

Adapting A Statistical Skin Colour Model To Illumination Changes

Moritz Storrang and Erik Granum

Computer Vision and Media Technology Laboratory

Institute of Electronic Systems, Aalborg University

Aalborg, Denmark

Email: mst,eg@cvmt.dk

Abstract

Skin colour segmentation is important for human face tracking. An often used approach is to approximate the skin chromaticity distribution with a statistical model, e.g. with the distribution's covariance matrix. The advantage of this approach is that it is invariant to size and orientation and fast to compute. A disadvantage is that it is sensitive to changes of the illumination colour.

This paper investigates how accurately the covariance matrix of facial skin chromaticity distributions might be modelled for different illumination colours using a physics-based approach. Results are presented using real image data taken under different illumination colours and from subjects with different shades of skin. The eigenvectors of the modelled and measured covariances deviate in orientation about 4° . This seems to be within a useful range for skin colour segmentation, and hence allow the statistical model to adapt to illumination changes.

Introduction

Robust human face tracking has many applications, e.g. in new human computer interfaces and surveillance systems. Computer vision based face tracking systems are becoming more robust by fusing several cues such as motion and shape.^{3,14,10} An often used cue is skin colour segmentation. Several approaches have been proposed, some statistically based, e.g., Refs. 6 and 15, and some physics based, e.g., Refs. 9 and 12.

A problem when using skin colour as a feature arises under varying lighting conditions. In particular changes in the spectral composition of the scene illumination may result in failures of colour segmentation methods.⁵

Yang *et.al.*¹⁵ showed that the facial skin chromaticity distribution of an individual under a single light source may be approximated by a multivariate normal distribution in the red-green chromaticity plane. They proposed an adaptive statistical skin colour model updating the mean vector and the covariance matrix of the red-green chromaticities as the lighting conditions change. The model is used in a real-time face tracker and works under slightly changing indoor illumination conditions.

McKenna *et.al.*⁶ use Gaussian mixtures to model the skin colour distribution in Hue-Saturation space. The

model parameters are updated over time in order to adapt to changes in illumination and viewing direction.

A problem with adapting the parameters of a statistical colour model during tracking is the lack of ground-truth of the region of interest,⁶ i.e. the colour model might adapt to image regions which do not belong to the skin coloured object and, hence, result in false positives and/or false negatives.

In Storrang *et.al.*¹² skin chromaticities for different illuminations are modelled with a good approximation by a physics-based approach. The model uses knowledge about the camera parameters and assumes that commonly used in- and outdoor light sources can be modeled by blackbody radiators.⁴ The skin chromaticities for a variety of illuminations with different correlated colour temperatures (CCT) form a 'skin locus' which follows the curvature of the Planckian locus of blackbody radiators. This might be used to constrain the search area for skin colour in the chromaticity plane.

Soriano *et.al.*⁹ presented a face tracking system working outdoors under changing illumination conditions. They constrained the search area by the skin locus. Inside the skin locus a non-parametric skin colour model is learned and updated by histogram back-projection. Histogram backprojection has the same drawback as adapting the statistical model, i.e. the histogram might adapt to non-skin coloured objects in the background.

However, this effect might be avoided if the skin colour model would be constrained by physics-based knowledge about possible skin distributions. In this paper a statistical model is constrained using a physics-based approach. In particular, it is investigated

1. How well may a two dimensional skin chromaticity distribution be approximated by a normal distribution, i.e. by mean values and covariance matrices.
2. How accurately may the eigenspace of a skin chromaticity covariance matrix be modelled for illuminations with arbitrary CCTs by linking it with a physics-based approach.

Modelling of the covariance matrix has application in adaptive statistical models as used in Refs. 6, 9, and 15. It might give an indication on the current confidence about that the segmented skin area is the same as the one, e.g., in the previous frames or before an illumination change. The confidence measure might be obtained by matching the measured and modelled eigenspaces against

each other. Confidence measures are especially of interest in systems where several tracking cues are fused.³

Theory and Background

This section provides a brief overview of the reflection properties of human skin and how they might be approximated with a statistical and a physics-based model.

