2009 Ninth International Conference on Intelligent Systems Design and Applications

Improved Fuzzy Snakes applied to Biometric Verification Problems

J. Vélez, A. Sánchez
Dpto. Ciencias de la Computación
Universidad Rey Juan Carlos
28933 Madrid (Spain)
{jose.velez, angel.sanchez}@urjc.es,

F. Fernández
Dpto. Tecnología Fotónica
Universidad Politécnica de Madrid
28660 Madrid (Spain)
ffernandez@fi.upm.es

Abstract— **Some types of biometric patterns can be represented as a collection of variable-length interconnected lines. This is the case of handwriting signature strokes, palmprint lines or infrared hand vein data. Typical variations in size, shape and orientation of these patterns for the same person make difficult to develop reliable biometric verification systems for them. Fuzzy snakes have been successfully applied to the off-line signature verification problem where the corresponding energy function is described by a set of fuzzy rules. In this paper, we extend the fuzzy shape-memory snake model by introducing a new external energy term: the difference between the angle of the tangent to the snake in a control point and the angle of the tangent to a specific stroke point (for all the strokes of the test pattern). Experimental results for both off-line signature and palmprint verifications have shown that the new fuzzy approach outperforms other snake models.**

Keywords- snakes; biometrics; off-line verification problem; handwritten signatures; palmprints.

I. INTRODUCTION

Computer biometrics refers to specific modes of uniquely recognizing or authenticating humans based upon one or more intrinsic physical or behavioral characteristics [1]. Two types of authentication methods are distinguished in biometrics: identification and verification. Identification is based on comparing biometric measures of a person to the corresponding ones of enrolled individuals in the entire database (1:*N* problem). Verification only performs just one comparison to determine the degree of similarity between a test pattern and a reference model to determine if both correspond to the same individual (1:1 problem). The specific requirements of tolerance to imprecision and uncertainty, robustness, higher recognition rates and flexibility on biometric systems made that soft-computing is increasingly being used in biometric applications. The soft-biometrics paradigm [2] encourages the use of soft-computing for the development of biometric applications. In the context of biometric verification, the controlled variations in size, shape and orientation corresponding to patterns of the same individual, made the modeling and application of fuzzy logic a promising solution.

Snakes [3] are energy-minimizing splines based on the analysis of the movement of a closed or open parametric contour over an image to which it tries iteratively to adjust. The *internal or shape energy* of the snake is related to various restrictions of elasticity and flexibility imposed on it. The *external or image energy* component is caused by the influence of some image features (i.e. intensity values of pixels, edges, corners, etc.) which guide the snake movements. The aim is to iteratively minimize the energy of the snake which is attracted to specific image features. Due to some known limitations of traditional snakes (i.e. initialization of the parametric curve in the image, selection of snake parameters, existence of local minima in the minimization function), different authors have proposed improved snakes algorithms [4][5]. Höwing et al. [6] first introduced a fuzzy snake algorithm that integrates uncertain a priori knowledge into the snake model, and the proposed active contour energy function was described by a set of fuzzy rules.

In this paper we extend the fuzzy shape-memory snake model [7] that is suitable for shape analysis and verification. We introduce a new external energy term on fuzzy shape-memory snakes: the difference between the angle of the tangent to the snake in a control point and the angle of the tangent to a specific stroke point (for all the strokes contained in the test biometric pattern). Experiments on two different biometric modalities (off-line signature and palmprint, respectively) applied to the verification problem have shown that the new approach improves classical crisp ones and our previous fuzzy proposals.

978-0-7695-3872-3/09 $26.00 © 2009 IEEE
DOI 10.1109/ISDA.2009.81

II. Fuzzy shape-memory snakes

This section summarizes the crisp and fuzzy (generic and specific) snake energy formulations as presented in [7] for shape-memory snakes.

