Chapter 1

Enhancement of fingerprint images by shape-adapted scale-space operators

Andrés Almansa

CeCal, Engineering School, University of Uruguay

J. Herrera y Reissig 565, p. 5, 11400 Montevideo, Uruguay

Tony Lindeberg

Computational Vision and Active Perception Laboratory (CVAP)

Department of Numerical Analysis and Computing Science

KTH, S-100 44 Stockholm, Sweden

1.1 Introduction

¹ Automated Fingerprint Identification Systems (AFIS) rely on the ridge structure of a fingerprint for comparing it to other fingerprints in a database. The structure of current AFIS closely resembles the manual procedure used by human experts (see [23]), and can be briefly described as follows:

- *Enhance* the fingerprint image. This usually involves a filtering step to suppress noise. The output from this step can be either a better grey-level image or a binary image in which the ridge structure of the original is preserved.
- *Classify* the fingerprint according to its ridge structure at a coarse scale. This reduces the search space, thus speeding up the procedure.

¹This research has been supported by BID-CONICYT project number 96/94 and by the BITS collaboration program between KTH and the Engineering School at the University of Uruguay. A. Almansa would like to thank the CeCal and CVAP staffs, especially R. Curbelo, G. Drets, O. Bergengruen and R. Oliveira for their support, and for making this project possible.

Figure 1.1: Left: Original sample image. Center: Ridge direction produced by a spectral-based ridge enhancement method (Bergengruen 1994). Right: Skeleton produced by the same method.

- Extract the *ridge structure* of the fingerprint, *i.e.*, build a graph-like representation of the skeletonized ridges and their incidence relations.
- Search for *minutiae*, *i.e.* singularities in the ridge structure, such as bifurcations and ridge endings. Then, build a feature vector of the fingerprint.
- Store the feature vectors in a database for later use and/or search for fingerprints with *matching* feature vectors (which will most likely correspond to the same person).

Traditional methods for fingerprint image enhancement are based on Fourier transforms and Gabor filters, dating back to the work of Nakamura [24] and Asai [3]. Variations of such methods include [4, 1, 7, 15]. By and large, these approaches consist of applying a suitable Gabor or similar linear filter at each point in the image, where the filter selection is usually based on local estimates of ridge orientation and width. In some cases, multi-scale processing is performed.

These methods turn out to be useful for estimating the distance between ridges. Moreover, the main orientation field (see figure 1.1), has been successfully used in classification methods [7]. Such methods, however, fail to produce accurate skeletons of the fingerprint image, as needed by matching algorithms, since fairly noisy singularities are destroyed or transformed in many cases.

The subject of this article is to present an image enhancement algorithm that can be used as part of an AFIS. Such an algorithm should provide an enhanced image and a *ridge orientation* field (*i.e.* a coarse estimate of the main ridge direction at each point) on which either classification, ridge structure extraction, or matching algorithms should perform better than on the original, noisy image with no directional information.

1.2 Shape-adapted smoothing

The method we shall propose for enhancing the ridge structure in fingerprint images is based on shape adaptation of scale-space operators in the affine Gaussian scale-space representation. This approach builds upon work by Lindeberg [19, 22]

which was originally aimed at reducing the shape distortions that occur in filter based algorithms for obtaining shape from texture and disparity gradients. It also builds upon the non-linear filtering ideas proposed by Nitzberg and Shiohata [25], and the application of “tensor based” non-linear diffusion schemes to fingerprint images suggested by Weickert [31]. In these respects, the approach bears similarities with non-linear diffusion methods, as summarized in [30]. The major difference is that the proposed approach will be constructed from a set of linear scale-space representations, from which interesting data are selected by non-linear scale selection and shape adaptation mechanisms. In this respect, the approach bears closer relationships to the open-ended suggestion by Florack [9] to regard non-linear scale-space concepts as linear scale-space representations on transformed domains.

