Hierarchical Graph-Grammar Model for Secure and Efficient Handwritten Signatures Classification

Marcin Piekarczyk

(ICS, Pedagogical University of Krakow, Poland marp@up.krakow.pl)

Marek R. Ogiela

(AGH University of Science and Technology, Krakow, Poland mogiela@agh.edu.pl)

Abstract: One important subject associated with personal authentication capabilities is the analysis of handwritten signatures. Among the many known techniques, algorithms based on linguistic formalisms are also possible. However, such techniques require a number of algorithms for intelligent image analysis to be applied, allowing the development of new solutions in the field of personal authentication and building modern security systems based on the advanced recognition of such patterns. The article presents the approach based on the usage of syntactic methods for the static analysis of handwritten signatures. The graph linguistic formalisms applied, such as the IE graph and ETPL(k) grammar, are characterised by considerable descriptive strength and a polynomial membership problem of the syntactic analysis. For the purposes of representing the analysed handwritten signatures, new hierarchical (two-layer) HIE graph structures based on IE graphs have been defined. The two-layer graph description makes it possible to take into consideration both local and global features of the signature. The usage of attributed graphs enables the storage of additional semantic information describing the properties of individual signature strokes. The verification and recognition of a signature consists in analysing the affiliation of its graph description to the language describing the specimen database. Initial assessments display a precision of the method at a average level of under 75%.

Keywords: handwritten signature verification, hierarchical attributed random graph, signature-based authentication, biometric security, intelligent computing, secure verification.

Categories: I.2.4, I.2.10, I.4.8, I.4.10, I.5.1, F.4.2, F.4.3

1 Introduction

Today, biometric technologies are more and more commonly used to ensure identity verification or the authorisation of access to sensitive data. Certain biometric characteristics, such as dermatoglyphics, are already being introduced, while in some countries it is planned to introduce them as a permanent element of passports and other identity documents. For historical reasons, the handwritten signature continues to be the most commonly accepted form of confirming transactions, civil law contracts, acts of volition, or one's identity. Even the modern means of utilising digital monies - such as payment cards and credit cards, which are being used with increasing

frequency - often require that a bill be confirmed by a handwritten signature. Unfortunately, this universality carries with it an increased risk of tangible financial loss due to numerous attempts at forging signatures, e.g. on bank cheques or credit contracts. This problem may be resolved to a certain extent by the introduction of automatic recognition systems, which are being successfully used to effectively analyse large quantities of biometric data, for example dermatoglyphics. Research in this regard, which refers to the static analysis of handwritten signatures, has resulted in the elaboration of a number of techniques and methods enabling the automatic identification and verification [Plamondon and Srihari, 2000] [Radhika et al., 2008] of data of this type. In this regard, use is made primarily of techniques based on DTW (Dynamic Time Warping), HMMs (Hidden Markov Models), SVMs (Support Vector Machines), or utilising neutral networks (NN). Structural methods, and in particular ones based on graph languages, are used considerably less frequently. This is strongly connected with the problem of calculation complexity, which for the majority of nontrivial graph grammar classes - of interest from an application point of view - is NP-complete [Flasinski, 1998]. For this reason, the study presents a mathematical model of the description of handwritten signatures, constructed on the basis of IE graphs and class ETPL(k) grammars. These formalisms have sufficient descriptive power for representing even complex scenes and polynomial membership problem. For the purposes of the language describing the permitted shapes of specimen signatures, use has additionally been made of the theory of random IE [Skomorowski, 1996] [Skomorowski, 1999] graphs and statistic graph grammars of the ETPL(k) class [Flasinski and Skomorowski, 1998].

Systems for analysing handwritten signatures and authenticating persons built based on the formalisms described below may contribute to the development of new classes of IT systems for ensuring the confidentiality and integrity of data stored as well as selective the control of access to it using secure techniques for verifying biometric data. Such systems will be based on algorithms included in the branch of informatics called computational intelligence. It is also quite obvious that in the future such modern systems will facilitate the quick and universal analysis of any data that can confirm a person's identity, be it digital biometric data or traditional handwritten signatures. The authors have preliminarily introduced such a subject in [Piekarczyk, 2010] [Ogiela and Tadeusiewicz, 2008].