A. Crisp energy formulation

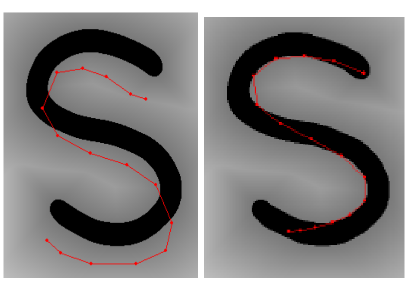
The discrete formulation of the snake energy definition by Kass et al [3] is:

$$E_{snake}(S) = E_{image}(S) + E_{shape}(S) \tag{1}$$

where S represents the snake or deformable contour in 2D (in our case, a polygonal open line), E_{image} is the snake external energy that guides it towards the image and E_{shape} is the snake internal energy that specifies the restrictions on the snake shape. To reduce the effect of locality and excessive deformation on the snake, the internal energy term E_{shape} is defined. The internal energy E_{image} need from the potential map M [8] of the $N_R \times N_C$ digital image I: $M=\{m_I(x,y)|1\leq x\leq N_R \wedge 1\leq y\leq N_C\}$, defined as the Euclidean distance in pixels from each point of the signature to the snake closest control point $v_i \in S$ (where $i \in [1..N_S]$ and N_S represents the number of control points in the snake):

$$E_{image}(S) = E_{image}(v_i,M) = m_I(v_{i-1})+m_I(v_i)+m_I(v_{i+1}) \tag{2}$$

Fig.1 shows the snake (the red color) adjustment on an 'S' shape using the potential map of this image.



(a) **(b)**

Figure 1. Snake adjustment using the potential map of the image: (a) initialization and (b) convergence after 50 iterations.

When snakes are used for a shape verification application, an excessive snake deformation is a problem. To avoid this effect, the snake "remembers" its original geometry (in particular, the relative proportions of snake segments and the angle between adjacent segments) during the iterative adjustment to the object boundary. Therefore, the term E_{shape} in (1) is expressed as:

$$E_{shape}(S) = E_{angle}(S) + E_{prop}(S) \tag{3}$$

where the term E_{angle} is used to maintain the angle between each pair of adjacent snake segments within the specified bounds of a controlled interval and E_{prop} is introduced to preserve the proportions between adjacent segments in S. Detailed formulations of E_{angle} and E_{prop} are found in [7].

B. Generic fuzzy energy formulation

In the previous crisp snake model, it becomes difficult to adjust the parameters of the internal energy term E_{shape}. When a fuzzy shape-memory energy model is introduced, the adjustment is made in a more comprehensive way also producing a better experimental performance. We use a zero-order Takagi-Sugeno (TS) system [9] which is a rule-based model with trapezoidal fuzzy antecedents and crisp consequent values:

$$R_i : IF\ (x_0\ is\ \tilde{n}_{i,0,k})\ AND...AND\ (x_j\ is\ \tilde{n}_{i,j,k})\ AND...AND\ (x_{P-1}\ is\ \tilde{n}_{i,P-1,k})\ THEN\ E_{snake} = E_i \tag{4}$$

where R_i denotes the i-th fuzzy rule for i=0..R-1 (R is the number of fuzzy rules), $\overline{x} = [x_0,..,x_{P-1}]$ is the input vector (P is the number of scalar variables), $\tilde{n}_{i,j,k}$ denotes the k-th antecedent fuzzy number (for k=0..K-1, where K represents the index of fuzzy number) associated to the j-th variable in the i-th fuzzy rule, E_i is a constant snake energy output value for the i-th rule, and E_{snake} is the output crisp snake adjustment energy value of the MISO (Multiple Input Single Output) system. In general, we used fuzzy sets of trapezoidal shape defined by four vertex parameters which are experimentally adjusted. Although a Mamdani system would be equivalent and more intuitive to the used zero-order TS system, this last model is in general better suited to mathematical analysis and also more computationally efficient (i.e. fuzzy controllers) [9].

The system output computation E_{snake} can be reduced to:

$$E_{snake} = \sum_{i=0}^{R-1} E_i \prod_{j=1}^{P-1} \tilde{n}_{i,j,k}(x_j) \tag{5}$$

where $\tilde{n}_{i,j,k}(x_j)$ represents the degree of fulfilment of the fuzzy number $\tilde{n}_{i,j,k}$ for the variable x_j. In our TS model, to greatly simplify the corresponding computation, two membership functions, forming a partition of unity are defined, in each interval of every variable $x_j \in \overline{x}$:

$$\tilde{n}_{i,j,k} \in [\tilde{n}_{i,j,0}, \tilde{n}_{i,j,1}] = [\tilde{n}_{i,j,0}, 1-\tilde{n}_{i,j,0}] \tag{6}$$

where: $0 \leq i \leq R$-1 and $0 \leq j \leq P$-1..

