DIFFUSION FILTERING FOR ILLUMINATION INVARIANT FACE RECOGNITION

Illumination Approximation with Diffusion Filters within Retinex Context

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Abstract: Face recognition becomes a very important technology in recent years for a lot of various applications. One major problem of the most state-of-the-art algorithms are different lightning conditions which can decrease recognition rates dramatically. To reduce the influence of illumination in the recognition process normalization methods can be used. In this paper we introduce illumination normalization algorithms based on diffusion filters. Further we compare our approaches with selected established algorithms. Finally we present our evaluation results based on well known face recognitions techniques and an appropriate face database. The results show that the diffusion filter approaches outperforms all other algorithms which demonstrates the capabilities of the diffusion filter technology for illumination normalization in face recognition.

1 INTRODUCTION

Face recognition is in the focus of challenging research and besides a widely used technology in a multitude of applications. However, there are still effects that hinder the recognition process in most systems dramatically e.g. varying facial expression or pose. In this paper we focus on the problem of varying illumination.

Similar to (Gross and Brajovic, 2003) we concentrate on preprocessing techniques that do ”not require any training steps, knowledge of 3D face models or reflective surface models”. This type of preprocessing algorithms ranges from simple histogram modifications or local operations (Villegas-Santamaria and Paredes-Palacios, 2005) up to elaborated human perception inspired algorithms based on retinex theory e.g. (Rahman et al., 1996).

Within this paper these algorithms are extended by diffusion filter methods which are known from other image processing task e.g. medical imaging (Westin et al., 2002).

This paper is organized as follows. In section 2 we give a review of related algorithms. The use of diffusion filter in image processing and especially for illumination normalization is described in section 3. In section 4 we depict the used face recognition algorithms and the database setup as well as the detailed evaluation result. Finally conclusions are drawn form the normalization performance.

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Figure 1: The appearance difference caused by varying illumination can be more then the appearance difference between two individuals (Adini et al., 1997). Figure is based on Yale Face Database B (Georghiades et al., 2001).

2 BACKGROUND AND RELATED WORK

In recent years a lot of different approaches for illumination normalization in face recognitions were presented. In this section we simply focus on algorithms that are related to the retinex theory. The retinex model, named after retina and cortex, was introduced by (Land, 1977) to explicate its model of the human visual perception.

One of the most interesting points of the theory is that the perceived intensity $I(x,y)$ depends on

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the reflection $R(x,y)$ and the surrounding illumination $L(x,y)$ which can be calculated by the pixel neighborhood.

$$I(x,y) = R(x,y) \cdot L(x,y) \tag{1}$$

Regarding to the idea that the perceived illumination depends on the neighborhood the following algorithms try to estimate an illumination approximation based on the pixel neighborhood of the image I.

The *Single-Scale Retinex (SSR)* introduced by (Jobson and Woodell, 1995) defines a Gaussian kernel to estimate the neighborhood illumination. Equation 2 with a single Gaussian ($S = 1$) can be used for calculating SSR.

$$log(R(x,y)) = \sum_{s=1}^{S} (\log[I(x,y)] - \log[I(x,y) * G_s(x,y)]) \tag{2}$$

The *Multi-Scale Retinex (MSR)* extends the SSR by using multiple Gaussian kernels (Rahman et al., 1996). The aim of using different Gaussian filters with varying σ_s is a better approximation of the illumination. The multiple results are combined by accumulating the single normalizations. Figure 2 shows the results of SSR and MSR.

The next step to enhance the illumination estimation with retinex methods is additionally considering the image structure. A first step to more adaptive methods is made by (Wang et al., 2004) who introduce the *Self Quotient Image (SQI)*. Additional to MSR the SQI weights the multiple Gaussian filters to keep edges within the approximated illumination.

The most sophisticated algorithm is the illumination estimation according to *Gross and Brajovic (GBR)* (Gross and Brajovic, 2003). It refers to Weber's Law which describes the effect in human perception that just noticeable difference of stimulus ΔI depends on the previous stimulus I.

$$\frac{\Delta I}{I} = \rho \tag{3}$$

Instead of convolving with Gaussian filters the GBR uses an minimization approach to estimate the illumination L.

$$E(L) = \int\int_{\Omega} \rho(x,y) \cdot [L(x,y) - I(x,y)]^2 dxdy + \lambda \int\int_{\Omega} (L_x^2 + L_y^2) dxdy \tag{4}$$

The weighting function $\rho(x,y)$ is applied to handle the local contrast ratio based on equation 3. The second term of equation 4 describes a smoothing constraint with λ as weighting factor.

