On-Line and Off-Line Handwriting Recognition: A Comprehensive Survey

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Abstract—Handwriting has continued to persist as a means of communication and recording information in day-to-day life even with the introduction of new technologies. Given its ubiquity in human transactions, machine recognition of handwriting has practical significance, as in reading handwritten notes in a PDA, in postal addresses on envelopes, in amounts in bank checks, in handwritten fields in forms, etc. This overview describes the nature of handwritten language, how it is transduced into electronic data, and the basic concepts behind written language recognition algorithms. Both the *on-line case* (which pertains to the availability of trajectory data during writing) and the *off-line case* (which pertains to scanned images) are considered. Algorithms for preprocessing, character and word recognition, and performance with practical systems are indicated. Other fields of application, like signature verification, writer authentification, handwriting learning tools are also considered.

Index Terms—Handwriting recognition, on-line, off-line, written language, signature verification, cursive script, handwriting learning tools, writer authentification.

1 Introduction

1.1 The Nature of Handwriting

Handwriting is a skill that is personal to individuals. Fundamental characteristics of handwriting are threefold. It consists of artificial graphical marks on a surface; its purpose is to communicate something; this purpose is achieved by virtue of the mark's conventional relation to language [33]. Writing is considered to have made possible much of culture and civilization. Each script has a set of icons, which are known as characters or letters, that have certain basic shapes. There are rules for combining letters to represent shapes of higher level linguistic units. For example, there are rules for combining the shapes of individual letters so as to form cursively written words in the Latin alphabet.

1.2 Survival of Handwriting

Copybooks and various writing methods, like the Palmer method, handwriting analysis, and autograph collecting, are words that conjure up a lost world in which people looked to handwriting as both a lesson in conformity and a talisman of the individual [231]. The reason that handwriting persists in the age of the digital computer is the convenience of paper and pen as compared to keyboards for numerous day-to-day situations.

Handwriting was developed a long time ago as a means to expand human memory and to facilitate communication. At the beginning of the new millennium, technology has once again brought handwriting to a crossroads. Nowadays, there are numerous ways to expand human memory as well as to facilitate communication and in this perspective, one might ask: Will handwriting be threatened with extinction, or will it enter a period of major growth?

Handwriting has changed tremendously over time and, so far, each technology-push has contributed to its expansion. The printing press and typewriter opened up the world to formatted documents, increasing the number of readers that, in turn, learned to write and to communicate. Computer and communication technologies such as word processors, fax machines, and e-mail are having an impact on literacy and handwriting. Newer technologies such as personal digital assistants (PDAs) and digital cellular phones will also have an impact.

All these inventions have led to the fine-tuning and reinterpreting of the role of handwriting and handwritten messages. Each time, the niche occupied by handwriting has become more clearly defined and popularized. As a general rule, it seems that as the length of handwritten messages decreases, the number of people using handwriting increases [165].

Widespread acceptance of digital computers seemingly challenges the future of handwriting. However, in numerous situations, a pen together with paper or a small notepad is much more convenient than a keyboard. For example, students in a classroom are still not typing on a notebook computer. They store language, equations, and graphs with a pen. This typical paradigm has led to the concept of pen computing [139], where the keyboard is an expensive and nonergonomic component to be replaced by a pentip position sensitive surface superimposed on a graphic display that generates electronic ink. The ultimate handwriting computer will have to process electronic handwriting in an unconstrained environment, deal with many writing styles and languages, work with arbitrary

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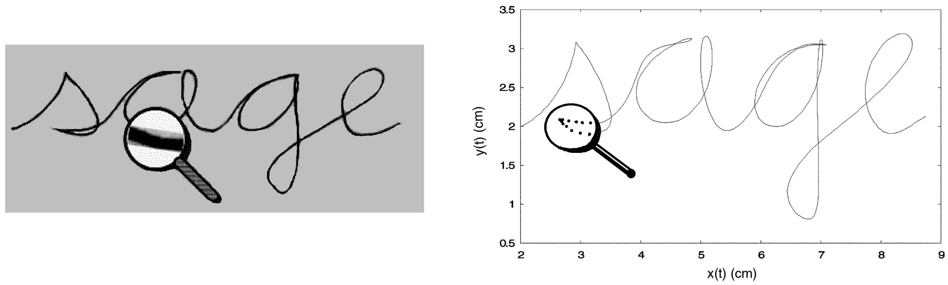
Manuscript received 23 July 1999; accepted 4 Nov. 1999.
Recommended for acceptance by K. Bowyer.
For information on obtaining reprints of this article, please send e-mail to: tpami@computer.org, and reference IEEECS Log Number 110293.



(a) (b)

Fig. 1. (a) Off-line word. The image of the word is converted into gray-level pixels using a scanner. (b) On-line word. The x, y coordinates of the pentip are recorded as a function of time with a digitizer.

user-defined alphabets, and understand any handwritten message by any writer.

1.3 Recognition, Interpretation, and Identification

Several types of analysis, recognition, and interpretation can be associated with handwriting. *Handwriting recognition* is the task of transforming a language represented in its spatial form of graphical marks into its symbolic representation. For English orthography, as with many languages based on the Latin alphabet, this symbolic representation is typically the 8-bit ASCII representation of characters. The characters of most written languages of the world are representable today in the form of 16-bit Unicode [232]. *Handwriting interpretation* is the task of determining the meaning of a body of handwriting, e.g., a handwritten address. *Handwriting identification* is the task of determining the author of a sample of handwriting from a set of writers, assuming that each person's handwriting is individualistic. *Signature verification* is the task of determining whether or not the signature is that of a given person. Identification and verification [171], which have applications in forensic analysis, are processes that determine the special nature of the writing of a specific writer [15], while handwriting recognition and interpretation are processes whose objectives are to filter out the variations so as to determine the message. The task of reading handwriting is one involving specialized human skills. Knowledge of the subject domain is essential as, for example, in the case of the notorious physician's prescription, where a pharmacist uses knowledge of drugs.