Skin Chromaticities

Reflections of human skin may be modelled with the Dichromatic Reflection Model⁸ as surface and body/matte reflections. Most of the facial skin area shows 'pure' body reflections.^{2,12} Even under direct illumination highlights occur usually not on the entire face but only on some areas, e.g. the nose, forehead, or cheeks, and might be removed by filtering.¹³ In the following only body reflections are considered. Furthermore, it is assumed that the investigated skin areas are illuminated by a 'single' light source. This single light source may be a mixture of several sources having different spectral compositions. The constraint is that the mixture is uniform for the investigated skin area. For spatially non-uniform illumination see e.g. Ref. 1.

In colour machine vision usually each pixel is represented by a 3D vector C_{RGB} containing the red, green, and blue camera responses. For analysing colours independent of the scale of intensity, it is convenient to transform a colour vector C_{RGB} to its corresponding chromaticity C_{rgb} . This is done by normalising the colour vector elements (R, G, B) with their first norm ($N = R + G + B$)

$$c_r = \frac{R}{N}, c_g = \frac{G}{N}, c_b = \frac{B}{N} \quad (1)$$

Statistical Modelling of Skin Chromaticities

The rg-chromaticities $c_{rg,i}$ of a skin area with $i = 1 \dots n$ pixels may simply be modelled by their mean value μ_{rg} and covariance matrix S_{rg} .

In figure 1 skin chromaticities of one subject are shown which were taken under four different CCTs. The asterisks (*) are the mean values of the respective distributions. The dashed lines are 85% confidence ellipses calculated by the Mahalanobis-distance (Eq. 2) with a χ^2 for two degrees of freedom.

$$\chi^2 \geq (c_{rg,i} - \mu_{rg})^T S_{rg}^{-1} (c_{rg,i} - \mu_{rg}) \quad (2)$$

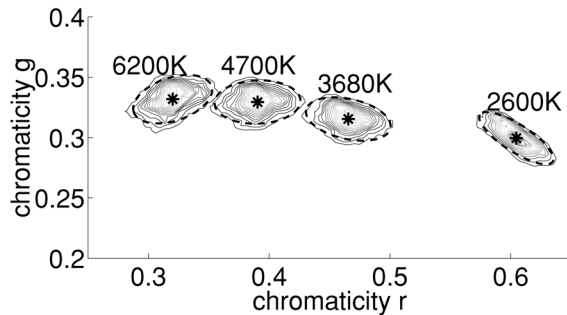


Figure 1. Skin chromaticity distributions of an Asian subject under four different CCTs.

Physics-based Modelling of Skin Chromaticities

The chromaticities of the body reflections of human skin can be modelled using reflectance curves of skin, the spectral sensitivities of the camera, and the spectral composition of the light source.^{7,12} The RGB values C'_{RGB} are obtained by spectral integration and the corresponding chromaticities c_{rgb} by Eq. 1.

The reflectance curves of human skin may be modeled as a function of the melanin concentration in the epidermis and the blood content in the dermis.^{7,12} Negro skin has a high melanin concentration whereas Caucasian skin has a low melanin concentration. The melanin concentration for one subject is not constant but has a certain spatial variation range. The lower and upper limits of the blood content b_{min} and b_{max} are rather constant for all ethnic groups. The skin chromaticity distribution for an individual is approximated by a minimum and a maximum melanin concentration m_{min} and m_{max} . In other words it is approximated by the area between the four chromaticities modelled with the reflectance curves using: (b_{min}, m_{min}) , (b_{min}, m_{max}) , (b_{max}, m_{min}) , and (b_{max}, m_{max}) .

The chromaticities of general purpose light sources, e.g. daylight and fluorescent light, have only a small deviation from the Blackbody radiator with the corresponding CCT. Finlayson and Schaefer⁴ measured 172 light sources, including daylights and fluorescent. They report that the illuminant chromaticities fall on a long thin band in the chromaticity plane which is very close to the Planckian locus of Blackbody radiators. Light sources will in the following be approximated by Blackbody radiators of the same CCT as the light source, which was successfully done in Ref. 12.

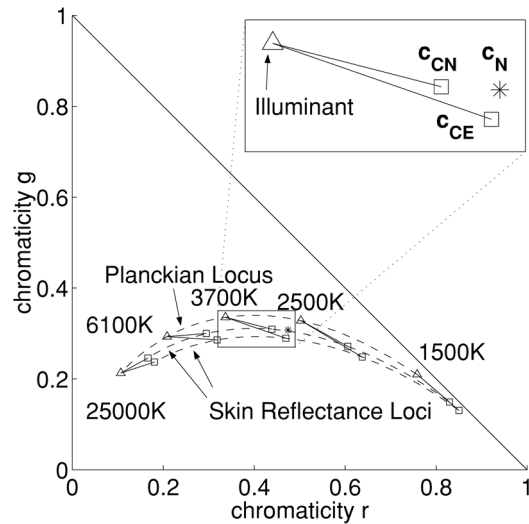


Figure 2. Illuminant- and body reflection-chromaticities of skin modelled for a number of Blackbody illuminants (Planckian locus), from Ref. 12.