Given any image $f : \mathbb{R}^2 \rightarrow \mathbb{R}$, and given any symmetric positive semi-definite matrix Σ_0 , the *affine Gaussian scale-space representation* [19] L of f is for this Σ_0 defined as the solution of the anisotropic diffusion equation

$$\partial_t L = \frac{1}{2} \nabla^T \Sigma_0 \nabla L \quad (1.1)$$

with initial condition $L(\cdot; 0) = f$. The approach we shall follow, as suggested in different forms in [25, 19, 22, 31], is to adapt the shape of Σ_0 to the local image structure based on *second-moment descriptors* [14, 11, 6, 29, 5, 27, 21, 12]:

$$\mu(\cdot; \Sigma_t, \Sigma_s) = \begin{pmatrix} \mu_{11} & \mu_{12} \\ \mu_{12} & \mu_{22} \end{pmatrix} = g(\cdot, \Sigma_s) * (\nabla L(\cdot; \Sigma_t) \nabla L(\cdot; \Sigma_t)^T) \quad (1.2)$$

computed as the exterior product of gradient vectors by themselves at *local scale* Σ_t in the scale-space representation L of f and then averaged using an affine Gaussian kernel with *integration scale* Σ_s as weight

$$g(x; \Sigma_s) = \frac{1}{(2\pi|\Sigma_s|^{1/2})} \exp -x^T \Sigma_s^{-1} x / 2. \quad (1.3)$$

To obtain an intuitive understanding of operation, let us expand the tensor product and introduce $P = \mu_{11} + \mu_{22} = g(\cdot; \Sigma_s) * (L_x^2 + L_y^2)$, $C = \mu_{11} - \mu_{22} = g(\cdot; \Sigma_s) * (L_x^2 - L_y^2)$, and $S = 2\mu_{12} = 2g(\cdot; \Sigma_s) * (L_x L_y)$. Then, it can be seen that P is a measure of operator strength (local image contrast measured by average gradient magnitude). The other two entities contain directional information, which can be summarized into the two *anisotropy* measures

$$Q = \sqrt{C^2 + S^2}, \quad \tilde{Q} = \frac{Q}{P}. \quad (1.4)$$

The *normalized anisotropy* $\tilde{Q}$ is always in the range $[0, 1]$, and the extreme cases $\tilde{Q} = 0$ and $\tilde{Q} = 1$ correspond to rotationally and translationally symmetric patterns. The eigenvalues of μ are $\lambda_{\max, \min} = \frac{1}{2}(P \pm Q)$.

If we interpret the symmetric positive definite matrix μ as a quadratic form, the corresponding ellipses will be elongated in the direction of the gradient. Therefore, multiples of μ^{-1} constitute natural choices for scale matrices, since we want a larger

amount of smoothing along ridges than across them. Computation of μ , however, requires determination of *local* and *integration scale matrices* Σ_t and Σ_s . So what one can be looking for is a *fixed point* M such that

$$\mu(\cdot; \Sigma_t, \Sigma_s) = M, \quad \Sigma_t = tM^{-1}, \quad \Sigma_s = sM^{-1}. \quad (1.5)$$

In [22] it was shown that this fixed point is preserved under affine transformations. Moreover, a rapidly convergent algorithm was proposed to find this fixed point. It is the process of reaching such fixed points that is referred to as *shape adaptation*.

1.3 Enhancement of ridges by shape adaptation

When to express a shape adaptation procedure in practice, it turns out that a number of technical problems have to be addressed.

Defining the size of the scale matrices. Assuming for a moment that the scale selection problem can be avoided by available initial size information, a technical problem concerns how to relate this scalar size information to the size of possibly non-isotropic covariance matrices. Experiments on several fingerprint images showed that the minor axis of the corresponding ellipse constitutes a better choice than, for example, the major axis or the square root of the ellipse area. A motivation for this choice is that it ensures a certain minimum amount of smoothing as a means of noise suppression [19]. Thus, for non-isotropic Σ , we define the local scale by $\Sigma_t = t \frac{\Sigma}{\|\Sigma\|_{\lambda_{\min}}}$.