In the consequent of rules R_i for the considered zero-order TS model, only two energy values E_i are considered: $[E_0, E_1]=[E_{Low}, E_{High}]$. Therefore, the fuzzy inference system (FIS) is composed by 2^P rules, where P is the number of system input variables.

C. Specific fuzzy energy formulation

In particular, let $\vec{v} = (d, \theta, p)$ be the 3-tuple vector of input variables defining the snake adjustment energy E_{snake}. At each iteration t, this energy results from the contributions of the snake control points in the adjustment process. The input variables are: d representing the distance from any control snake point to the closest one in the test signature (obtained using the potential map M), θ defining the variation of the angle formed by any three adjacent snake control points with respect to its initial position, and p that represents the variation of the proportions of two consecutive snake segments with respect to its initial proportions.

The vector of membership functions $U\widetilde{P}_{\vec{v}}$ of each input variable is:

$$U\widetilde{P}_{\vec{v}} = (U\widetilde{P}_d, U\widetilde{P}_\theta, U\widetilde{P}_p) \quad (7)$$

where: $U\widetilde{P}_d = (\widetilde{d}_o, \widetilde{d}_1), U\widetilde{P}_\theta = (\widetilde{\theta}_0, \widetilde{\theta}_1), U\widetilde{P}_p = (\widetilde{p}_0, \widetilde{p}_1)$ (8)

The subscript '0' in the fuzzy sets represents the linguistic label 'small' and the subscript '1' in the fuzzy sets represents the linguistic label 'large' (for distances, angle and proportion variations, respectively).

In our specific signature verification problem, given the input vector $\vec{v} = (d, \theta, p)$, the proponed zero-order TS inference system has 2^3=8 fuzzy rules which define the snake adjustment energy E_{snake}:

$$\begin{aligned} &R_0 : IF\ (d\ is\ \widetilde{d}_0)AND(\theta\ is\ \widetilde{\theta}_0)AND(p\ is\ \widetilde{p}_0)\ THEN\ E_{snake} = E_{Low} \\ &R_1 : IF\ (d\ is\ \widetilde{d}_1)AND\ (\theta\ is\ \widetilde{\theta}_0)AND\ (p\ is\ \widetilde{p}_0)\ THEN\ E_{snake} = E_{High} \\ &\quad\quad .... \\ &R_7 : IF\ (d\ is\ \widetilde{d}_1)AND\ (\theta\ is\ \widetilde{\theta}_1)AND\ (p\ is\ \widetilde{p}_1)\ THEN\ E_{snake} = E_{High} \end{aligned} \quad (9)$$

Using the energy expression E_{snake} of eq. (5) and due to the all considered fuzzy numbers for each input variable belong to a partition of unity, the final snake adjustment energy E_{snake} for the zero-order TS system in (9) can be simply computed as:

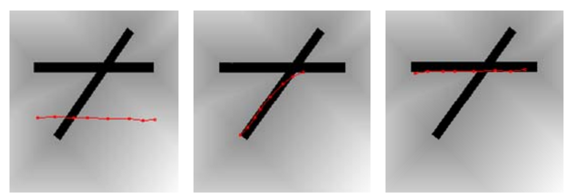
$$\begin{aligned} E_{snake} &= \alpha_0 E_{Low} + (1-\alpha_0)E_{High} = \\ &= [\mu_{\widetilde{d}_0}(d)\cdot\mu_{\widetilde{\theta}_0}(\theta)\cdot\mu_{\widetilde{p}_0}(p)]E_{Low} + [1-\mu_{\widetilde{d}_0}(d)\cdot\mu_{\widetilde{\theta}_0}(\theta)\cdot\mu_{\widetilde{p}_0}(p)]E_{High} \end{aligned} \quad (10)$$

where α_0 is a real value in [0..1]. It is important to observe that the previous fuzzy formulation makes it possible to obtain discrete bounded snake energy values in a natural way.