1.4 Handwriting Input

Handwriting data is converted to digital form either by scanning the writing on paper or by writing with a special pen on an electronic surface such as a digitizer combined with a liquid crystal display. The two approaches are distinguished as *off-line* and *on-line* handwriting, respectively. In the on-line case, the two-dimensional coordinates of successive points of the writing as a function of time are stored in order, i.e., the order of strokes made by the writer is readily available. In the off-line case, only the completed writing is available as an image. The on-line case deals with a spatio-temporal representation of the input, whereas the off-line case involves analysis of the spatio-luminance of an image. Fig. 1 shows typical input signals that can be analyzed in both cases. The raw data storage requirements are widely different. The data requirements for an average cursively written word are: in the on-line case (Fig. 1b), a few hundred bytes, typically sampled at 100 samples per second, and in the off-line case (Fig. 1a), a few-hundred kilo-bytes, typically sampled at 300 dots per inch. From a global perspective, paper documents, which are an inherently analog medium, can be converted into digital form by a process of scanning and digitization. This process yields a digital image. For instance, a typical 8.5 x 11 inch page is scanned at a resolution of 300 dots per inch to create a gray-scale image of 8.4 megabytes. The resolution is dependent on the smallest font size that needs reliable recognition, as well as the bandwidth needed for transmission and storage of the image.

The recognition rates reported are much higher for the on-line case in comparison with the off-line case. For example, for the off-line, unconstrained handwritten word recognition problem, recognition rates of 95 percent, 85 percent, and 78 percent have been reported for top choice lexicon sizes of 10, 100, and 1,000, respectively [216]. In the on-line case, larger lexicons are possible for the same accuracy; a top choice recognition rate of 80 percent with pure cursive words and a 21,000 word lexicon has been reported [204]. Higher performance numbers have been achieved in recent years; however, all recognition performance numbers are dependent on the particular test set.

1.5 The State of the Art

The state of the art of automatic recognition of handwriting at the dawn of the new millenium is that as a field it is no longer an esoteric topic on the fringes of information technology, but a mature discipline that has found many commercial uses. On-line systems for handwriting recognition are available in hand-held computers such as PDAs. The performance of PDAs is acceptable for processing handprinted symbols, and, when combined with keyboard entry, a powerful method for data entry has been created.

Off-line systems are less accurate than on-line systems. However, they are now good enough that they have a significant economic impact on for specialized domains such as interpreting handwritten postal addresses on envelopes and reading courtesy amounts on bank checks.

The success of on-line systems makes it attractive to consider developing off-line systems that first estimate the trajectory of the writing from off-line data and then use on-line recognition algorithms [151]. However, the difficulty of recreating the temporal data [13], [46], [174] has led to few such feature extraction systems so far.

The objective of this paper is to present a comprehensive review of the state of the art in the automatic processing of handwriting. It reports many recent advances and changes that have occurred in this field, particularly over the last decade. Various psychophysical aspects of the generation and perception of handwriting are first presented to highlight the different sources of variability that make handwriting processing so difficult. Major successes and promising applications of both on-line and off-line approaches are indicated here. Finally, attempts to incorporate contextual knowledge, particularly from linguistics, to improve system performance are presented. Due to space limitations, we mostly limit our survey of this topic to applications dealing with the Latin alphabet. Moreover, in many subtopics, previous surveys have been done to highlight, among other things, how the problem attack was launched, what the major milestones of development in the field were, etc. In these cases, we refer specifically to the papers and build up our report upon those.

2 Handwriting Generation and Perception

The study of handwriting covers a very broad field dealing with numerous aspects of this very complex task. It involves research concepts from several disciplines: experimental psychology, neuroscience, physics, engineering, computer science, anthropology, education, forensic document examination, etc. [56], [161], [170], [208], [209], [235], [236], [237], [241].

From a generation point of view, handwriting involves several functions. Starting from a communication intention, a message is prepared at the semantic, syntactic, and lexical levels and converted somehow into a set of allographs (letter shape models) and graphs (specific instances) made up of strokes so as to generate a pentip trajectory that can be recorded on-line with a digitizer or an instrumented pen. In many cases, the trajectory is just recorded on paper and the resulting document can be read later with an off-line system.

The understanding of handwriting generation is important in the development of both on-line and off-line recognition systems, particularly in accounting for the variability of handwriting. So far, numerous models have been proposed to study and analyze handwriting. These models are generally divided into two major classes: top-down and bottom-up models [173]. Top-down models refer to approaches that focus on high-level information processing, from semantics to basic motor control problems. Bottom-up models are concerned with the analysis and synthesis of low-level neuromuscular processes involved in the production of a single stroke, going upward to the generation of graphs, allographs, words, etc.

Most of the top-down models have been developed for language processing purposes. They are not exclusively dedicated to handwriting and deal with the integration of lexical, syntactic, and semantic information to process a message. We will come back to some of these in Section 5. The bottom-up models are generally divided into two groups: oscillatory [87] and discrete [39] models. The former consider oscillation as a basic movement and the generation of complex movements result from the control of the amplitude, phase, and frequency of a fundamental wave function [26], [53], [59], [198], [233]. Discrete models consider complex movements as the result of a temporal superimposition of a set of simple, discontinuous strokes [20], [143], [144], [167]. In the oscillatory approach, a single stroke is seen as a specific case of an abrupt, interrupted oscillation, while in the discrete case, continuous movements emerge from the time-overlap of discontinuous strokes.

Fig. 2 summarizes and illustrates a typical discrete model [167]. This model describes a single stroke as resulting from the coactivation of two neuromuscular systems, one agonist and the other antagonist, that control the velocity of the pentip. The magnitude of the velocity as a function of time is described by a delta-lognormal function [164] and each stroke is represented by nine parameters reflecting the instantiation and amplitude of the input command $(t_0, \overrightarrow{D}_1, \overrightarrow{D}_2)$, the time delays and response time of the two systems $(\mu_1, \mu_2, \sigma_1^2, \sigma_2^2)$, as well as a basic postural information (C_0, P_0, θ_0).

In this context, the generation of handwriting is described as the vector summation of discontinuous strokes. The fluency of the trajectory emerges from the time-superimposition of strokes due to anticipatory effects. In other words, and according to this kinematic theory [164], once a stroke is initiated to reach a target, a writer knows how long it will take to reach that target and with what spatial precision. This allows the subject to start a new stroke prior to the end of the previous one. The immediate consequence of this anticipation phenomenon is that any observable signal from this trajectory at a given time is affected both by at least the previous and the successive strokes.

Fig. 2a depicts the block diagram of the model. Fig. 2b shows a typical action plan described by a sequence of virtual targets (diamonds) linked by circular strokes (truncated lines). Once this action plan is activated, it is fed through the neuromuscular agonist and antagonist systems to produce a trajectory that leaves, for example, a handwritten trace on a piece of paper (continuous line). Fig. 2c, Fig. 2d, and Fig. 2e show the typical executions of this action plan with increasing anticipatory effects. As seen in Fig. 2e, too much anticipation greatly degrades the visibility of the message. Similar problems can emerge from the variability of any of the nine stroke parameters of this model.