Bounding the eccentricity of the ellipses. Another technical problem concerns highly anisotropic regions, where Σ becomes near singular, and shape adaptation may lead to an exaggerated amount of blurring in some direction. To avoid this effect, we use a *regularized diffusion matrix* (having the same eigenvectors)

$$\Sigma = (\mu + \varepsilon I)^{-1}. \quad (1.6)$$

From the eigenvalues of μ , we have $\text{cond}(\Sigma) = \text{cond}(\mu + \varepsilon I) = 1 + 2Q/(2\varepsilon + P - Q)$. Since $(P - Q) \geq 0$, it follows that $\text{cond}(\Sigma) \leq 1 + \frac{Q}{\varepsilon} = \kappa$ and the natural choice $\varepsilon = Q/(\kappa - 1)$ ensures a uniform (user supplied) upper bound κ on the eccentricity of Σ , preventing ellipses from becoming too elongated.

Isotropic integration scale improves efficiency. When implementing this scheme in practice, the second stage integration smoothing corresponds to the largest computational work. With respect to the fixed point requirement, however, the local scale matrix causes the largest effect in practice. Hence, to improve the computational efficiency, we use isotropic integration scale matrices, *i.e.*, $\Sigma_s = sI$.

Ensuring size consistency. At any stage, it is essential that the size of the integration scale matrix is larger than the size of the local scale matrix [22]

$$\|\Sigma_s\| \geq \gamma^2 \|\Sigma_t\|. \quad (1.7)$$

Failure to satisfy this relation might lead to unreliable estimates of the ridge directions when computing μ for shape adaptation, which in turn might lead to undesirable enhancement of spurious directional fine-scale structures. In this case, we have used the $\|\cdot\|_{\text{det}}$ -norm when comparing local and integration scale matrices with different shape, and the size consistency condition assumes the form

$$s \geq \gamma^2 t \sqrt{\kappa}. \quad (1.8)$$

A motivation for this approach is that it enforces large integration scales when the ellipses are highly eccentric, while allowing for smaller integration scales in more isotropic regions. Hence, this choice allows the second moment descriptors to adapt to rapidly varying ridge directions around minutiae

Experimental Results. Based on the abovementioned ideas, we implemented an iterative ridge enhancement algorithm. In each iteration, the diffusion equation is solved up to a certain local scale, and the diffusion matrix for the next iteration is adapted to the measured second moment descriptors. (Isotropic smoothing was used in the bootstrapping stage.) The local scale parameter was manually selected to $t = 2.4$ (determined from manual measurements of the distance between ridges). The safety factor γ and the bound κ on the ellipse eccentricity were set to 2 and 10. Then, based on (1.8), the integration scale was chosen to be $s = 30$.

Figure 1.2: Results of shape adaptation. (a) smoothed grey-level image, (b) second moment descriptors, (c) skeleton overlaid on original image. (Parameters: $t = 2.4$, $\kappa = 25$, $\gamma = 2$, $s = 30$, and 5 iterations.)

As can be seen in figure 1.2, the results are at least as good as for the spectral method. In particular, the ridge orientation estimates are more reliable. Furthermore, the skeleton computed by the proposed method preserves bifurcations slightly better than the spectral based method. Similar conclusions were obtained for a larger number of fingerprints taken from the NIST fingerprint database 4.

1.4 Automatic scale selection

In the scheme outlined so far, all scale levels have been determined manually. There are, however, important reasons to consider automatic ways of tuning them.

First of all, a good choice of t is always related to the characteristic distance between the ridges. This entity may take very different values for different fingerprints, and may vary substantially even within the same fingerprint. For this reason, a mechanism is needed for adapting the local scale parameter t to the local image structure. Furthermore, the integration scale should on one hand be sufficiently small, to allow rapid variations in ridge directions around minutiae to be resolved. On the other hand, it should be sufficiently large, such that these variations are slow enough and satisfy the consistency requirement (1.7). To tune these scale levels, an explicit scale selection mechanism is required.