After the adjustment, a classification stage is required to determine the similarity between a test pattern and the reference snake. A set of features [7] extracted from the adjustment of the snake to the test pattern are used to train the considered classifier.

III. IMPROVED FUZZY SHAPE-MEMORY SNAKES

The snake models described in Section 2 have the property of approximately preserving its original shape. However, as a consequence of a not suitable snake initial placement and/or the presence of noise in the image, an incorrect snake adjustment on a shape can happen. This is illustrated by the example of Fig. 2. The shape is composed by two crossing lines (with respective orientations of 0º and 60º), its associated image potential map is also created and the snake (in red) is placed on this image (see Fig. 2(a)). The snake segments have an approximate 0º orientation. As the snake control points are spatially closer to the 60º line using the fuzzy formulation, the snake reaches the incorrect final position presented in Fig 2(b) instead the desirable convergence position presented in Fig. 2(c).



(a) **(b)** **(c)**

Figure 2. Snake adjustment error: (a) snake initialization on potential map image, (b) incorrect final snake position after convergence and (c) desirable snake position.

In order to achieve correct snake convergence results, we introduce a new external energy term $E_{d\gamma}$ on fuzzy shape-memory snakes: the difference between the angle of the tangent to the snake in a control point and the angle of the tangent to a specific stroke point (for all the strokes contained in the test biometric pattern). Therefore, the eq. (2) is modified to include the contribution of the tangent angle distance $d\gamma$ between the snake control point $v_i \in S$ and the image line $l_j \in I$ (also considering the attached potential map). This distance $d\gamma$ can be expressed as:

$$d\gamma(\gamma_{v_i}, \gamma_{l_j}) = \min_{v_i \in S, l_j \in I}(\min(\gamma_{v_i}, \gamma_{l_j}) + 180 - \max(\gamma_{v_i}, \gamma_{l_j}), \max(\gamma_{v_i}, \gamma_{l_j}) - \min(\gamma_{v_i}, \gamma_{l_j})) \quad (11)$$

where γ_{v_i} and γ_{l_j} respectively represent the angle at the tangent of the snake control point v_i and the angle at the tangent of the image line l_j (it approximately corresponds the point p with the longest segment passing through l_j and contained in it). Fig. 3 illustrates the definition of the new tangent angle distance that consider the angle dimension (where d_1 and d_2 respectively represent the new distances from the snake control point v to point p_1 in line l_1 and from v to point p_2 in line l_2).

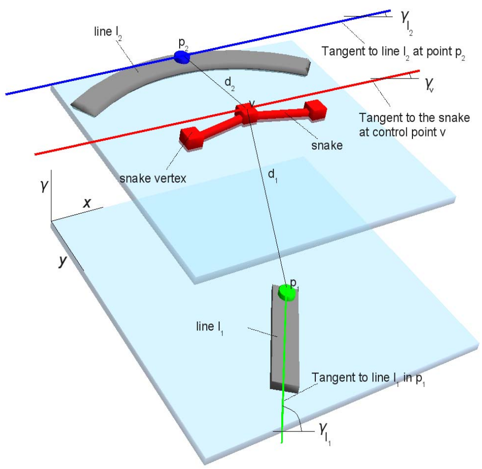


Figure 3. Graphical representation of the tangent angle distance.

In consequence, the new specific fuzzy shape-memory snake energy formulation (see Subsection 2.3) is described as follows. Let $\vec{v} = (d, \theta, p, \gamma)$ now be the 4-tuple vector of input variables defining the snake adjustment energy E_{snake} (where γ describes the tangent angle distance $d\gamma$). After fuzzyfing the inputs, the new vector of fuzzy partitions $U\widetilde{P}_{\vec{v}}$ associated to each input variable (see eq (8)) is:

$$U\widetilde{P}_{\vec{v}} = (U\widetilde{P}_d, U\widetilde{P}_\theta, U\widetilde{P}_p, U\widetilde{P}_\gamma) \qquad (12)$$

where the new variable γ also has an associated partition of unity: $U\widetilde{P}_\gamma = (\widetilde{\gamma}_0, \widetilde{\gamma}_1)$, where subscripts '0' and '1' have a similar interpretation for variable γ as explained in Subsection 2.3.

