on Signal Processing*. Stevens Point, Wisconsin, USA: World Scientific and Engineering Academy and Society, 2010, pp. 52–57.

[11] H. Kruppa, M. A. Bauer, and B. Schiele, "Skin Patch Detection in Real-World Images," in *Pattern Recognition*. Springer, 2002, pp. 109–116.

[12] P. Kakumanu, S. Makrogiannis, and N. Bourbakis, "A Survey of Skin-Color Modeling and Detection Methods," *Pattern Recognition*, vol. 40, no. 3, pp. 1106–1122, 2007.

[13] M. Kawulok, J. Nalepa, and J. Kawulok, "Skin Detection and Segmentation in Color Images," in *Advances in Low-Level Color Image Processing*. Springer, 2014, pp. 329–366.

[14] S. L. Phung, A. Bouzerdoum, and D. Chai Sr, "Skin Segmentation using Color Pixel Classification: Analysis and Comparison," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 27, no. 1, pp. 148–154, 2005.

[15] B. D. Zarit, B. J. Super, and F. K. Quek, "Comparison of Five Color Models in Skin Pixel Classification," in *International Workshop on Recognition, Analysis, and Tracking of Faces and Gestures in Real-Time Systems.* IEEE, 1999, pp. 58–63.

[16] K. Sobottka and I. Pitas, "Face Localization and Facial Feature Extraction based on Shape and Color Information," in *International Conference on Image Processing.*, vol. 3. IEEE, 1996, pp. 483–486.

[17] A. Cheddad, J. Condell, K. Curran, and P. Mc Kevitt, "A Skin Tone Detection Algorithm for an Adaptive Approach to Steganography," *Signal Processing*, vol. 89, no. 12, pp. 2465–2478, 2009.

[18] R.-L. Hsu, M. Abdel-Mottaleb, and A. K. Jain, "Face Detection in Color Images," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 24, no. 5, pp. 696–706, 2002.

[19] M. Soriano, B. Martinkauppi, S. Huovinen, and M. Laaksonen, "Skin Detection in Video under Changing Illumination Conditions," in *15th International Conference on Pattern Recognition*, vol. 1. IEEE, 2000, pp. 839–842.

[20] J. Kovac, P. Peer, and F. Solina, "Human Skin Color Clustering for Face Detection," in *International Conference on Computer as a Tool*, vol. 2. IEEE, Sep. 2003, pp. 144–148.

[21] S. L. Phung, D. Chai, and A. Bouzerdoum, "Adaptive Skin Segmentation in Color Images," in *International Conference on Multimedia and Expo*, vol. 3, 2003, pp. III–173.

[22] J. Fritsch, S. Lang, M. Kleinehagenbrock, G. A. Fink, and G. Sagerer, "Improving Adaptive Skin Color Segmentation by Incorporating Results from Face Detection," in *11th IEEE International Workshop on Robot and Human Interactive Communication*, 2002, pp. 337–343.

[23] M. J. Taylor and T. Morris, "Adaptive Skin Segmentation via Feature-based Face Detection," in *SPIE Photonics Europe*. International Society for Optics and Photonics, May 2014, p. 91390P.

[24] M. Kawulok, "Energy-based Blob Analysis for Improving Precision of Skin Segmentation," *Multimedia Tools and Applications*, vol. 49, no. 3, pp. 463–481, 2010.

[25] ——, "Fast Propagation-based Skin Regions Segmentation in Color Images," in *10th IEEE International Conference and Workshops on Automatic Face and Gesture Recognition*, 2013, pp. 1–7.

[26] J. Ruiz-del Solar and R. Verschae, "Skin Detection using Neighborhood Information," in *Sixth IEEE International Conference on Automatic Face and Gesture Recognition*. IEEE, 2004, pp. 463–468.

[27] E. W. Dijkstra, "A Note on Two Problems in Connection with Graphs," *Numerische Mathematik*, vol. 1, pp. 269–271, 1959.

[28] X. Wang, X. Zhang, and J. Yao, "Skin Color Detection under Complex Background," in *International Conference on Mechatronic Science, Electric Engineering and Computer*, 2011, pp. 1985–1988.

[29] R. Gonzalez, R. Woods, and S. Eddins, *Digital Image Processing using MATLAB*. Gatesmark Publishing, 2009.

[30] W. R. Schwartz and H. Pedrini, "Color Textured Image Segmentation based on Spatial Dependence using 3D Co-occurrence Matrices and Markov Random Fields," in *15th International Conference in Central Europe on Computer Graphics, Visualization and Computer Vision*, Plzen, Czech Republic, 2007, pp. 81–87.

[31] P. Ng and C.-M. Pun, "Skin Color Segmentation by Texture Feature Extraction and K-means Clustering," in *Third International Conference on Computational Intelligence, Communication Systems and Networks*. IEEE, 2011, pp. 213–218.

[32] Z. Jiang, M. Yao, and W. Jiang, "Skin Detection using Color, Texture and Space Information," in *Fourth International Conference on Fuzzy Systems and Knowledge Discovery*, vol. 3, 2007, pp. 366–370.

[33] K. I. Laws, "Rapid Texture Identification," in *24th Annual Technical Symposium*. International Society for Optics and Photonics, 1980, pp. 376–381.

[34] R. Achanta, A. Shaji, K. Smith, A. Lucchi, P. Fua, and S. Susstrunk, "SLIC Superpixels Compared to State-of-the-Art Superpixel Methods," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 34, no. 11, pp. 2274–2282, 2012.

[35] P. Viola and M. J. Jones, "Robust Real-Time Face Detection," *International Journal of Computer Vision*, vol. 57, no. 2, pp. 137–154, 2004.

[36] A. Santos and H. Pedrini, "A Self-Adaptation Method for Human Skin Segmentation Based on Seed Growing," in *10th International Conference on Computer Vision Theory and Applications*, Berlin, Germany, Mar. 2015, pp. 455–462.

[37] A. Santos, J. L. de Paiva, C. F. Toledo, and H. Pedrini, "Improved Human Skin Segmentation Using Fuzzy Fusion based on Optimized Thresholds by Genetic Algorithms," in *Hybrid Soft Computing for Image Segmentation*, S. Bhattacharyya, P. Dutta, S. De, and G. Klepac, Eds. Springer, 2016.

[38] A. Santos and H. Pedrini, "Human Skin Segmentation Improved by Saliency Detection," in *16th International Conference on Computer Analysis of Images and Patterns*, Valetta, Malta, Sep. 2015, pp. 146–157.

[39] ——, "Human Skin Segmentation Improved by Texture Energy under Superpixels," in *20th Iberoamerican Congress on Pattern Recognition*, Montevideo, Uruguay, Nov. 2015, pp. 35–42.