Selection of integration scales. A powerful methodology for automatic scale selection is by maximizing a suitable normalized measure of operator strength over scales [17, 19]. In this study, we have found the *pseudo quadrature measure* [18, 20]

$$\mathcal{P}_{\text{norm}}L = t(L_x^2 + L_y^2) + t^2(L_{xx}^2 + 2L_{xy}^2 + L_{yy}^2) \quad (1.9)$$

useful for estimating the distance between ridges. This measure approximates the power spectrum, and we will use the scales $t_{\mathcal{P}L}$ at which this entity assumes *local maxima over scales* for selecting integration scales. This approach agrees with the common practice in classical fingerprint enhancement methods, where the ridge distance is estimated from peaks in local power spectra. Here, however, we avoid explicit computations of local Fourier transforms (with the associated problems of determining window sizes) and use $\mathcal{P}_{\text{norm}}L$ instead, which can be easily computed within the scale-space framework. Once $t_{\mathcal{P}L}$ has been calculated, we set s to the smallest possible value that satisfies the consistency relation in (1.7)

$$s = \gamma^2 \|\Sigma_{t_{\mathcal{P}L}}\|_{\text{det}}. \quad (1.10)$$

Figure 1.4 shows an example of applying this approach in the neighborhood of a bifurcation. Note how finer scales are selected at the singularity, which is essential for resolving the more rapid variations in the ridge directions.

Figure 1.3: Properties of the scale selection mechanism in the neighborhood of a bifurcation. The three-dimensional graphs show scale-space signatures of $\mathcal{P}_{\text{norm}}L$, $\tilde{Q}$, and Q_{norm} , respectively, computed along a vertical cross-section through the image center. The vertical axis represents the operator strength at different positions and different scales, whereas the curve in the horizontal plane shows how the selected scales vary along the cross-section (logarithmic scale axis between $t = 0.5$ and $t = 32$).

Selection of local scales. In the work of shape from texture and disparity gradients in [19, 12], maximization of $\tilde{Q}$ over scales was used for automatic selection of local scales. Here, we shall multiply this anisotropy measure by the strength measure P expressed in terms of normalized derivatives $\partial_{x_i} = \sqrt{t}\partial_{x_i}$, and thus maximize the anisotropy measure $Q_{\text{norm}} = tQ$ over scales. The idea behind this approach is to select scale levels where the following criteria hold simultaneously: (i) the local image structure should be highly non-isotropic, corresponding to a high value of $\tilde{Q}$, and (ii) the scale value should reflect the size of the dominant image structures, corresponding to a high value of $P_{\text{norm}} = tP$.

Composed algorithm for shape adaptation and scale selection. By combining the components described in previous sections, we obtain a scheme for iterative shape adaptation and scale selection. In each iteration, local and integration scales are selected according to the previous paragraphs. Then, the diffusion matrices are adapted to second moment descriptors according to section 1.3. The procedure stops when the relative updates are sufficiently small for both the local and integration scales and for the diffusion matrix.

This algorithm was tested on 25 images from NIST fingerprint database 4. The parameters γ and κ were set to the same values as in section 1.3, and the maximum numbers of iterations were 3 for scale selection and 5 for shape adaptation.

Figure 1.4 illustrates how estimates of μ are improved relative to a shape adaptation scheme at a fixed scale. The result is a much more reliable skeleton of the ridge structure, where errors due to missing or misclassified minutiae are reduced to a minimum (see figure 1.5). Similar results were obtained for other fingerprints in the database. This improvement is important for the later stages of an AFIS, since many matching procedures rely on comparisons between these minutiae.

Concerning limitations of the approach, we have observed that the performance of this method may decrease substantially in highly noisy regions. A plausible explanation is that the current implementation of the algorithm only handles the

Figure 1.4: Comparison between second moment descriptors computed by the shape adaptation scheme (a) without and (b) with a scale selection mechanism. Note the ability of the latter approach to better adapt the estimates of μ around minutiae.