Using nonlinear regression, a set of individual strokes and stroke parameters can be recovered from the shape and the velocity data of a handwritten trace, and both the velocity signal, and the handwritten word can be reconstructed (see Fig. 3a, Fig. 3b for examples). Each of the recovered strokes can be analyzed for the purpose of word segmentation and recognition [74], [167]. From this perspective, bottom-up models provide information about neuromotor processes that are involved, at the lowest level of abstraction, in handwriting recognition. Many cues about

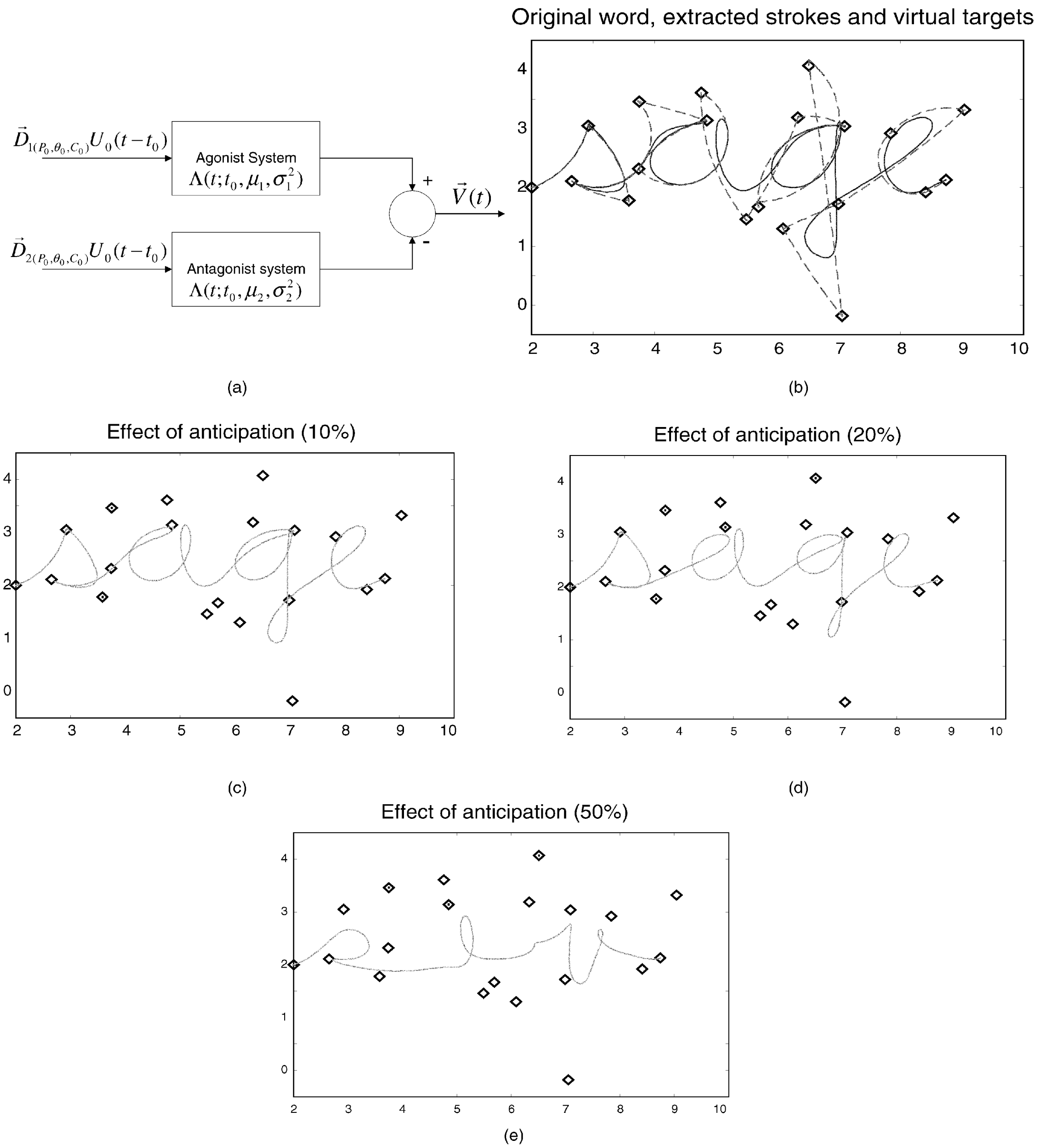


Fig. 2. (a) A handwriting generation model. (b) A typical action plan made up of a sequence of virtual targets (diamonds) linked with circular strokes (dotted lines). This information has been extracted from a specific instance of the word (continuous lines) using the model of Fig. 2a. (c)-(e) Incorporating anticipation effect, which is activating the next stroke before the completion of the present one, modifies the general shape of a word. (c)-(e) shows the effect of increasing the contextual anticipatory phenomenon.

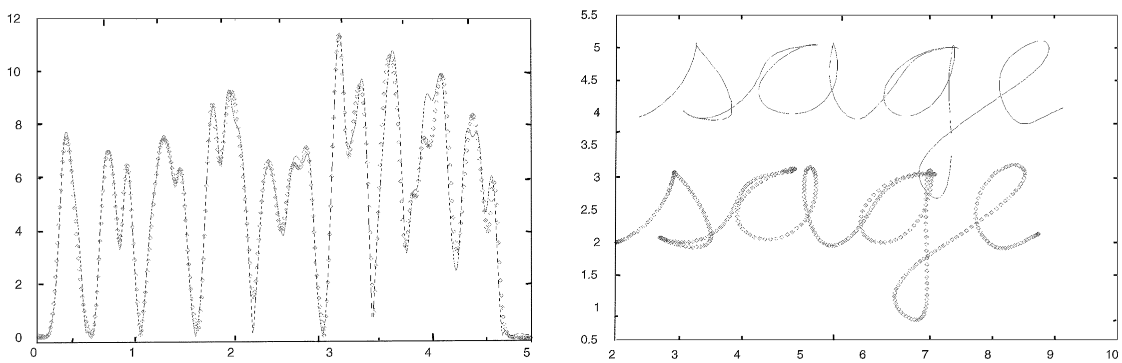
letters detection and word recognition have emerged from similar studies.