Therefore, the proponed zero-order TS inference system of eq. (9) has been slightly adapted, and it has now a total of 2^4=16 fuzzy rules which define the new snake adjustment energy E'_{snake} in a similar form as expressed by the eq. (10):

$$\begin{aligned} E'_{snake} &= \alpha_0 E_{Low} + (1-\alpha_0) E_{High} = \\ &= [\mu_{\widetilde{d}_0}(d) \cdot \mu_{\widetilde{\theta}_0}(\theta) \cdot \mu_{\widetilde{p}_0}(p) \cdot \mu_{\widetilde{\gamma}_0}(\gamma)] E_{Low} + \\ &\quad [1 - \mu_{\widetilde{d}_0}(d) \cdot \mu_{\widetilde{\theta}_0}(\theta) \cdot \mu_{\widetilde{p}_0}(p) \cdot \mu_{\widetilde{\gamma}_0}(\gamma)] E_{High} \end{aligned} \qquad (13)$$

IV. BIOMETRIC APPLICATIONS OF NEW FUZZY SNAKES

This section presents two biometric verification applications of the new proposed fuzzy snakes. The first one corresponds to off-line signatures (behavioral biometrics) and the second one to palmprints verification (physiological biometrics).

A. *Off-line signature verification*

Automatic signature verification is a one-to-one pattern recognition problem where a test signature is compared with a reference signature to decide whether or not this test signature is genuine or it is a forgery. Handwritten signatures are usually considered as legal means for verifying a subject identity by financial and administrative institutions [1]. Signature verification can be classified in terms of the sensing technology as off-line and on-line. In the off-line approach, signatures are scanned from paper documents and in the on-line case, the signatures are captured using some electronic devices [1]. The off-line signature problem is more difficult than the corresponding on-line one since the signature to be verified is properly scanned time after the subject signed and none additional dynamic information from the act of signing is available (i.e. pen pressure, stroke sequence, speed and time, etc). A recent survey on the stages and involved techniques for automatic off-line signature verification is [10].

In our approach, the signature verification task is performed by a method [7] that can be decomposed in two main stages:

1) *Adjustment*: an ad hoc created snake model (using only one signature per writer) is adjusted over the test signature image to be verified using the fuzzy shape-memory snake models presented in Sections 2 and 3.

2) *Classification*: the similarity degree between the test signature and the snake model is determined by a zero-order Takagi-Sugeno model. This fuzzy inference system (FIS) is trained using three discriminative features [7] (coincidence, distance and energy factors), which measure the degree of adjustment achieved in the previous stage.

B. Low-resolution palmprint verification

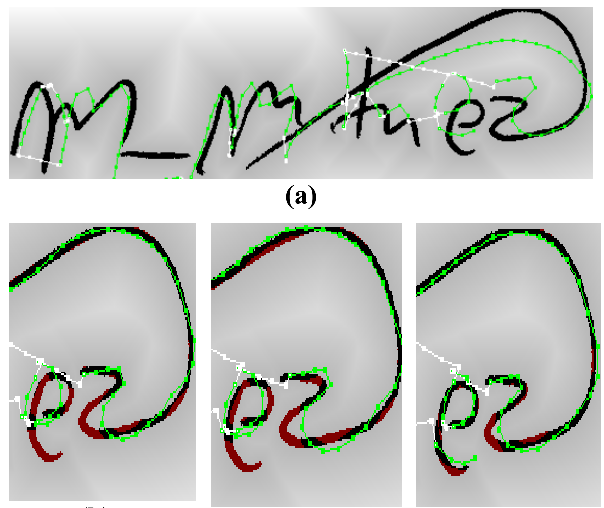
The inner surface of the palm normally contains flexion creases, secondary creases and ridges [11]. Palmprint verification compares an input pattern with a palmprint template by matching the input to the claimed identity template stored in a database [12]. If the dissimilarity between the input and the template is below a predefined threshold, the palmprint input is verified possessing same identity as the claimed one. Palmprint biometric employs either high or low resolution images [11]. The first ones are suitable for forensics applications and the second ones for access control applications. A digital scanner can usually be used for obtaining low resolution palmprint images (150 dpi or less). Due to the contact with the scanner the palm image is distorted and this makes more difficult the verification problem. Verification algorithms can be classified as line-based using edge detectors to extract palm lines, subspace-based using data dimensionality reduction techniques (like PCA or LDA) and statistic-based approaches in the spatial or in transformed domains. Kong et al [11] present an updated survey of palmprint recognition and verification techniques.