Figure 1.5: Results of composed scale selection and shape adaptation: (a) smoothed grey-level image, (b) measured second moment descriptors, (c) skeleton overlaid on original image.

first local extremum over scales, which implies that the scale selection procedure cannot distinguish between minutiae and extremely noisy areas. We are currently studying different ways of dealing with this issue.

1.5 Summary and Discussion

We have presented a novel methodology for fingerprint image enhancement, and compared it to a classical spectral-based method by applying it to a well established set of sample fingerprint images. The experiments led us to the conclusion that the proposed method: (i) is in most cases less prone to miss minutiae or to confuse ridge endings and bifurcations; (ii) produces equally reliable and more useful *directional fields* since they are continuous both in space and magnitude; (iii) avoids the “checkerboard effect” present in the grey-level output of spectral based methods. Thus, this shape adaptation approach addresses key weaknesses of traditional fingerprint image enhancement methods, and should be suitable for use within an AFIS. This application is currently being evaluated.

More generally, this technique provides an interesting connection between linear and non-linear scale-space approaches, in the sense that the smoothing operation is purely linear and is separated from the non-linear shape adaptation and scale selection procedures. Whereas the more general implications of this approach have not been explored in detail, this technique has the general attractive property of leading to a larger amount of smoothing along edges than across them, while presenting a more conservative behavior around non-edge areas, allowing more complex structures, such as corners or branching points, to be preserved [25, 19]. We believe that non-uniform smoothing schemes based on this general idea should be applicable to a large number of other purposes in image processing.

Bibliography

- [1] A. Almansa. Ridge enhancement of fingerprint images. Technical Report 2, CeCal, Engineering School, University of Uruguay, Montevideo, Uruguay, 1994.
- [2] E. Almeida, R. Caro, R. Curbelo, and G. Ulivi. Clasificación de huellas dactilares. Technical Report 2, CeCal, Engineering School, University of Uruguay, Montevideo, Uruguay, 1993. (Taller V).
- [3] K. Asai, Y. Hoshino, N. Yamashita, and S. Hratsuoka. Fingerprint identification system. In *Second USA-Japan Computer Conference*, page 30, 1986.
- [4] O. Bergengruen. Preprocessing of poor quality fingerprint images. In *XIV International Conference of the Chilean Computer Science Society*, October 1994.
- [5] J. Bigün, G. H. Granlund, and J. Wiklund. Multidimensional orientation estimation with applications to texture analysis and optical flow. *IEEE Trans. Pattern Analysis and Machine Intell.*, 13(8):775–790, August 1991.
- [6] L. G. Brown and H. Shvaytser. Surface orientation from projective foreshortening of isotropic texture autocorrelation. *IEEE Trans. Pattern Analysis and Machine Intell.*, 12(6):584–588, June 1990.
- [7] G. T. Candela, P. J. Grother, C. I. Watson, R. A. Wilkinson, and C. L. Wilson. PCASYS - A pattern-level classification automation system for fingerprints. U.S. Department of Commerce, Technology Administration, National Institute of Standards and Technology, Visual Image Processing Group, Gaithersburg, MD 20899, 1995.
- [8] L. Casamayú, R. Curbelo, Alejandro Gutiérrez G. Gómez, R. Oliveira, and H. Steffen. Convenio facultad de ingeniería - suprema corte de justicia. Facultad de Ingeniería, Universidad de la República, 1992.
- [9] L. M. J. Florack. *The Syntactical Structure of Scalar Images*. PhD thesis, University of Utrecht, November 1993. Cum Laude.
- [10] L. M. J. Florack, B. M. ter Haar Romeny, J. J. Koenderink, and M. A. Viergever. Scale and the differential structure of images. In *Image and Vision Computing*, volume 10:6, pages 376–388, 1992.