From an opposite point-of-view, the reading of a handwritten document relies on a basic knowledge about perception [199], [222]. Psychological experiments in human character recognition show two effects: 1) a character that either occurs frequently, or has a simple structure to it, is processed as a single unit without any decomposition of the character structure into simpler units and 2) with infrequently occurring characters, and those with complex structure, the amount of time taken to recognize a character increases as its number of strokes increases [10], [226], [228], [253]. The former method of recognition is referred to as *holistic* and the latter as *analytic*, both of which are discussed further in Section 4.3.

The perceptual processes involved in reading have been discussed extensively in the cognitive psychology literature [10], [226], [228]. Such studies are pertinent in that they can form the basis for algorithms that emulate human performance in reading [18], [36] or try to do better [224]. Although much of this literature refers to the reading of machine-printed text, some conclusions are equally valid for handwritten text. For instance, the saccades (eye movements) fixate at discrete points on the text, and at each fixation the brain uses the visual peripheral field to infer the shape of the text. Algorithmically, this again leads to the holistic approach to recognition.

3 On-Line Handwriting Recognition

As previously mentioned, on-line recognition refers to methods and techniques dealing with the automatic processing of a message as it is written using a digitizer



(a) (b)

Fig. 3. (a) Original (continuous line) and reconstructed (dotted line) curvilinear velocity of the word "sage." (b) Original (continous line) and reconstructed (dotted line) of the word "sage."

or an instrumented stylus that captures information about the pentip, generally its position, velocity, or acceleration as a function of time (see Fig. 4a, Fig. 4b, Fig. 5a, and Fig. 5b for examples of typical signals).

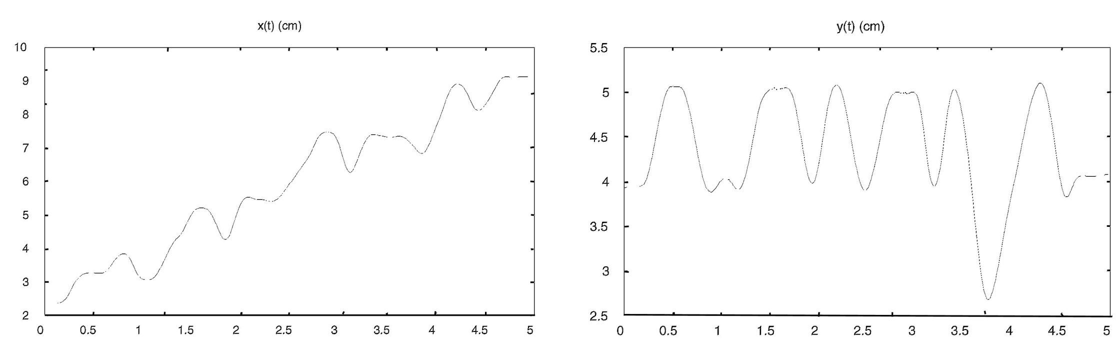
This problem has been a research challenge since the beginning of the sixties, when the first attempts to recognize isolated handprinted characters were performed [52], [54], etc. Since then, numerous methods and approaches have been proposed and tested; many have already been summarized in a few exhaustive survey papers [152], [172], [227], [240].

Over the years, these research projects have evolved from being academic exercises to developing technology-driven applications. We will focus on three of these technical domains in this section: pen-based computers, signature verifiers, and developmental tools. The first group refers to the recognition of handwritten messages and gesture commands to interact with pen computing platforms. The second deals with signatures, a very specific type of well-learned handwriting, with the purpose of verifying the identity of a person. The third class incorporates various systems that exploit the neuromotor characteristics of handwriting to design systems for education and rehabilitation purposes.

3.1 Pen-Based Computers

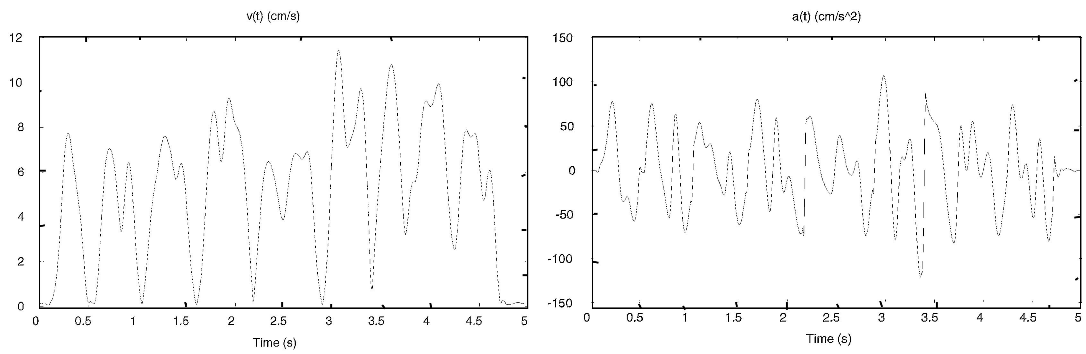
The concept of a pen computer was first proposed by Kay in 1968 [37]. Since then, many research teams have been working on the implementation of the "Dynabook" concept [195], trying to integrate into a single light and ergonomic system a transparent position-sensing device with a graphical display, under the control of a powerful microcomputer. The ultimate goal here is to mimic and extend the pen and paper metaphor by the automatic processing of electronic ink. Apart from the numerous hardware problems that still have to be solved [139], the use of electronic penpads mostly relies on the on-line recognition of command gestures and handwritten messages [55], although most of the systems do not process the full timing information available from the signal but only the stroke sequence.

Prior to any recognition, the acquired data is generally preprocessed to reduce spurious noise, to normalize the various aspects of the trace, and to segment the signal into meaningful units [75], [152], [172], [227]. The noise originates from several sources: the quantization noise of the digitizer as well as the digitizing process itself, erratic hand, or finger movements (see Section 2), the inaccuracies of the pen-up/pen-down indicator, etc. The main approaches to noise reduction deal with data smoothing, signal filtering, dehooking and break corrections [152].



(a) (b)

Fig. 4. (a) Values of the x coordinate of the pentip as a function of time $x(t)$, for the word depicted in Fig. 1b. (b) Values of the x coordinate of the pentip as a function of time $x(t)$, for the word depicted in Fig. 1b.



(a) (b)

Fig. 5. (a) Values of the magnitude of the pentip velocity $v(t) = [(\frac{dx(t)}{dt})^2 + (\frac{dy(t)}{dt})^2]^{\frac{1}{2}}$ as a function of time for the word depicted in Fig. 1b. (b) Values of the acceleration of the pentip $a(t) = \frac{dv(t)}{dt}$ as a function of time for the word depicted in Fig. 1b.