2 Syntactic Description of Single Signature

The methodology of using a mathematical linguistic approach to intelligently analyses digital signature patterns consists of three basic stages. In the first, certain basic image pre-processing operations are executed, making it possible to extract the signature itself for further analysis. The second stage consists in introducing a linguistic description for analysed patterns. For this reason it is necessary to define the appropriate components describing such signatures as well as relations that can exist between them. The last stage is the implementation of a parser which executes the analysis proper and which determines the status of the given signature. Subsequent stages are briefly characterised in the subsections below.

2.1 Preprocessing and stroke extraction

At the first stage, signatures are processed to a digital format (scanning) as multitone images (8 bits per pixel) with a resolution of at least 300 dpi (fig. 1a). Next, they are subjected to initial filtration (e.g. lowpass median filter), decimal-to-binary conversion using Otsu's method [Otsu, 1979] (fig. 1b), strokes enhancement (if necessary) [Shi and Govindaraju, 1996], and thinning (Zhang and Suen algorithm [Zhang and Suen, 1984]) (fig. 1c).

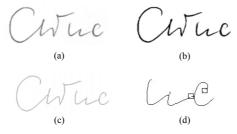


Figure 1: Preprocessing stages: (a) original grayscale image (8 bits per pixel), (b) signature after thresholding, (c) thinned signature and (d) detecting of broken strokes connections.

The resultant thinned image obtained may have structural defects, which ensue from the difficulties and limitations encountered at the decimal-to-binary conversion stage. This concerns primarily the possible interruption of line continuity at unauthorised points, which may radically alter the spatial structure of the thinned signature.

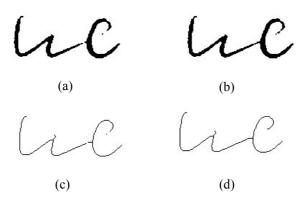


Figure 2: Image enhancement: (a) binary image before, (b) binary image after, (c) thinned signature before and (d) thinned signature after.

In order to eliminate this problem, potential points of such interruptions are sought out in the thinned signature (fig. 1d) and marked as areas requiring correction. The next step consists in strengthening the lines of the signature at indicated image subareas by means of averaging filtration, morphological operations (closure), and repeated decimal-to-binary conversion and thinning (fig. 2a-d). The final stage consists in cleaning the image of any residual thinning artefacts.

2.2 Feature encoding

The thinned signature is used as a basis for creating a structural description. The primary components are curves contained between the ends and the points of intersection of lines of the thinned signature. For each such component we designate a parametric shape description utilising Zernike moments [Zernike, 1924], which are coefficients of development of the function of two real variables – representing the image – with respect to complex Zernike polynomials. These polynomials are defined in a complex form in accordance with formula (1), where n, m are natural numbers and fulfil the condition $0 \le m \le n$, and n-m is even, ρ, θ are polar coordinates, and $R_n^m(\rho)$ is a radial polynomial of form (2).

$$V_{nm}(x,y) = V_{nm}(\rho,\theta) = R_{nm}(\rho)e^{jm\theta}$$
(1)

$$R_{nm}(\rho) = \sum_{s=0}^{(n-|m|)/2} (-1)^s \frac{(n-s)!}{s! (\frac{n+|m|}{2})! (\frac{n-|m|}{2})!} \rho^{n-2s}$$
 (2)

These polynomials constitute an orthogonal set within the unitary circle (4). The Zernike moment of order n and repetition m for a two-dimensional discrete image represented by the function f(x, y) is calculated using formula (3). In addition, it is assumed that this function is two-way $\{0,1\}$ throughout its domain.

$$A_{nm} = \frac{n+1}{\pi} \sum_{x} \sum_{y} f(x, y) V_{nm}^{*}(\rho, \theta)$$
 (3)

$$x^2 + y^2 \le 1 \tag{4}$$

Each curve is represented by a vector made up of sixteen complex moments to an order of 6 inclusive (similarly to [Baran, 2001]).