Figure 2 shows the red and green chromaticities of a number of Blackbody illuminants ranging from 1500 to 25000K (Planckian locus), plotted as triangles (Δ). The figure is modelled for a Blackbody radiator with a CCT=3700K as canonical light source (white balance source). Two body reflection chromaticities, plotted as

squares ($\square$), are modelled for each illuminant using the Caucasian reflectance curves for low and for high blood content, called c_{CN} and c_{CE} , respectively. The solid lines indicate the corresponding illuminant and body chromaticities. The asterisk (*) shows the body reflectance chromaticity for Negro skin C_N , i.e. with high melanin concentration.

Adapting Statistical Models to Changing Illumination

The method proposed in this paper uses physics-based knowledge to estimate how the statistical model will change as the illumination changes. A necessary condition for this is to find how these types of models can be related.

Firstly, we consider how the distributions of the skin chromaticities change as illustrated in figure 1. They change position along the skin locus and the major and minor axes (eigenspace of the covariance matrix) change in orientation and aspect ratio.

The physics-based model describes an expected area for the chromaticities given the CCT and some biological parameters of the human skin. This area can also be described by a major and minor axes, hence an eigenspace, such that if the biological parameters for a given individual are known, the eigenspace can be estimated for any CCT.

The question is if the physics-based and the statistical model can be adequately related via their eigenspaces described above. If so, an initial 'calibration' of the two models can be established from a reference image, and parameters of the statistical model can then be estimated for any CCT.

To demonstrate and test if the eigenspace description may have practical use, we present a procedure including two steps, initialisation for calibration, and then estimation of eigenspaces for arbitrary CCTs.

Initialisation

Given is a reference image with a pre-segmented area of facial skin, and with known CCT of the illumination. The corresponding skin chromaticities form a distribution M_{rs} . The eigenvectors v_M and - values λ_M of M_{rs} are calculated.

The next step is to find the physics-based model, which through maximum and minimum melanin and blood parameters defines an area with an eigenspace v_E , λ_E that matches v_M , λ_M .

An iterative procedure scans through relevant combinations of these parameters testing for the orientation deviation between v_M and v_E . Among those configurations with a deviation below some threshold, here 0.8° , we chose the best fitting aspect ratio defined as

$$\min \left(\left| \frac{\lambda_{M,1}}{\lambda_{M,2}} - \frac{\lambda_{E,1}}{\lambda_{E,2}} \right| \right) \quad (3)$$

From the selected configuration we get the melanin parameters as the major result of the initialisation. To compensate for coarseness of our model (e.g. blood content independent of individuals/ethnic groups) we also introduce a diagonal matrix k relating the modelled and measured eigenvalues,

$$k_{11} = \frac{\lambda_{M,1}}{\lambda_{E,1}} \quad k_{22} = \frac{\lambda_{M,2}}{\lambda_{E,2}} \quad (4)$$

Estimating Eigenspaces for Arbitrary CCTs

Using the parameters estimated from the reference image we get four skin reflectance curves. Together with the camera sensitivities, and the Blackbody spectrum of the CCT in question an expected area for the skin chromaticities can be computed. Hence, an eigenspace (v_E , λ_E) can be estimated for any CCT. This eigenspace can be used to estimate the expected covariance matrix S_E of the measurements for the CCT in question,

$$S_E = v_E \cdot \lambda_E \cdot k \cdot v_E^{-1}. \quad (5)$$

Test Results

The method is tested using one reference CCT and 3 test CCTs. Images of 8 subjects having different ethnic backgrounds (China, Iran, Cameroun, Latvia, Greece, Spain, Denmark, and India) were captured, so that altogether 32 images were used. For each reference there are 3 test images used to compare the estimated statistical model with the measurements.