- [11] M. A. Föstner and E. Gülch. A fast operator for detection and precise location of distinct points, corners and centers of circular features. In *ISPRS Intercommission Workshop*, 1987.
- [12] J. Gårding and T. Lindeberg. Direct computation of shape cues using scale-adapted spatial derivative operators. *International Journal of Computer Vision*, 17(2):163–191, 1996.
- [13] R. C. V. Kameswara. Pattern recognition techniques applied to fingerprints. Linköping Studies in Science and Technology. Dissertations No. 19, Linköping, 1977.
- [14] K. Kanatani. Detection of surface orientation and motion from texture by stereological technique. In *Journal of Artificial Intelligence*, volume 23, pages 213–237, 1984.
- [15] E. Kaymaz and S. Mitra. Analysis and matching of degraded and noisy fingerprints. In *Applications of Digital Image Processing XV*, volume 1771 of *SPIE*, pages 498–508, 1992.
- [16] J. J. Koenderink. The structure of images. In *Biol. Cyb.*, volume 50, pages 362–370, 1984.
- [17] T. Lindeberg. On scale selection for differential operators. In *8th Scandinavian Conference Image Analysis*, pages 857–866, Tromsø, Norway, May 1993.
- [18] T. Lindeberg. Scale selection for differential operators. Technical Report ISRN KTH/NA/P-94/03-SE, KTH, 1994. Submitted.
- [19] T. Lindeberg. *Scale-Space Theory in Computer Vision*. Kluwer Academic Publishers, 1994.
- [20] T. Lindeberg. Feature detection with automatic scale selection. Technical Report ISRN KTH/NA/P-96/18-SE, KTH, May 1996. Submitted.
- [21] T. Lindeberg and J. Gårding. Shape from texture from a multi-scale perspective. Technical Report ISRN KTH/NA/P-93/03-SE, Dept. of Numerical Analysis and Computing Science, May 1993. Shortened version in *Proc. 4th Int. Conf. on Computer Vision*, Berlin, Germany, May 1993, pp. 683–691.
- [22] T. Lindeberg and J. Gårding. Shape-adapted smoothing in estimation of 3-D shape cues from affine distortions of local 2-D brightness structure. In *3rd European Conference on Computer Vision*, volume 800 of *LNCS*, pages 389–400, Stockholm, Sweden, May 1994. Springer-Verlag.
- [23] R. McCabe, C. Willson, and D. Grubb. *Research considerations regarding FBI-IAFIS tasks & requirements*. NISTIR 4892, National Institute of Standards and Technology, July 1992.
- [24] O. Nakamura, Y. Nagaoka, and T. Minami. A restoration algorithm of fingerprint images. In *Systems and Computers in Japan*, volume 17:6, page 31, 1986.

- [25] M. Nitzberg and T. Shiota. Non-linear image filtering with edge and corner enhancement. In *IEEE Transactions on Pattern Analysis and Machine Intelligence*, volume 14:8, pages 826–833, 1992.
- [26] U.S. Department of Justice. The science of fingerprints. Washington, D.C., 1984.
- [27] A. R. Rao and B. G. Schunk. Computing oriented texture fields. *Computer Vision, Graphics, and Image Processing : Graphical Models and Image Processing*, 53(2):157–185, March 1991.
- [28] G. Sasco and A. Almeida. Reconocimiento de huellas dactilares. Master’s thesis, CeCal, Engineering School, University of Uruguay, Montevideo, Uruguay, 1995. Taller V.
- [29] B. J. Super and A. C. Bovik. Shape-from-texture by wavelet-based measurement of local spectral moments. In *Proc. IEEE Comp. Soc. Conf. on Computer Vision and Pattern Recognition*, pages 296–301, Champaign, Illinois, June 1992.
- [30] B. M. ter Haar Romeny, editor. *Geometry-Driven Diffusion in Computer Vision*. Kluwer Academic Publishers, 1994.
- [31] J. Weickert. Multiscale texture enhancement. In *6th International Conference on Computer Analysis of Images and Patterns*, Prague, Sep 1995.
- [32] A. P. Witkin. Scale-space filtering. In *8th International Conference on Artificial Intelligence*, pages 1019–1022, Karlsruhe, Germany, August 1983.