An ordered set of moments (Table 1) constitutes a vector of shape describing the geometrical features of the curve (5). Each vector component contains a real and imaginary part.

$$V_{S} = [A_{00}, A_{11}, \dots, A_{66}] \tag{5}$$

Order	Moments	Quantity
0	A ₀₀	1
1	A ₁₁	1
2	A_{20}, A_{22}	2
3	A_{31}, A_{33}	2
4	A ₄₀ , A ₄₂ , A ₄₄	3
5	A_{51}, A_{53}, A_{55}	3
6	A ₆₀ , A ₆₂ , A ₆₄ , A ₆₆	4

Table 1: Set of Zernike moments

2.3 Measuring strokes similarity

In order to ensure the possibility of comparing individual vectors representing different image components, use is made of the Canberra distance obtained from formula (6), where v, w are vectors as in (5), while indexes $^R, ^I$ designate their real and imaginary parts respectively and s determines sensitivity of the measurement.

$$d_{ca}(v,w) = \frac{1}{s} \left(\sum_{i=1}^{16} \frac{\left| v_i^R - w_i^R \right|}{\left| v_i^R \right| - \left| w_i^R \right|} + \sum_{i=1}^{16} \frac{\left| v_i^I - w_i^I \right|}{\left| v_i^I \right| - \left| w_i^I \right|} \right)$$
(6)

The measure of similarity of curves SD is defined as the converse of this distance (7), while coefficient T_D determines the threshold.

$$SD_{v,w} = \frac{1}{d_e(v,w)} \ge T_D \tag{7}$$

2.4 Structural representation of signature's subparts

Connected fragments of the thinned signature (fig. 1c) are considered as complex graphemes and described by means of IE graphs (fig. 5). The structure of each grapheme is described by a separate graph. Graph nodes represent the primary components, while edges - the relation of direct contiguity (the touching of curves). A node label, designated from the set $V = \{a, b, c, d\}$, is assigned to each component. This is intended to ensure the initial classification of curve shapes in corresponding shape classes (fig. 3). The classification is performed by calculated the similarity of a curve to individual class objects using a shape vector (5) based on Zernike moments and measures of similarity (6). The size of class elements is appropriately scaled for each component individually.

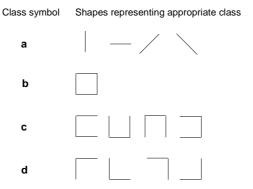


Figure 3: Etiquettes and shapes used in node labelling process.

The graph edges are assigned with appropriate directional labels determining spatial relations (fig. 4) with a resolution of 15 angle degrees, which are designated between the centres of gravity of adjacent curves. The node with index 1 represents the primary component located nearest to the left upper corner of the stage, and it is from there that the development of the graph commences.

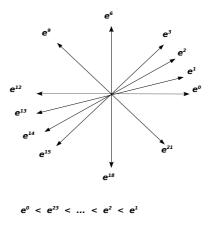


Figure 4: Ordered set of edge labels.

Additional use has been made of attributed IE graphs (def. 1 as per [Oleksik, 2000]), where certain semantic information may be associated with node and edge labels.

Definition 1. An attributed IE graph (aIE) is three $G = (G^*, \eta_V, \eta_F)$, where $G^* = (V, E, \Sigma, \Gamma, \phi)$ is an IE graph concordant with the definition in [Flasinski, 1998],

 η_V, η_E are representations attributing graph nodes (8) and edges (9), respectively:

$$\eta_V : V \to A = \bigcup_{S \in \Sigma} \Omega_{\delta} \tag{8}$$

$$\eta_{V}: V \to A = \bigcup_{\delta \in \Sigma} \Omega_{\delta}$$

$$\eta_{E}: E \to B = \bigcup_{\psi \in \Gamma} \Omega_{\psi}$$
(8)

and fulfilling conditions (10) and (11):

$$\forall v \in V \qquad \qquad \eta_{V}(v) \in \Omega_{\phi(v)} \tag{10}$$

$$\forall e = (u, \sigma, w) \in E \qquad \eta_E(e) \in \Omega_{\sigma} \tag{11}$$

In the proposed solution, additional information in the form of a shape vector is assigned only to node labels, i.e. the corresponding edge and node attributing functions have the form of: $\eta_{\scriptscriptstyle E}:E\to\varnothing$ and $\eta_{\scriptscriptstyle V}:V\to A=\bigcup_{\delta\in\Sigma}\Omega_\delta$, where the

set of values for the node attributing function is determined in the space of complex numbers $\Omega = C^{16}$ (5). An example of such a graph representation for a signature made up of two graphemes has been given in Fig. 5.