Image Acquisition

The images were captured with a JAI CV-M90 3CCD camera. Automatic gain control and automatic white balancing are switched off and gamma correction is set to one. The lens aperture and the shutter speed are manually adjusted to make optimal use of the dynamic range of the camera. The light sources are fluorescent lamps (Philips TLD 927, 940, 950, 965) with CCTs of 2600, 3680, 4700, and 6200K, respectively. The spectra of these lamps are provided from Philips and were additionally measured with a J&M TIDAS spectrometer. The measured spectra were used to calculate their CCTs. The illuminance on the faces is approximately 2000 lux as it is recommended by JAI. There are no pronounced highlights on the faces. The number of pixels of a face is between 5000 and 15000. The camera is white balanced to the 3680K lamp. An example image is shown in figure 3. All images were hand segmented into facial skin areas, which are used in the following for evaluating the method.

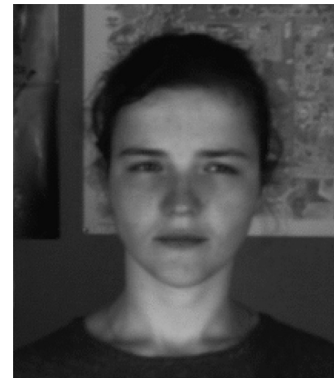


Figure 3. Example Image of a face. Examples of colour images are available at <http://www.cvmr.dk/~mst/ras.html>

Modelling Skin by Mean and Covariance

The measured skin distributions were tested for normality in the r and g chromaticity dimensions using a modified Kolmogorov-Smirnov test, which rejected the null hypothesis at a significance level of $\alpha = 0.2$. Furthermore, empirical quantile-quantile plots were made. Figure 4 is an example. It can be seen that the distribution is not perfectly normal distributed.

However, the distributions might be approximated by their covariance matrices. The 85% confidence ellipses are calculated using Eq. 2 (shown in figure 1) and the true positives inside are counted. Their percentage is shown in figure 5. The average is 88%.

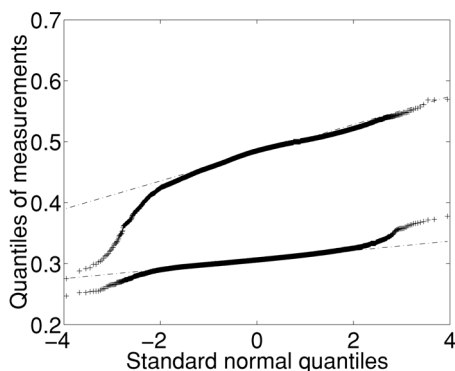


Figure 4. Example of a quantile-quantile plot of measured data (chromaticities) versus standard normal. The upper curve is along the red and the lower along the green chromaticity dimension.

Physics Based Modelling of Eigenspaces

The images taken at a CCT=3680K were used to estimate the parameters of the method as it was described in section 3.1. Then the covariance matrices for the CCT=2600, 4700, and 6200K, respectively, were modelled as described in section 3.2.

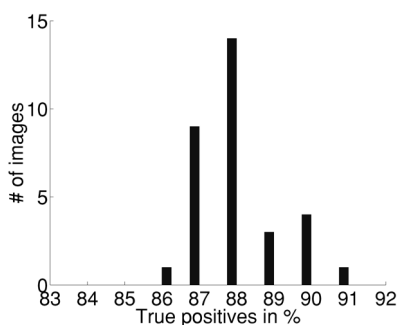


Figure 5. Percentage of true positives using 85% confidence ellipses with the measured covariance.

Figures 6 and 7 show example results with measured and modelled confidence ellipses. To allow comparison of the measured and the modelled covariances, their eigenvectors and eigenvalues are given in table 1. The average of the absolute angular deviation between measured and modelled orientation is about 4° and

maximal 9.8° . The average deviation between the lengths of the vectors is 6 %.

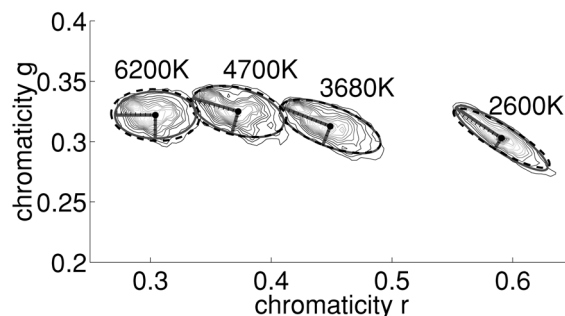


Figure 6. Skin chromaticities for a Caucasian subject under four different CCTs. The solid lines are the measured ellipses and the dashed lines are the modelled ellipses.