The illumination approximations and the normalized images of SQI and GBR are depicted in Figure 2.

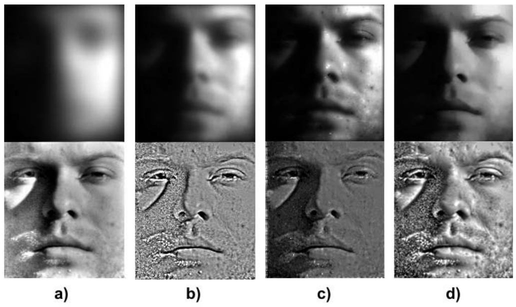

Figure 2: Each of the retinex related algorithms calculates an illumination estimations and afterwards a neutral illuminated image. The SSR (a) produces the worst approximation because of the single gaussian. The illumination estimation of the MSR (b) algorithm shows more details. The SQI (c) and the GBR (d) results show much more edge stability on the facial contours whereas the GBR results seems to be the best by visual impression.

3 DIFFUSION FILTER APPROACH

The diffusion approach was introduced in image processing as *Scale-Space-Theory (SST)* by (Witkin, 1983). In this theory image structures are handled at different scales. Based on that fact images are processed in single layers of a multi-resolutions pyramid (Weickert, 1998). To generate the resolution pyramid multiple Gaussian filters each for each layer can be used.

$$I(x,y,t) = I(x,y) * G(x,y,t) \tag{5}$$

The varying parameter t yields to images of different resolution. Another form to describe that context is the diffusion equation as used by (Koenderink, 1984):

$$\partial_t I = \nabla^2 I = (I_{xx} + I_{yy}) \tag{6}$$

The work of Cohen and Grossberg about neural dynamics of brightness perception (Cohen and Grossberg, 1984) shows that diffusion processes also take place in human brightness perception. Feature qualities like brightness are spread out diffusively to boundary contours in visual cortex. Derived from this theory any of the diffusion approaches can be used to compute a illumination estimation L.

To combine two perceptional inspired algorithms the illumination estimation based on diffusion is used in this work in a illumination normalization process according to the retinex theory, see equation 1.

To differ between diffusion algorithms we use the following systematization by (Weickert, 1998).

- Linear isotropic diffusion: spread out to all directions without responding to edges

- Nonlinear isotropic diffusion: takes attention to the intensity of edges
- Nonlinear anisotropic diffusion: takes attention to the intensity and the direction of edges

The impacts on noisy images of different diffusion filters are depicted in Figure 3. The disadvantage of the SST is the linear isotropic behavior.

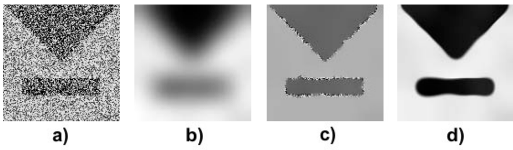

Figure 3: Different behaviors of diffusion filter for noise reduction with attention to structured elements: a) original, b) linear isotropic, c) nonlinear isotropic, d) nonlinear anisotropic (Weickert, 1998).

For a nonlinear isotropic diffusion according to the Weickert's systematization we use the well-know algorithm of *(Perona and Malik, 1990) (PER)*. This algorithm considers edges and reduces the diffusion by a diffusion coefficient c that depends on image gradient intensity.

$$\partial_t I = \nabla \cdot (c \cdot \nabla I) \tag{7}$$

Additionally we introduce the usage of a *tensor based nonlinear anisotropic diffusion filter (TNS)* algorithm for illumination normalization. That approach uses a gradient direction related tensor D instead of diffusion coefficient c to weaken the diffusion process.

The diffusion tensor D according to (van den Boomgaard, 2004) is based on a rotation matrix and can be measured as:

$$D = \frac{1}{(I_x)^2 + (I_y)^2} \cdot \begin{pmatrix} d_1(I_x)^2 + d_2(I_y)^2 & (d_2 - d_1)I_x I_y \\ (d_2 - d_1)I_x I_y & d_1(I_y)^2 + d_2(I_x)^2 \end{pmatrix} \tag{8}$$

Figure 4 shows the normalization results of the PER and the TNS.

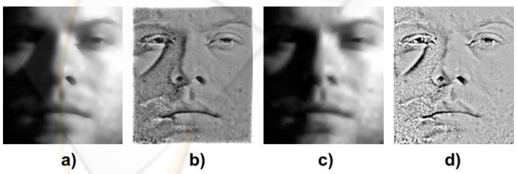

Figure 4: Illumination estimation and normalization results for the different diffusion filter algorithm. a) PER illumination est., b) PER result, c) TNS illumination est., d) TNS result. The PER and TNS show visual similar results with a slightly better approximation by the TNS algorithm.