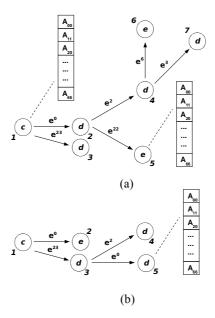


Figure 5: Complex grapheme representation in the form of attributed IE graph for signature depicted in Fig. 1: (a) left subpart, (b) right subpart.

2.5 Hierarchical graph representation of signature

In the majority of instances, a handwritten signature is made up of a few fragments (graphemes) that are visually separated from each other. These may range from a few to even a few dozen components, depending on the type of signature (full, simplified, based on ideograms, e.g. kanji) and the degree of complexity. In order to depict a global spatial arrangement of these components with respect to each other in the present approach, use is also made of a graph description in the form of a hierarchical graph (def. 2).

Definition 2. A hierarchical IE graph (HIE) constructed over languages L_1, \ldots, L_n is called a five $H_{IE(L_1, \ldots, L_n)} = (V, E, \Sigma, \Gamma, \phi)$, where:

V is a finite, non-empty set of graph edges that are IE graphs, to which there have been unequivocally assigned indexes such that $V = \{v_1, \ldots, v_n\}$, $n \in \mathbb{N}^+$, where $\forall_{i=1,\ldots,n} \quad v_i \in L$, and L is the language generated by grammar G, L = L(G), where $G \in acETPL(k)$,

 Σ , Γ , E and ϕ are determined as for the IE graph defined in accordance with [Flasinski, 1993].

It is constructed as a metastructure structured over the set base graph (the IE graph in the present case) in such a way that the nodes of the hierarchical graph are subgraphs of the base graph [Oleksik, 2000]. In other words, the nodes of the graph represent individual graphemes, while edge labels determine the spatial relations between them (Fig. 6). In consequence, we obtain a two-level structure that makes it possible to effectively represent the entire complexity of the signature. Level I (hierarchical graph) accounts for the global elements of the stage, while level II precisely describes the structure of individual graphemes (attributed IE graph) together with the inherent semantic information referring to the shape of individual primary components (shape vectors based on Zernike moments).

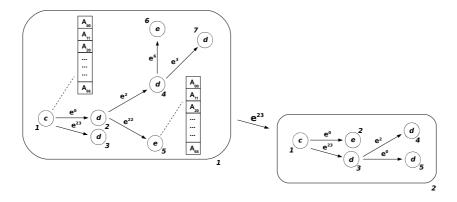


Figure 6: Hierarchical graph representation of handwritten signature depicted in Fig. 1 (visual presentation with encapsulated graphs).

Edge labels are assigned in an identical manner as for graphs representing the component parts of the signature. Use is made of an identical set of directional labels (Fig. 4), however with the difference that the directions are designated between the centres of gravity of entire graphemes. Difficulties arise when determining labels for graph nodes. From the point of view of a syntactic analysis, (ETPL(k) grammars originate from NLC (Node Label Controlled) grammars; these must be labels introducing certain information on structures represented thereby, which is subsequently used in the parsing process [Flasinski, 1993][Flasinski, 1998]. In the proposed solution, the labels are directly associated with information concerning the size of the graph (Table 2).

Number of nodes in the level II graph	Label
1 – 3	a
4 – 6	b
7 – 10	c
11 – 15	d
16 – 20	e
21 – 25	f
26 – 30	g

Table 2: Set of node labels for Hierarchical IE Graph

In the present instance, the size of the graph is understood to be the number of nodes in its structure. A similar method of labelling has been successfully used TGraph tree structures in [Baran, 2001]. Depending on requirements, the size of the set of labels may be extended outside of the set presented in Table II. The final form of the hierarchical graph from Fig. 6, having taken into consideration the described node labelling scheme with a hidden level II layer, has been presented in Fig. 7.



Figure 7: Final form of hierarchical graph depicted in Fig. 6 with labelled nodes.

3 Graph language describing the genuine signature's dataset

In order to ensure the completeness of the recognition system, the representation of individual handwritten signatures must be supplemented by a mechanism that makes it possible to store information about permitted specimen signatures for a given person in the form of a linguistic description (specimen database). To this end, formalisms utilising random rIE graphs [Skomorowski, 1996][Skomorowski, 1999] and stochastic

sETPL(k) grammars [Flasinski and Skomorowski, 1998] have been proposed. Random graphs are excellent for representing stages containing structural deformations or variants. In the case of handwritten signatures, we are dealing with such a natural process of variability, to a certain extent, of the shape of signatures apposed by one and the same person.