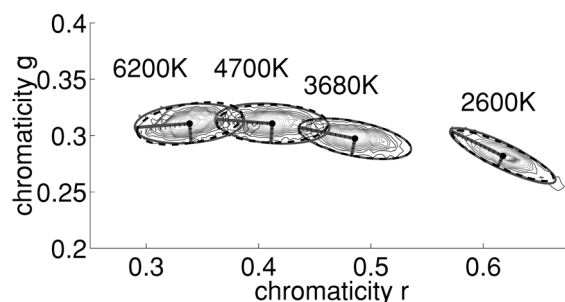


Figure 7. Skin chromaticities for a Negro subject under four different CCTs. The solid lines are the measured ellipses and the dashed lines are the modelled ellipses.

Figure 8 shows the true positives inside the 85% modeled confidence ellipses. The average is 87%. The area of the modelled ellipses is on average not bigger than the area of the measured ones.

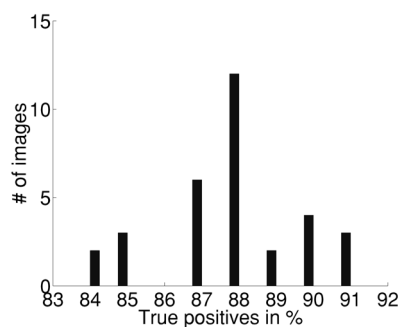


Figure 8. Percentage of true positives using 85% confidence ellipses with the modelled covariance.

Discussion

The proposed method aims to estimate the eigenspaces of an individual's skin chromaticity distribution for illuminations with arbitrary CCTs. We have tested this for 8 very different skin types, and with 3 illuminations for each. The average of the absolute deviation between

measured and estimated orientations of the eigenspaces is about 4° and the maximum about 10° . The average deviation between the lengths of the vectors is about 6%.

The deviations are due to measurement noise during the image acquisition and the approximations in modelling. The light spectra are approximated by blackbody radiators which very coarsely match spectra of fluorescent lamps. They may introduce a small error, especially in the green chromaticity.¹² Furthermore, the assumption that the range of blood concentrations is constant is convenient, but may as well contribute to the error.

If 85% confidence ellipses are used to approximate the distributions, the number of true positives of the measured pixels is in average 88% for the measured covariances and 87% for the modelled covariances. Hence, the skin distributions may for practical purposes be approximated with their covariances, which was also suggested in Ref. 15.

The method requires knowledge about an (approximate) CCT of the current illumination. This may be estimated from the mean value of the measured skin chromaticity distribution or, more accurately, by methods proposed in Refs. 11 and 13.

Figures 1, 6, and 7 show the distributions of an Asian, a Caucasian, and a Negro subject. A model for each individual is estimated. It can be seen that they differ from each other. If this difference is significant it might be useful to track and distinguish the skin of multiple faces in an image.

Table 1. Deviations between measured and modelled data for 3 test CCTs and 8 subjects. The angle error is the angle between the eigenvectors. The eigenvalue error is the deviation between the square roots of the measured and modelled eigenvalues in %. The numbers in brackets are from the initialisation data.

Illumination CCT	Angle error in degree		Eigenvalue errors in %			
			first		second	
	Mean	Max	Mean	Max	Mean	Max
2600	2.7	7.5	4.8	8.7	6.1	15.7
(3680)	(0.3)	(0.8)	(0.0)	(0.0)	(0.0)	(0.0)
4700	3.7	5.2	3.8	8.1	6.0	16.5
6200	4.5	9.8	6.5	12.2	8.0	16.9

Conclusions

In this paper the linking of a statistical with a physicsbased skin colour model was investigated. It was shown that facial skin chromaticity distribution may for practical purposes be approximated with their covariance matrices. It was demonstrated that the eigenspace of a two dimensional skin chromaticity distribution can be modeled for different illuminations using a physics-based approach. The average orientation error is about 4° , the average deviation between the lengths of the vectors is about 6 %.

The performance seems to be within a useful range to allow significant support of a statistical based approach by adapting it to changing illumination. This would improve the robustness of colour based skin segmentation to illumination changes.

In future work the skin reflection model could be improved by estimating also the blood concentration as a parameter, and by that possibly eliminate the correction matrix k .

Acknowledgements

We would like to thank all the persons who participated in the image acquisition. The work was funded in part by the Danish National Research Council project "The Staging of Virtual 3-D Spaces".