In general the PER resembles the GBR while PER uses the gradient as weighting function and GBR the Weber contrast.

4 EXPERIMENTS

To verify the power of the diffusion filter approaches and for eased comparability with other publication we choose well known recognition algorithms. Further we evaluate with a database especially created for varying illumination.

Face Recognition Algorithms. We use the *eigenface* (Turk and Pentland, 1991) and *fisherface* (Belhumeur et al., 1997) approaches which are appearance based subspace methods for face recognition. These algorithms interpret pixels of images as coordinates in a high-dimensional space and transform them into low dimensional subspace called facespace. Therefore a training process with observations of reference persons is needed. For comparison within the facespace the euclidic distance is used.

Because fisherfaces were originally introduced as more applicable for varying illumination we decided to use both algorithms to compare improvements of a varying illumination optimized and a non-optimized algorithm. That means a well performing normalization should produce similar results for both algorithms.

Database. The database setup of our experiments is as follows. We use the Yale Face Database B. It is well suited for evaluation of lightning influence as shown in (Georghiades et al., 2001). The database consist of 45 images of 38 persons with a size of 192x168 pixels. The images of the same persons differ extremely by illumination but little in expression and pose. Therefore it is possible to evaluate the illumination normalization without further influence. We use four of the already defined subsets with similar illumination conditions as shown in Figure 6.

In our experiments we used all possible combination of these subsets. This procedure is used to evaluate the very different conditions e.g. badly illuminated training images and well illuminated test images and vice versa. Based on that procedure we get 4 by 4 recognitions rates as depicted in Table 1. Finally we estimate the mean θ and the standard deviation σ of the 16 sub results.

Results and Discussion. Table 1 shows exemplarily the results of the TNS algorithm with eigenfaces. The results clearly demonstrate that the best recognition rates lie on the diagonal which means train and test images were from the same subset but not the same images. This shows that the recognition algorithm after normalization is still sensitive to the similarity in illumination of training and test data.

Figure 5: Examples of the Yale Face Database B subsets which have similar illumination conditions within each subset.

Hence the illumination impacts could not completely removed. On the other hand the absolute values show that usual varying illumination which can be found in subset 1-3 can nearly perfect normalized so that the overall result reaches 88,3 %.

Table 1: Evaluation results for the TNS algorithm with eigenface recognition algorithm.

	Test SS1	Test SS2	Test SS3	Test SS4
Train SS1	95,6 %	96,9 %	100,0 %	82,9 %
Train SS2	94,7 %	100,0 %	91,2 %	79,4 %
Train SS3	90,4 %	79,8 %	96,9 %	78,1 %
Train SS4	78,1 %	82,5 %	71,9 %	94,7 %
$\emptyset_{Final}$	**88,3%**			
σ_{Final}	9,2%			

Figure 6 shows the recognition results of the discussed algorithms. The original dataset is the recognition test without any normalization with results for eigenface 13,2 % and fisherface 22,7 %. This reference show already the better ability of the fisherfaces to handle worse illuminated images.

The SSR as worst algorithm in our evaluation comes up with an improvement of about 45 % for both recognition algorithm which is an enormous increasing of the recognition rate. The MSR and SQI algorithm results with similar recognition rates about 77 % for eigenface and about 87 % for fisherface. The improvement of the fisherface via the eigenface is for this normalization methods only about 7 % which is little in comparison with the original dataset.

The best results of the prior algorithms produces the GBR with 82,18 % and 92,63 %. This shows that besides the best visual impression the GBR returns also superior test results.

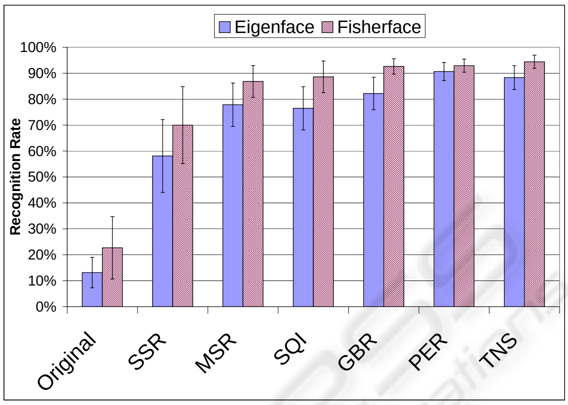

Figure 6: Evaluation results of all discussed algorithms for eigenface and fisherface recognition algorithm. The marked deviations shows the standard deviation between the results of the database subsets.