In our approach the low-resolution palmprint verification task is performed using the same adapted two-stage verification method proposed for off-line signatures [7].

V. EXPERIMENTAL RESULTS

We show some results for the two experimented biometric modalities. Figs. 4 and 5 respectively depict the corresponding snake adjustments for both off-line signature and palmprint verification patterns. Other possible biometric applications of our framework are IR hand vein [13] and retinal image [14] verification.

In the off-line signature verification example, Fig. 4(a) shows a sample test signature image (and its attached potential map) and the corresponding snake model (an open and connected polygonal line where only the green points are those ones where the adjustment energy is computed) initially placed on the image. Snake initialization is performed by making coincident both mass centers of the test signature and the snake and also by proportionally rescaling the snake height with respect to the test signature. Figs. 4(b), 4(c) and 4(d) respectively show the final adjustment detail for to the rightmost signature region corresponding to crisp model (Subsection 2.1), to the fuzzy model that considers only 2D spatial distances (Subsection 2.3) and to the improved fuzzy method where the tangent angle dimension is added (Section 3). To have a quantitative snake adjustment measure with respect to the test image (which provides us the verification criterion), two ratios were introduced in [7]: *coincidence* (f_c) and *distance* (f_d) values, respectively. Both ratios are normalized in the [0..1] interval and higher values of them mean a better adjustment result. Additionally, stroke fragments in red of Figs. 4(b) to 4(d), represent the snake adjustment errors. The f_c and f_d values in signature verification problem for the snake models are shown in Table 1.



(a) (b) (c) (d)

Figure 4. Snake adjustments for the signature verification example.

TABLE I. VALUES OF RATIOS ON THE SIGNATURE EXAMPLE FOR THE SNAKE MODELS

Ratios	f_c	f_d
Crisp snakes	0.76	0.65
Fuzzy snakes	0.80	0.67
Improved fuzzy snakes	0.82	0.75

For the low-resolution palmprint verification example, Fig. 5(a) shows a sample test palmprint image where main lines have been painted in black color. The corresponding snake model (in green) is similarly built from these lines and properly placed on the test potential-map palmprint image to minimize the adjustment energy in a way like in the signature case. Figs. 5(b), 5(c) and 5(d) respectively show the final adjustment (magnified images) corresponding to the crisp snake model, to the fuzzy model considering 2D spatial distances, and to the improved fuzzy method where the tangent angle dimension is added. In a similar way, we use as snake adjustment measure the coincidence (f_c) and distance (f_d) ratios. In a similar way, the stroke fragments in red represent the snake adjustment errors.