References

1. Hans J. Andersen and Erik Granum. Classifying illumination condition from two light sources by colour histogram assessment. *Journal of the Optical Society of America A*, 17(4):667–676, April 2000.
2. R. R. Anderson, J. Hu, and J. A. Parrish. Optical radiation transfer in the human skin and applications in *in vivo* remittance spectroscopy. In R. Marks and P. A. Payne, editors, *Bioengineering and the Skin*, chapter 28, pages 253–265. MTP Press Limited, 1981.
3. James L. Crowley and Francois Berard. Multi-modal tracking of faces for video communications. In *IEEE Conference on Computer Vision and Pattern Recognition*, pages 640–645, Puerto Rico, June 1997.
4. Graham D. Finlayson and Gerald Schaefer. Solving for colour constancy using a constrained dichromatic reflection model. *International Journal of Computer Vision*, 42(3):127–144, May 2001.
5. Brian Funt, Kobus Barnard, and Lindsay Martin. Is machine colour constancy good enough. In Hans Burkhardt and Bernd Neumann, editors, *5th European Conference on Computer Vision*, pages 445–459, Freiburg, Germany, June 1998.
6. Stephen J. McKenna, Yogesh Raja, and Shaogang Gong. Tracking colour objects using adaptive mixture models. *Image and Vision Computing*, 17(3–4):225–231, 1999.
7. Tomoyuki Ohtsuki and Glenn Healey. Using color and geometric models for extracting facial features. *Journal of Imaging Science and Technology*, 42(6):554–561, December 1998.
8. Steven A. Shafer. Using color to separate reflection components. *COLOR Research and Application*, 10(4):210–218, 1985.
9. Maricor Soriano, Birgitta Martinkauppi, Sami Huovinen, and Mika Laaksonen. Skin detection in video under changing illumination conditions. In *International Conference on Pattern Recognition*, volume 1, pages 839–842, Barcelona, Spain, September 2000.
10. Martin Spengler and Bernt Schiele. Towards robust multicue integration for visual tracking. In B. Schiele and G. Sagerer, editors, *International Workshop on Computer Vision Systems*, volume 2095 of *LNCS*, pages 93–106, Vancouver, Canada, July 2001.
11. Moritz St'orring, Hans J. Andersen, and Erik Granum. Estimation of the illuminant colour from human skin colour. In *4th IEEE International Conference on Automatic Face and Gesture Recognition*, pages 64–69, Grenoble, France, March 2000.
12. Moritz St'orring, Hans J. Andersen, and Erik Granum. Physics-based modelling of human skin under mixed

illuminants. *Journal of Robotics and Autonomous Systems*, 35(3–4):131–142, June 2001.

13. Moritz Störring, Erik Granum, and Hans J. Andersen. Estimation of the illuminant colour using highlights from human skin. In *First International Conference on Color in Graphics and Image Processing*, pages 45–50, Saint-Etienne, France, October 2000.
14. Jochen Triesch and Christoph von der Malsburg. Selforganized integration of adaptive visual cues for face tracking. In *4th IEEE International Conference on Automatic Face- and Gesture-Recognition*, pages 102–107, Grenoble, France, March 2000.
15. Jie Yang, Weier Lu, and Alex Waibel. Skin-color modeling and adaptation. In Roland Chin and Ting-Chuen Pong, editors, *3rd Asian Conference on Computer Vision*, volume 1352 of *LNCS*, pages 687–694, Hong Kong, China, January 1998.

Biography

Moritz Störring is assistant professor at the Computer Vision and Media Technology Laboratory (CVMT),

Aalborg University, Denmark. He studied Electrical Engineering at the Technical University of Berlin, Germany and at the Institut National Polytechnique de Grenoble, France. He graduated in 1998 in Berlin. From 1998 to 2001 he was a research assistant at CVMT within the European TMR project SMART II. His research interests include colour vision, outdoor computer vision, face and skin detection, vision based human-computer interaction, and augmented reality.

Erik Granum is professor of information systems and head of CVMT, Computer Vision and Media Technology Laboratory, and co-founder of VR Media Lab at Aalborg University, Denmark. He is and has been co-ordinator of several national and international research projects and networks in computer vision and virtual reality and partner of many others. His research interests cover pattern recognition, continually operating vision systems, colour vision, vision guided multimedia interfaces, visualisation, virtual reality, and autonomous agents.