Many recognition algorithms, which are based on the use of standardized allographs and shapes of a cursive word, first require that a handprinted character or a command gesture be normalized. Other approaches try to absorb some of these distortions [163]. Common normalization procedures involve correction of baseline drift [19], compensation of writing slant [21], [126] and adjustment of the script size [152].

Segmentation refers to the different operations that must be performed to get a representation of the various basic units that the recognition algorithm will have to process. It generally works at two levels. The first level deals with the whole message and focuses, for example, on line detection [85], [242], word segmentation [227] as well as separating nontextual inputs (gesture commands [186], [243], [247]), handwriting style [238], equations [43], diagrams [243], and diacritics [202] from text. At this level, the goal is to define spatial zones or temporal windows, or both, that allow the extraction of disjoint basic units. At the second level, the methodology focuses on the segmentation of the input into individual characters or even into subcharacter units, such as strokes. This operation is among the most challenging, particularly for the recognition of cursive script [172]. In most cases, this segmentation is tentative and is corrected later during classification. In some systems, this step is totally avoided by working at the word level [50], [51], [157]. However, this approach generally makes sense for small vocabulary applications only where a lexicon search is fast enough to accommodate a real-time system. Some methods combine holistic recognizers with segmentation-based algorithms [177]. This is generally performed at the shape level, at the lexical level (using a word-shape based lexicon), or at the level of output word lists.

The major problem with character segmentation is the difficulty of determining the beginning and ending of individual characters. The most common approaches used nowadays, unsupervised learning [82], [128] and data-driven knowledge-based methods [84], [166], are still insufficient for most applications. Some strategies start bottom-up, directly from the basic strokes that have been used to write a specific character. These strokes are generally hidden in the signal due to anticipation or time-superimposition effects (see Fig. 2b, Fig. 2c, Fig. 2d, and Fig. 2e) [144], [168]. Several operational approaches have been proposed to define and represent these basic strokes: segmentation at the point of maximum curvature [116], [141], at a vertical velocity zero crossing [98], at minima of the $y(t)$ coordinates [81], at minima of absolute velocity [197]. Some methods use a scale-space approach [94] or a component-based approach [64]. Others focus on perceptually important points [2], [119], [162], on a set of shape primitives [9], [14], [25], [120], etc. Model-based approaches start from a handwriting generation model and use nonlinear regression techniques to recover a full parametric description of each stroke [74]. Here also, some methods try to combine segmentation with recognition [212], [252].

A pen-based computer needs to process a handwritten message as it is produced. The steps, ranging from various shape classification processes to ultimate shape recognition, have to cope with one of the most difficult problems: taking into account the variability of message production. This variability mostly comes from four different factors: geometric variations, neuro-biomechanical noise, allographic variations, and sequencing problems [195]. Geometric variations refer to changes that occur in position, size, baseline orientation, and slant depending on the (postural) conditions that are imposed on a writer as he produces a message. Allographic variations deal with the various models that are associated with a single character by different populations of writers. As can be inferred from the previous Section 2, neurophysiological and biomechanical factors can greatly affect the quality of handwriting by modifying both the activation of an action plan or the production of individual strokes. Finally, the variation in the order in which handwriting strokes may be produced can also be a great source of problems. Posthoc editing, corrections of spelling errors, slips of the pen, letter omission, or insertion greatly complicate the task of an on-line recognizer. With a few exceptions [203], most of the systems do not deal with these issues.

To cope with all these variability problems, it is generally accepted that many recognition methods will have to be combined to design an efficient system [65], [83], [86], [111], [178], [225] and that the resulting system will have to be trained and tested using a very large international database [79]. To do so, heuristics from numerous disciplines will have to be taken into account in the design of a system: cues from paleography, writing instruments, biomechanics, forensic sciences, inquiries, and disabilities [125] as well as cues from psychophysics, neuropsychology, education, and linguistics. A writer-independent system will have to mimic human behavior as much as possible. It will need a hierarchical architecture, such that when difficulties are encountered in deciphering a part of a message using one level of interpretation, it will switch to another level of representation to resolve ambiguities. From this perspective, the various attempts that are made these days to optimize the design of systems that mostly work at a few levels of representation make sense. Somehow, in one way or another, a combination of these different prototypes will ultimately lead to genuine solutions. The better the individual components, the better the final solution.

Over the last decade, attempts to recognize handwriting have converged into two distinct families of classification methods: 1) formal structural and rule-based methods and 2) statistical classification methods [172].

3.1.1 Structural and Rules-Based Methods

The first family is based upon the idea that character shape can be described in an abstract fashion (for example, the action plan of Fig. 2b) without paying too much attention to the irrelevant shape variations that necessarily occur during the execution of that plan. The rule-based approach proposed in the 1960s was abandoned to a large extent because of the difficulties encountered in formulating general and reliable rules as well as in automating the generation of these rules from a large database of characters and words. This approach has been rejuvenated recently with the incorporation of fuzzy rules and grammars that use statistical information on the frequency of occurrence of particular features [159]. However, from a global point of view, for this approach to survive, robust and reliable rules will have to be defined. If this happens, recognizers exploiting this paradigm will have a few interesting properties: they will not require a large amount of training data and the number of features used to describe a class of patterns may vary from one class to another.

3.1.2 Statistical Methods

This latter property is lacking in the second family of methods, the statistical approaches, where a shape is described by a fixed number of features defining a multidimensional representation space in which different classes are described with multidimensional probability distributions around a class centroïd. Three groups of methods are based on this approach: explicit, implicit, and Markov modeling methods [172].

Explicit Methods. Explicit methods are derived directly or indirectly from linear discriminant analysis, principal component analysis and hierarchical cluster analysis and are thus well supported mathematically. The major problems with these approaches are two-fold: first, they generally rely upon hypotheses about the form or the parameters describing the statistical distribution; second, they generally require extensive computing and memory resources.

Implicit Methods. Implicit statistical approaches generally refer to methods relying on artificial neural networks. The classification behavior of these methods is fully determined by the statistical characteristics of the training data set [12]. Many systems have exploited multilayer perceptrons trained by the back propagation of errors without acceptable success. Recent developments focus mainly on Kohonen self-organized feature maps (SOFM) [107], [122] and convolutional time-delay neural networks (TDNN) [77], [194]. The former method allows the automatic detection of shape prototypes in a large training set of characters. This approach is analogous to k-means clustering or hierarchical clustering [196]. The vector quantization properties of the Kohonen SOFM are generally used in subsequent stages by mapping the shape codes to their possible interpretation in the language. The convolutional time-delay neural networks exploit the notion of convolution kernels for digital filtering. Fixed-size networks share weights along a single temporal dimension and they are used for space-time representation of handwriting signals. The overall approach is known to provide a useful degree of invariance to spatial and temporal variations.