However, the diffusion filter algorithms outperforms all other algorithms. With PER 90,65 % and 92,9 % as well as TNS with 88,32 % and 94,41 % each algorithm comes up with the best result for one recognition algorithm. With 2,25 % difference the PER algorithm comes up with the closest results between eigenface and fisherface which indicates a constant normalization.

The standard deviation of the results that can also be used to measure the stability of the normalization seems to be very close between the leading algorithm. In principle it varies by the absolute mean values e.g. TNS fisherface σ 5 % and θ 94,41 % as well as SSR fisherface σ 29,66 % and θ 69,98 %.

Furthermore the results show clearly that the more complex algorithm returns the best results. The complexity of all algorithm increased by the consequent use of human visual processing techniques based on the perceptional concepts. Within this tests the use of the diffusion tensor seems to be more applicable then the Weber contrast used by the GBR.

5 CONCLUSIONS

In this paper we introduced the application of diffusion filter algorithms for illumination invariant face recognition. Further we presented the evaluation results of four retinex based algorithms and two diffusion based methods. Within the evaluation we could show that the single problem of illumination can be handled very good by different algorithms. However, the novel used diffusion filter approaches could outperform the known algorithms with better and more stable recognition results.

We showed also that the algorithms which are closest to the visual perception could return the best results.

Based on that first evaluation results further investigation in diffusion filters for illumination normalization is definitely reasonable. Especially the diffusion tensor methods offer a lot of opportunities to improve the recognition results.

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REFERENCES

Adini, Y., Moses, Y., and Ullman, S. (1997). Face recognition: The problem of compensating for changes in illumination direction. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 19(7):721–732.

Belhumeur, P. N., Hespanha, J. P., and J.Kriegman, D. (1997). Eigenfaces vs. fisherfaces: Recognition using class specific linear projection. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 19(7):711–720.

Cohen, M. A. and Grossberg, S. (1984). Neural dynamics of brightness perception: Features, boundaries, diffusion, and resonance. *Perception and Psychophysics*, 36(5):428–456.

Georghiades, A. S., Belhumeur, P. N., and Kriegman, D. J. (2001). From few to many: Illumination cone models for face recognition under variable lighting and pose. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 23(6):643–660.

Gross, R. and Brajovic, V. (2003). An image preprocessing algorithm for illumination invariant face recognition. *4th International Conference on Audio- and Video-Based Biometric Person Authentication*, pages 10–18.

Jobson, D. J. and Woodell, G. A. (1995). Properties of a center/surround retinex: Part 2 - surround design. Technical report, NASA Technical Memorandum 110188.

Koenderink, J. (1984). The structure of images. *Biological cybernetics*, pages 363–370.

Land, E. H. (1977). The retinex theory of color vision. *Scientific American*, 237(6):108–120, 122–123, 126, 128.

Perona, P. and Malik, J. (1990). Scale-space and edge detection using anisotropic diffusion. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 12(7):629–639.

Rahman, Z., Jobson, D. J., and Woodell, G. A. (1996). Multi-scale retinex for color image enhancement. *International Conference on Image Processing*.

Turk, M. A. and Pentland, A. P. (1991). Face recognition using eigenfaces. *IEEE Proceedings of Computer Vision and Pattern Recognition*, pages 586–591.

van den Boomgaard, R. (2004). Geometry driven diffusion. Lecture Notes at University of Amsterdam.

Villegas-Santamaria, M. and Paredes-Palacios, R. (2005). Comparison of illumination normalization for face recognition. *Third COST 275 Workshop Biometrics on the Internet*, pages 27–30.

Wang, H., Li, S. Z., and Wang, Y. (2004). Face recognition under varying lighting conditions using self quotient image. *Sixth IEEE International Conference on Automatic Face and Gesture Recognition*, pages 819–824.

Weickert, J. (1998). *Anisotropic Diffusion in Image Processing*. Teubner-Verlag, Stuttgart.

Westin, C.-F., Maier, S., Mamata, H., Nabavi, A., Jolesz, F., and Kikinis, R. (2002). Processing and visualization for diffusion tensor mri. In *Medical Image Analysis, Volume 6, Number 2*, pages 93–108.

Witkin, A. P. (1983). Scale space filtering. *Proceedings International Joint Conference on Artificial Intelligence*, pages 1019–1023.