The process of constructing a representation of a specimen database should be effected automatically. To this end, use has been made of grammatical concluding mechanisms for class ETPL(k) grammars, which for deterministic grammars have been formally defined by Flasinski in [Flasinski, 1992]. Due to the structure of ETPL(k) grammars, this problem for stochastic type grammars may be also solved within a reasonable calculation time. A computational complexity of the syntactic inference stage is at the level of $O(n^4)$ when the single graph based algorithm is considered (similarly as for deterministic grammars). The proposed solution is based on ideas presented in [Flasinski, 1992], and suggests the extension of the recognition mechanism to the class of stochastic ETPL(k) grammars. The specimen database is constructed over a number of stages on the basis of finite set of positive language examples – a set of genuine handwritten signatures of a given person (Fig. 8).

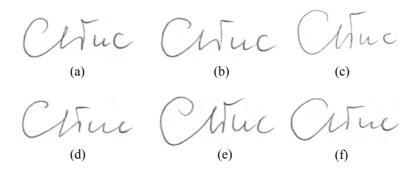


Figure 8: Hypothetical set of genuine signatures (collection of patterns).

At the first stage, a structural representation is created for each signature (cf. section 2) in the form of a hierarchical HIE graph. The graph description of signatures from Fig. 8 in the form of graphs of the layer of the first and second level has been presented successively in Fig. 9 and 10.

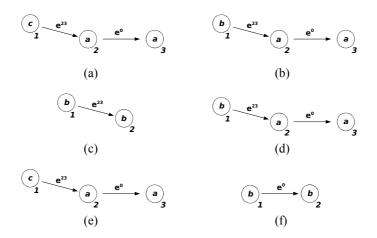


Figure 9: HIE graphs for signatures depicted in Fig. 8.

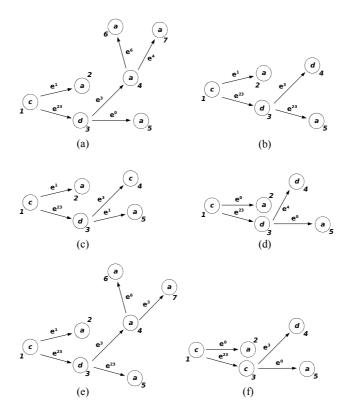


Figure 10: Examples of aIE graphs (hidden layer) for signatures depicted in Fig. 8 (only graphs encapsulated in nodes indexed by 1 are presented).

We can easily observe that the graph representation displays certain structural similarities both in the first and second level layer. Between certain graphs there occurs a structural isomorphism, which may be described by means of random graphs. In the case of the second level layer, we define for this purpose (def. 3) attributed random IE graphs (arIE), for in addition to random labels it is necessary to associate semantic information about the shapes of primary components (as in the rIE graph from a single signature).

Definition 3. The attributed random IE graph (arIE) is known as a three $G = (G^*, \eta_V, \eta_F)$, where:

 $G^* = (V, E, \Sigma, \Gamma, \phi)$ is a random IE graph concordant with the definition in [Skomorowski, 1996][Skomorowski, 1999],

 η_V , η_E are representations attributing graph nodes (12) and edges (13), respectively:

$$\eta_V : V \to A = \{A_i\} \quad A_i = \bigcup_{\delta \in \Sigma} \Omega_{\delta}$$
(12)

$$\forall i \neq j \quad A_i \cap A_j = \emptyset$$

$$\eta_E : E \to B = \{B_i\} \qquad B_i = \bigcup_{\psi \in \Gamma} \Omega_{\psi}$$
(13)

$$\forall i \neq j \ B_i \cap B_j = \emptyset$$

and fulfilling conditions (14) and (15):

$$\forall v \in V \qquad \qquad \eta_{V}(v) \in A_{i} \tag{14}$$

$$\forall e = (u, \sigma, w) \in E \qquad \eta_E(e) \in B_i \tag{15}$$

In the case of graph representation for the first level layer (def. 4), apart from the randomness, a change was also made in the formal language category (based on arIE graphs), and thus also in the type of grammar, to an attribute controlled stochastic acsETPL(k) grammar (def. 5).