Markov Modeling. The third group of methods takes advantage of Markov modeling [3], [130], [150], [180]. A Hidden Markov Model (HMM) process is a doubly stochastic process: an underlying process which is hidden from observation and an observable process which is determined by the underlying process. This underlying process is characterized by a conditional state transition probability distribution, where a current state is hidden from observation and depends on the previous states, generally the previous one. On the other hand, the observable process is characterized by a conditional symbol emission probability distribution, where a current symbol depends either on the current state transition, or simply the current state.

These systems can be based on two different event models: discrete or continuous symbol observations. The former requires conversion of the input feature vector into a discrete symbol using a vector quantization algorithm. The occurrence probabilities of these symbols for the stroke shapes in a sliding window form the basis of the HMM algorithm. The continuous approach uses the variances and covariances of the features to estimate the probability of the occurrence of an observed feature vector under the assumption of a specific feature distribution, generally Gaussian. The goal of the HMM algorithm is to find the probability that a specific class is the most likely to occur, given a sequence of observations. The essence of this approach is to determine the a posteriori probability for a class, given an observed sequence where the jump from one state to another is described by a Markov process. Recent developments incorporate HMMs into a stochastic language model [88], combine discrete and continuous approaches [183], or use a hybrid neuralnet/HMM approach [8].

So far, neither of these approaches, structural or statistical, has led to commercially acceptable results for the processing of cursive script [131]. Although the performance of on-line systems is generally higher than that of off-line systems, the user requirements of almost no on-line recognition errors have limited the market to simple applications based on well-segmented, handprinted alphanumeric symbols. From this point of view, the specific provisions for postprocessing reading errors and rejections give a commercial advantage to off-line systems since their success relies on any cost reduction compared to manual keying-in of an existing document.

Apart from a few exceptions [7], [108], cursive script recognizers do not properly take into account contextual anticipatory phenomena: for example, once handwriting is well learned, the neuromuscular effectors involved in that task normally act concurrently to speed up the execution. This generally leads to coarticulation and context effects. The sequence of strokes is not produced in a purely serial manner, i.e., one after the other, but parallel articulatory activity does occur and there is important overlap between successive strokes or graphemes. The production of an allograph is thus affected by the surrounding allographs: it depends both on the preceeding and following units [229], [230], [245]. Many methods take into account the effect of the previous stroke over the actual stroke being processed but often neglect the simultaneous effect of the forthcoming stroke.

One approach to make on-line systems more attractive to users is to incorporate provision for personal adaptation [50], [139], [142]. A basic user-dependent system then comes with a set of recognizable allographs for each character, but it allows the user to define his own set of symbols or gestures in order to accomodate his preferences. This is a promising way to take into account cultural determinants, handwriting learning systems as well as personal styles, and evolution of handwriting habits over a long period of time. However, to be successful, such an approach must allow a user to add new symbols with a minimum of training and without any symbol confusion.

3.2 Signature Verifiers

Signature verification refers to a specific class of automatic handwriting processing: the comparison of a test signature with one or a few reference specimens that have been collected as a user enrolls in a system. It requires the extraction of writer-specific information from the signature signal, irrespective of its handwritten content. This information has to be almost time-invariant and effectively discriminant. This problem has been a challenge for about three decades. Two survey papers [114], [171], and a journal special issue [160] have summarized the evolution of this field through 1993. We will thus briefly update these studies by focusing on the major works by the various teams involved in this field.

Signature verification tries mainly to exploit the singular, exclusive, and personal character of the writing. In fact, signature verification presents a double challenge. The first is to verify that what has been signed corresponds to the unique characteristics of an individual, without necessarily caring about what was written. A failure in this context, i.e., the rejection of an authentic signature, is referred to as a type I error. The second challenge is more demanding than the first and consists of avoiding the acceptance of forgeries as being authentic. The second type of error is referred to as a type II error.

The tolerance levels for applications in which signature verification is required is smaller than what can be tolerated for handwriting recognition, for both type I and type II errors. In some applications, a bank, for example, might require (unrealistically) an error of 1 over 100,000 trials for the type I error [71] and even less for the type II error. Current systems are still several orders of magnitude away from these thresholds. System designers have also had to deal with the trade-offs between type I and type II errors and the intrinsic difficulty of evaluating and comparing different approaches. Actually, the majority of the signature verification systems work with an error margin of about 2 percent to 5 percent shared between the two errors. All reduction of one type of error inevitably increases the other.

The evaluation of signature verification algorithms, as for many pattern recognition problems, raises several difficulties, making any objective comparison between different methods rather delicate, and in many cases, impossible. Moreover, signature verification poses a serious difficulty, which is the problem of type II error evaluation, or the real risk of accepting forgeries. From a theoretical point of view, it is not possible to measure type II errors, since there is no mean by which to define a good forger and to prove his (or her) existence, or even worse, his (or her) nonexistence. However, from a practical point of view, several methods of type II error estimation have been proposed in the literature. The simplest ones rely on the use of random forgeries, i.e., that is picking up on a random basis the true signature of a person and considering it as a forgery of the signature of another person. Many studies incorporate unskilled forgeries, and in some rare cases, highly skilled forgeries are used. The definitions of all this terminology, random, skilled, and unskilled imitations, are rather discretionary and vary enormously from one benchmark to another as well as from one research team to another, making the evaluation of this type of error extremely vague and certainly underestimated [171]. The most recent large-scale public experiment in the field was an imitation contest against four target signatures. A type II error of less than 0.003 percent (two false acceptances out of 86,500 trials) has been reported [169].

An overview of recent publications since 1993 does not show a clear breakthrough either in signature verification techniques or in the kind of analysis and characteristic selection process. A variety of new techniques suggests either adjustments or combinations of known methods and has been used with more or less success. For verification techniques, the main methods that have been tested are: probabilistic classifiers [6], [105], [115], time warping or dynamic matching [91], [133], [134], [246], signal correlation [113], [149], neural networks [80], [249], hidden Markov models [47], [254], Euclidian or other distance measure [97], [136], hierarchical approach combining a few methods [250], [251], and Baum-Welch training [132]. At the analysis level, the main approaches have focussed on: spectral analysis [80], [248], cosine transforms [136], direction encoding [97], [135], [254], distance encoding [246], velocity, timing, and shape features sets [6], [91], [105], [115], and shape features [149], force, pressure, and angle functions [132], [133], [134].