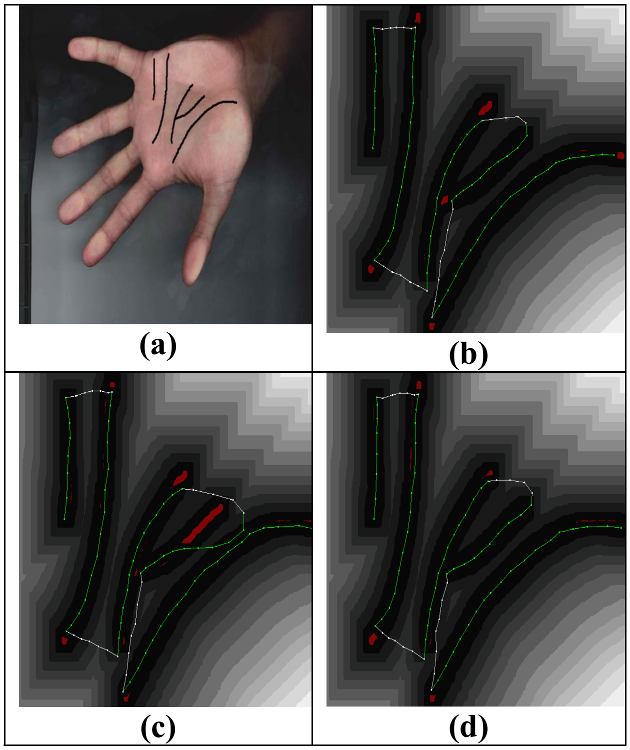


Figure 5. Snakes adjustments for the palmprint verification example.

Table 2 shows the f_c and f_d values in the low-resolution palmprint verification problem for the three snake models in the considered example.

TABLE II. VALUES OF RATIOS ON THE PALMPRINT EXAMPLE FOR THE SNAKE MODELS

Ratios	f_c	f_d
Crisp snakes	0.94	0.78
Fuzzy snakes	0.88	0.61
Improved fuzzy snakes	0.96	0.79

VI. CONCLUSION

This paper presented an improved 3D fuzzy shape-memory snake model that is suited to biometric patterns represented by a collection of variable-length interconnected lines. This approach was successfully compared to other crisp and fuzzy snakes for two different biometric modalities.

As future work, we plan to apply our improved snake model to other verification biometrics (in particular, IR hand vein images and retinal images), and to other shape verification problems.

ACKNOWLEDGEMENTS

This work is supported by the Spanish Ministerio de Ciencia e Innovación project TIN2008-06890-C02-02.

REFERENCES

[1] R. Bolle et al, *Guide to Biometrics*, Springer, 2004.
[2] K. Franke et al, “Soft Biometrics”, *Intl. J. Fuzzy Systems* 4, 2002, pp. 665-672.
[3] M. Kass et al, “Snakes: Active Contour Models”, *Intl. J. Computer Vision* 1(4), 1988, pp. 321-331.
[4] N. Davison et al, “Snakes simplified”, *Pattern Recognition* 33(10), 2000, pp. 1651-1664.
[5] C. Ciofolo and C. Barillot, “Shape analysis and fuzzy control for 3D competitive segmentation of brain structures with level sets”, LNCS 3951, Springer, 2006, pp. 458-470.
[6] F. Höwing et al, “Fuzzy Snakes”, *Proc. Intl. Conf. Image Processing and its Applications*, vol. 2, 1997, pp. 627-630.
[7] J. Vélez et al, “Fuzzy shape-memory snakes for the automatic off-line signature verification problem”, *Fuzzy Sets and Systems* 160, 2009, pp. 182-197.
[8] L. D. Cohen and I. Cohen, “Finite element method for active contour models and balloons for 2-D and 3-D images”, *IEEE Trans. PAMI* 5(11), 1993, pp. 1131-1147.
[9] T. Takagi and M. Sugeno, “Fuzzy identification of systems and its application to modelling and control”, *IEEE T. on Systems, Man and Cybernetics* 15, 1985, pp. 116-132.
[10] D. Impedovo and G. Pirlo, “Automatic Signature Verification: The State of the Art”, *IEEE Trans. on Systems, Man and Cybernetics – Part C* 38(5), 2008, pp. 609-635.
[11] A. Kong et al, “A survey of palmprint recognition”, *Pattern Recognition* 42, 2009, pp. 1408-1418.
[12] L. Zhang et al, “Palmprint verification using complex wavelet transform”, *Proc. IEEE Intl. Conf. on Image Processing* (ICIP’07), vol. 2, 2007, pp. 417-420.
[13] L. Wang, G. Leedham and D. Cho, “Minutiae feature analysis for infrared hand vein pattern biometrics”, *Pattern Recognition* 41, 2008, pp. 920-929.
[14] M. Ortega et al, “Personal verification based on extraction and characterisation of retinal feature points”, *J. Visual Languages and Computing* 20, 2009, pp. 80-90.