Definition 4. A hierarchical random IE graph (HrIE) constructed over stochastic languages L_1, \ldots, L_n is known as a seven $H_{IE(L_1, \ldots, L_n)} = (V, E, \Sigma, \Gamma, \phi, \eta_V, \eta_E)$, where:

- a) $V = \{v_1, \dots, v_n\}$ is a finite, non-empty set of random nodes, to which there have been unequivocally assigned indexes such that $V = \{v_1, \dots, v_n\}$, $n \in \mathbb{N}^+$, where $\forall_{i=1,\dots,n} \quad v_i \in L$, and L is the language generated by grammar G, L = L(G), where $G \in acsETPL(k)$,
- b) Σ , Γ , E and ϕ are determined as for the random IE graph defined in accordance with [Skomorowski, 1996][Skomorowski, 1999],

Passage from a deterministic description (Fig. 9 and 10) to a random description is effected by creating subsets of structurally isomorphic graphs and constructing random graphs on their basis. First, this operation is effected in the hierarchical layer (Fig. 11), and subsequently for each node of the hierarchical graph in the second level layer (Fig. 12).

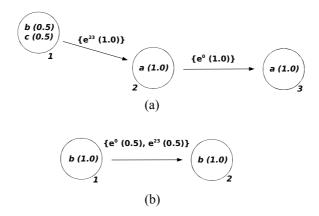


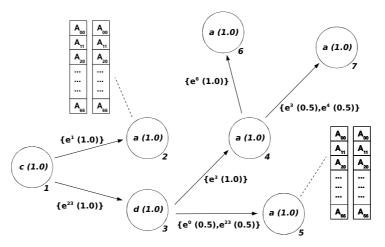
Figure 11: Hierarchical random IE graphs constructed on the basis of subsets of structurally isomorphic graphs depicted in Fig. 9.

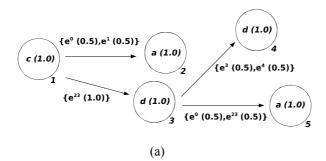
Definition 5. A stochastic attribute controlled graph grammar of class ETPL(k) above sets of attributes A, B is known as a six $G = (\Sigma, \Delta, \Gamma, P, Z, f_z)$, where:

- a) Σ, Δ, Γ, Z are determined as for the grammar sETPL(k) defined in accordance with [Flasinski and Skomorowski, 1998],
- b) $f_Z: \Theta_{A,B}(\overline{D}) \to \{\mathit{TRUE}, \mathit{FALSE}\}\$ is a starting predicate, where the graph \overline{Z} is created from the start symbol Z by removing non-terminal nodes,
- c) P is a production set of the form p=(1, D, C, f), where:
 - (l, D, C) is a probabilistic production in accordance with the definition of the sTLP grammar (definition in [Flasinski and Skomorowski, 1998]),
 - $f: \Theta_{A,B}(\overline{D}) \to \{TRUE, FALSE\}$ is the predicate of applicability of production p, where the graph \overline{D} is created from graph G by the removal of non-terminal nodes.

The next step consists in defining the appropriate grammars capable of generating arIE and HrIE graphs. In the first case, this is an attribute controlled acsETPL(k) grammar (def. 5). The applicability predicates [Oleksik, 2000] added thereto allow us to determine, this on the basis of the semantic context (attribute values, in this case a set of Zernike moments), whether a specific production may be applied at a given stage of argumentation. Thus, at the parsing stage usage is made of information about

the shapes of individual primary components. The appropriate stochastic TLsETPL(k) grammar is defined analogically (def. 6); this makes it possible to generate random HrIE graphs describing the structure of the signature (stage) in a global context.





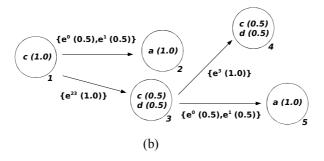


Figure 12: Collection of attributed random IE graphs (hidden layer) connected respectively with: (a) and (b) first layer graphs depicted in Fig. 11.