In the age of chip cards and the possibility of implanted ID transponders, on-line signature verification systems occupy a very specific niche among the identification systems. On the one hand, they differ from systems based on the possession of something (key, card, etc.) or the knowledge of something (passwords, personal information, etc.) because they rely on a specific, well-learned gesture. On the other hand, they also differ from systems based on the biometric properties of an individual (fingerprints, voice print, retinal prints, etc.) because the signature is still the most socially and legally accepted means for identification. Its unique, self-initiated, motoric act provides an active means to simultaneously authenticate both a transaction and a transactioner. In this context, the most promising applications that will emerge will be related to identifying partners in groupware design projects, long distance authorization in process control, and even personalization and tracking of electronic money and documents [234].

3.3 Developmental Tools

In parallel with the various attempts made to design handwriting recognizers and signature verifiers, a few research groups have been working on other types of applications requiring directly or indirectly the automatic processing of handwriting. Many of these works were isolated efforts that have not been published via the regular channels known to the pattern recognition community [208], [235], [236], [241], and we present here, a brief survey of some of these typical applications, particularly in the field of the development of human motor control. The dominant class of tools in this domain is the interactive system to help children to learn handwriting or to help disabled persons to partly recover fine motor control through handwriting and drawing exercises.

In recent years, some educational software for teaching handwriting to children has been developed [23]. The handwriting lessons in most of this software mainly deal with showing letter models drawn on the computer screen, the main goal being to awaken children to handwriting. Some of these systems also use a digitizer tablet, where the children can write and see their writing on the screen. Recently, systems dedicated specially to handwriting learning are beginning to exploit new technological tools such as an LCD display combined with a digitizer [32], [45], [118], [127], [207]. With these systems, children can write with a pen directly on-screen without having to lift up their heads to look at what has been written. Many of these systems include multimedia capabilities. With these new hardware tools, we have reached the technological capability needed to build interactive systems to assist in teaching handwriting to children. The aim of these systems is to help young children to become good writers with fluent movements and a good quality of writing in a shorter time frame. From a pedagogical point of view, these advanced technological tools have to integrate efficient dynamic training programs with real-time feedback about the quality of writing. This latter goal has not yet been reached because of a lack of knowledge in many domains dealing with human behavior, like understanding how a human makes a representation of a form, what strategies are used to coordinate sequences of movements to draw a form, how representation and fine motor system coordination capabilities evolve with age from youth to adulthood, and what kind of training exercises can improve these capabilities.

Most education specialists agree that teaching handwriting must begin with learning to write separate letters, then simple words, and then complex words. Acquiring handwriting skill takes a long time. It is well known from classical studies of human behavior that the process of learning handwriting skills begins (in many countries) around age five and finishes approximately at fifteen, during which time the motor system control passes through evolutionary steps, each one being characterized by the acquisition of different performance skills. In many schools, there are programs to stimulate drawing and painting at the kindergarden level. After that, the teachers follow various strategies to teach handwriting, beginning with printing, then evolving to cursive characters or a mix of the two types. For beginners, education specialists have defined the sequence of strokes to be used by teachers when they are demonstrating how to form a letter. This sequence, named the ductus of a letter, is usually illustrated by arrows along the letter image.

Over the last two decades, many studies using a digitizing tablet have emerged to improve the psychomotor behavior of children [32], [118], [207]. The majority of these studies report results of experiments that highlight the complexity of the human process involved in handwriting. These studies can be grouped into four basic classes:

1. Studies involving experiments with normal adults in order to understand the human motor control system, e.g., [137], [138].
2. Studies involving experiments with adults who suffer from diseases, such as Parkinson's, who use drugs or who have constraints in handwriting, e.g., [58], [176].
3. Studies dealing with children suffering various disabilities, like dyslexia or dysgraphia, e.g., [181], [200].
4. Studies dealing with handwriting of normal children, e.g., [35], [112].

These experiments attempt to highlight some underlying mechanisms between the internal representation of a letter and the neuromotor system involved in the generation of that letter. Some theories formalize the motor control system involved in handwriting, e.g., [167], [193], [221], [239], [244]. There are also studies dealing with the efficiency of a training program in learning handwriting where a commonly used exercise is the copy exercise [32], [95], [96], [118], [127], [207]. Finally, the idea of using a computer to teach handwriting has led to many studies about the ergonomic aspects of the tool and how not only to make it simple to use by children, but also to provide an enjoyable environment for handwriting [32], [40], [73], [118], [137], [207].

The market for learning tools based on handwriting is expected to emerge in the forthcoming years. Although, more children will certainly learn to type earlier with the integration of computers in schools, keyboard typing is not sufficient to improve the development of fine motor activities. Handwriting plays such a role by helping young children to better control motor-perception interactions. From this perspective, learning tools to help children draw and write will not only find their place in a scholarly environment, but they will also find other application niches, particularly in the fields of rehabilitation and geriatrics to help the disabled to recover or aged people to better control their movements.

4 Off-Line Handwriting Recognition

The central tasks in off-line handwriting recognition are character recognition and word recognition. A necessary preliminary step to recognizing written language is the spatial issue of locating and registering the appropriate text when complex, two-dimensional spatial layouts are employed—a task referred to as document analysis.

4.1 Preprocessing

It is necessary to perform several document analysis operations prior to recognizing text in scanned documents. Some of the common operations performed prior to recognition are: thresholding, the task of converting a gray-scale image into a binary black-white image; noise removal, the extraction of the foreground textual matter by removing, say, textured background, salt and pepper noise and interfering strokes; line segmentation, the separation of individual lines of text; word segmentation, the isolation of textual words, and character segmentation, the isolation of individual characters [28], typically those that are written discretely rather than cursively.

4.1.1 Thresholding

The task of *thresholding* is to extract the foreground (ink) from the background (paper) [192]. The histogram of gray-scale values of a document image typically consists of two peaks: a high peak corresponding to the white background and a smaller peak corresponding to the foreground. So, the task of determining the threshold gray-scale value (above which the gray-scale value is assigned to white and below which it is assigned to black) is one of determining an "optimal" value in the valley between the two peaks [156].

One method [155] regards the histogram as probability values and defines the optimal threshold value as one that maximizes the between-class variance, where the distributions of the foreground and background points are regarded as two classes. Each value of the threshold is tried and one that maximizes the criterion is chosen. There are several improvements to this basic idea, such as handling textured backgrounds similar to those encountered on bank checks. One such method measures attributes of the resulting foreground objects to conform to standard document types [123].