Definition 6. A stochastic hierarchical TLsETPL (n,k) grammar generating HrIE graphs is known as $G = (\Sigma_I, \Delta_I, \Gamma_I, P_I, Z_I, \{G_{IIi}\})$, where:

- n determines the number of sETPL(k) grammars on which the TLsETPL(k) grammar is based,
- Σ_I is a finite, non-empty set of node labels of the layer of the hierarchical graph known as the first level layer,
- Γ_I is a finite, non-empty set of edge labels of the first level layer,
- P_1 is a set of probabilistic productions (l, D, C) such that the grammar $G = (\Sigma_I, \Delta_I, \Gamma_I, P_I, Z_I)$ is an sETPL(k) grammar,
- $Z_{\rm I}$ is the starting graph known as the grammar axiom belonging to $HrIE_{\Sigma_{\rm I},\Gamma_{\rm I}}$,
- {G_{IIi}} is a set of acsETPL(k) grammars comprising the layer of the base graph, known as the second level layer, such that G_{IIi} is a class acsETPL(k_i) grammar for a certain k_i,
- **■** k fulfils the condition: $\forall G_{lli} \in acsETPL(k_i) \ k_i \leq k$,
- Σ_{II} , Δ_{II} , Γ_{II} , Z_{II} are determined as for the acsETPL(k) grammar defined in accordance with [Flasinski, 1993].

The final stage consists in generating, on the basis of random graphs of the I and II level (considered as positive language samples), of appropriate stochastic grammars acsETPL(k) and TLsETPL(k).

4 Recognition system

Once we have prepared the appropriate specimen database, the corresponding process of signature recognition and verification is based on syntactic analysis mechanisms. An analysis is performed of the affiliation of the graph description of the tested signature in the form of an HIE graph to the language generated by the TLsETPL(k) grammar representing specimens (Fig. 13).

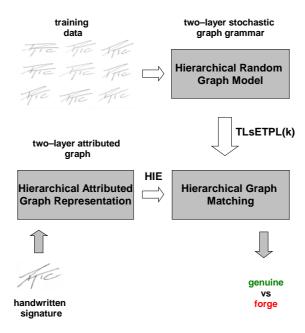


Figure 13: Recognition/verification process.

Thanks to the utilisation of syntactic formalisms based on class ETPL(k) grammars, the parsing process itself is effective as regards calculations (polynomial membership problem) [Flasinski and Skomorowski, 1998] [Skomorowski, 1999].

5 Conclusion

This paper describes new algorithms for the effective and secure analysis of hand-written signatures aimed at their recognition. These techniques are based on advanced linguistic formalisms belonging to Computational Intelligence methods. In the future, the solutions presented can be used in new generation intelligent IT systems dedicated to the semantic interpretation of patterns as well as to collecting identifying and biometric data. The methods described have turned out to be extremely universal and they will extend the capabilities of secure personal authentication to include the analysis of handwritten signature patterns.

Research has been conducted on the techniques presented in this text to estimate their preliminary operating efficacy.

An initial assessment of the precision of the method has been effected on a small signature database. Five volunteers apposed 24 signatures, with 6 additional counterfeit signatures being made for each person (simple and skilled forgeries). Furthermore, 6 random forgeries were added to the pool. In effect, 12 genuine

signatures and 12 counterfeit signatures were obtained for each person. The specimen database was constructed on the basis of 12 randomly selected (from 24) genuine signatures in each instance. The results obtained in the form of FRR (False Rejecting Rate) errors and FAR (False Acceptance Rate) errors have been presented in Table 3.

FAR*100%	FRR*100%
11.6	21.6

Table 3: Accuracy (5 writers/24 signatures each)

The future direction of research shall concentrate on improving the effectiveness of the mechanism. The effectiveness is considered as the quality indicator of the recognition algorithm expressed in the form of FAR/FRR ratio. To obtain further significant reduction of the error rates it appears necessary to take into consideration certain dynamic characteristics of signatures, which may be easily effected by extending the scope of attribute values assigned to individual primary components. Such information would make it possible for the algorithm to better cope with skilled and high-skilled signatures.

References

[Baran, 2001] Baran, M. (2001): Structural Pattern Recognition of Printed Circuit Boards. 2nd Conference on Computer Recognition Systems – KOSYR'01, pp. 287-293.

[Chen and Srihari, 2005] Chen, S., Srihari, S. (2005): Use of Exterior Contours and Shape Features in Off-line Signature Verification. Proc. of 8th International Conference on Document Analysis and Recognition, pp. 1280-1284.

[Flasinski, 1992] Flasinski, M. (1992): Structural pattern recognition using ETPL(k) graph grammar. Jagiellonian University, D. Sc. Thesis, Cracow, Poland, 1992.

[Flasinski, 1993] Flasinski, M. (1993): On the Parsing of Deterministic Graph Languages for Syntactic Pattern Recognition. Pattern Recognition, 26(1), pp. 1-16.

[Flasinski, 1998] Flasinski, M. (1998): Power Properties of NLC Graph Grammars with a Polynomial Membership Problem. Theoretical Computer Science, 201(1), pp. 189-231.

[Flasinski and Skomorowski, 1998] Flasinski, M., Skomorowski, M. (1998): Parsing of Random Graph Languages for Automated Inspection in Statistical-based Quality Assurance Systems. Machine GRAPHICS & VISION International Journal, 7(3), pp. 565-623.

[Oleksik, 2000] Oleksik, P. (2000): Syntactic pattern recognition in visual inspection system using stochastic ETPL(k) graph grammars. AGH University of Science and Technology, Ph.D. thesis, Cracow, Poland.

[Otsu, 1979] Otsu, N. (1979): A threshold selection method from gray level histograms. IEEE Trans. on Systems, Man and Cybernetics, 9(1), pp. 62-66.

[Piekarczyk, 2010] Piekarczyk, M. (2010): Hierarchical Random Graph Model for Off-line Handwritten Signatures Recognition. Proc. of International Conference on Complex, Intelligent and Software Intensive Systems 2010 (CISIS2010/IMIS2010), IEEE CS Press, pp. 860-865

[Plamondon and Srihari, 2000] Plamondon, R., Srihari, S. N. (2000): On-line and off-line handwriting recognition: a comprehensive survey. IEEE Trans. on Pattern Analysis and Machine Intelligence, 22(1), pp. 63-84.

[Radhika et al., 2008] Radhika, K. R., Venkatesha, M. K., Sekhar, G. N. (2008): Pattern Recognition Techniques in Off-line hand written signature verification – A Survey. Proc. of World Academy of Science, Engineering and Technology, 36, pp. 905-911.

[Shi and Govindaraju, 1996] Shi, Z., Govindaraju, V. (1996): Character image ehnacement by selective region-growing. Pattern Recognition Letters, 17(5), pp. 523-527, Elsevier Science B. V.

[Skomorowski, 1996] Skomorowski, M. (1996): On the parsing of random graphs for syntactic pattern recognition. Machine GRAPHICS & VISION International Journal, 5, pp. 433-464.

[Skomorowski, 1999] Skomorowski, M. (1999): Use of random graph parsing for scene labelling by probabilistic relaxation. Pattern Recognition Letters, 20(9), pp. 949-956.

[Tadeusiewicz and Ogiela, 2004] Tadeusiewicz, R., Ogiela, M. R. (2004): Medical Image Understanding Technology. Artificial Intelligence and Soft-Computing for Image Understanding. Volume 156 in Studies in Fuzziness and Soft Computing, Springer-Verlag.

[Ogiela et al., 2006a] Ogiela, L., Tadeusiewicz, R., Ogiela, M. R. (2006): Graph-Based Structural Data Mining in Cognitive Pattern Interpretation. Lecture Notes in Artificial Intelligence, 4201, pp. 349-350, Springer-Verlag.

[Ogiela et al., 2006b] Ogiela, M. R., Tadeusiewicz. R., Ogiela. L. (2006): Image Languages in Intelligent Radiological Palm Diagnostics. Pattern Recognition, 39, pp. 2157-2165.

[Ogiela and Tadeusiewicz, 2008] Ogiela, M. R., Tadeusiewicz, R. (2008): Modern Computational Intelligence Methods for the Interpretation of Medical Images, Volume 84 in Studies Computational Intelligence, Springer-Verlag.

[Ogiela and Ogiela, 2009] Ogiela, L., Ogiela, M. R. (2009): Cognitive Techniques in Visual Data Interpretation, Volume 228 in Studies Computational Intelligence, Springer-Verlag.

[Sun et al. 2010] Sun, J., Wang, Y., Si, H., Yuan, J., Shan, X. (2010): Aggregate Human Mobility Modeling Using Principal Component Analysis, Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications, Vol. 1 (2/3), pp. 83-95

[Zernike, 1924] Zernike, F. (1924): Physica, 1, pp. 689.

[Zhang and Suen, 1984] Zhang, T. Y., Suen. C. Y. (1984): A fast parallel algorithm for thinning digital patterns. Communications of the ACM (CACM), 27(3), pp. 236-239.