4.1.2 Noise Removal

Noise removal is a topic in document analysis that has been dealt with extensively for typed or machine-printed documents. For handwritten documents, the connectivity of strokes has to be preserved. Digital capture of images can introduce noise from scanning devices and transmission media. Smoothing operations are often used to eliminate the artifacts introduced during image capture. One study [206], describes a method that performs selective and adaptive stroke "filling" with a neighborhood operator which emphasizes stroke connectivity, while at the same time, conservatively checks aggressive "over-filling."

Interference of strokes from neighboring text lines is a problem that is often encountered. One approach [148] is to follow strokes in thinned images to segment the interfering strokes from the signal. A similar approach [217] uses Gestalt principles to disambiguate the stroke following at cross points.

Algorithms for thinning [110] are frequently considered for converting off-line handwriting to nearly on-line-like-data. Unfortunately, thinning algorithms introduce artifacts, such as spurs, which make their use somewhat limited [175].

4.1.3 Line Segmentation

Segmentation of handwritten text into lines, words, and characters has many sophisticated approaches. This is in contrast to the task of segmenting lines of text into words and characters, which is straight-forward for machine-printed documents. It can be accomplished by examining the horizontal histogram profile at a small range of skew angles [218]. The task is more difficult in the handwritten domain. Here, lines of text might undulate up and down and ascenders and descenders frequently intersect characters of neighboring lines. One method [104] is based on the notion that people write on an imaginary line which forms the core upon which each word of the line resides. This imaginary baseline is approximated by the local minima points from each component. A clustering technique is used to group the minima of all the components to identify the different handwritten lines.

4.1.4 Word and Character Segmentation

Line separation is usually followed by a procedure that separates the text line into words. Few approaches in the literature have dealt with word segmentation issues. Among the ones that have dealt with segmentation issues, most focus on identifying physical gaps using only the components [129], [201]. These methods assume that gaps between words are larger than the gaps between the characters. However, in handwriting, exceptions are commonplace because of flourishes in writing styles with leading and trailing ligatures. Another method [101] incorporates cues that humans use and does not rely solely on the one-dimensional distance between components. The author's writing style, in terms of spacing, is captured by characterizing the variation of spacing between adjacent characters as a function of the corresponding characters themselves. The notion of expecting greater space between characters with leading and trailing ligatures is enclosed into the segmentation scheme.

Isolation of words in a textual line is usually followed by recognizing the words themselves. Most recognition methods call for segmentation of the word into its constituent characters. Segmentation points are determined using

Fig. 6. Examples of handwritten characters segmented from images.

features like ligatures and concavities [102]. Gaps between character segments (a character segment can be a character or a part of character) and heights of character segments are used in the algorithm.

4.2 Character Recognition

The basic problem is to assign the digitized character to its symbolic class. In the case of a print image, this is referred to as optical character recognition (OCR) [93], [146]. In the case of handprint, it is loosely referred to as intelligent character recognition (ICR). To limit this part of our survey, we will discuss here some of the issues in the recognition of English orthography in its handwritten form. While we mention specific techniques, also relevant are methods for combining several different recognition approaches [63], [86], [89], [106], [178].

The typical classes are the upper and lower case characters, the ten digits and special symbols such as the period, exclamation mark, brackets, dollar and pound signs, etc. A pattern recognition algorithm is used to extract shape features and to assign the observed character to the appropriate class. Artificial neural networks have emerged as fast methods for implementing classifiers for OCR. Algorithms based on nearest-neighbor methods have higher accuracy but are slower.

Recognition of a character from a single, machine-printed font family on a well-printed paper document can be done very accurately. Difficulties arise when handwritten characters are to be handled. Some examples of segmented handwritten characters are shown in Fig. 6. A survey on character segmentation can be found in [24]. In difficult cases, it becomes necessary to use models to constrain the choices at the character and word levels. Such models are essential in handwriting recognition due to the wide variability of handprinting and cursive script.

There is extensive literature on isolated handwritten character recognition [1], [72], [147], [223]. Some recent surveys are [145], [215], [219].

4.3 Word Recognition

A word recognition algorithm attempts to associate the word image to choices in a lexicon [210]. Typically, a ranking is produced. This is done either by the *analytic* approach of recognizing the individual characters or by the *holistic* approach of dealing with the entire word image. The latter approach is useful in the case of touching printed characters and handwriting. A higher level of performance is observed by combining the results of both approaches [89], [178]. There exist several different approaches to word recognition using a limited vocabulary [69].

One method of word recognition based on determining presegmentation points followed by determining an optimal path through a state transition diagram is shown in Fig. 7 [16], [57]. Applications of automatic reading of postal addresses, bank checks, and various forms have triggered a rapid development in handwritten word recognition in recent years.

While methods have differed in the specific utilization of the constraints provided by the application domain, their underlying core structure is the same. Typically, the methodology involves preprocessing, a possible segmentation phase which could be avoided if global word features are used, recognition and postprocessing. The upper and lower profiles of word images are represented as a series of vectors describing the global contour of the word image and bypass the segmentation phase in [158].

The methods of feature extraction are central to achieving high-performing word recognition. One approach utilizes the idea of "regular" and "singular" features. Handwriting is regarded as having a regular flow modified by occasional singular embellishments [211]. A common approach is to use an HMM to structure the entire recognition process [27], [140]. In [140], the observations are modeled as one-column-wide pixels. The letters are sub-HMMs containing the same number of states. During training, all letters are normalized to a fixed width of 24 columns. Standard reestimation formulae are used.

Another method deals with a limited size dynamic lexicon [102]. Words that are relevant during the recognition task are not available during training because they belong to an unknown subset of a very large lexicon. Word images are over segmented such that after the segmentation process no adjacent characters remain touching. Instead of passing on combinations of segments to a generic OCR, a lexicon is brought into play early in the process. A combination of adjacent segments is compared to only those character choices which are possible at the position in the word being considered. The approach can be viewed as a process of accounting for all the segments generated by a given lexicon entry. Lexicon entries are ordered according to the "goodness" of match.

Dynamic Programming (DP) is a commonly used paradigm to string the potential character candidates into word candidates; some methods [66] combine heuristics with DP to disqualify certain groups of primitive segments from being evaluated if they are too complex to represent a single character. The DP paradigm also takes into account compatibility between consecutive character candidates.

4.4 Application of Off-Line Handwriting Recognition

There has been significant growth in the application of off-line handwriting recognition during the past decade.

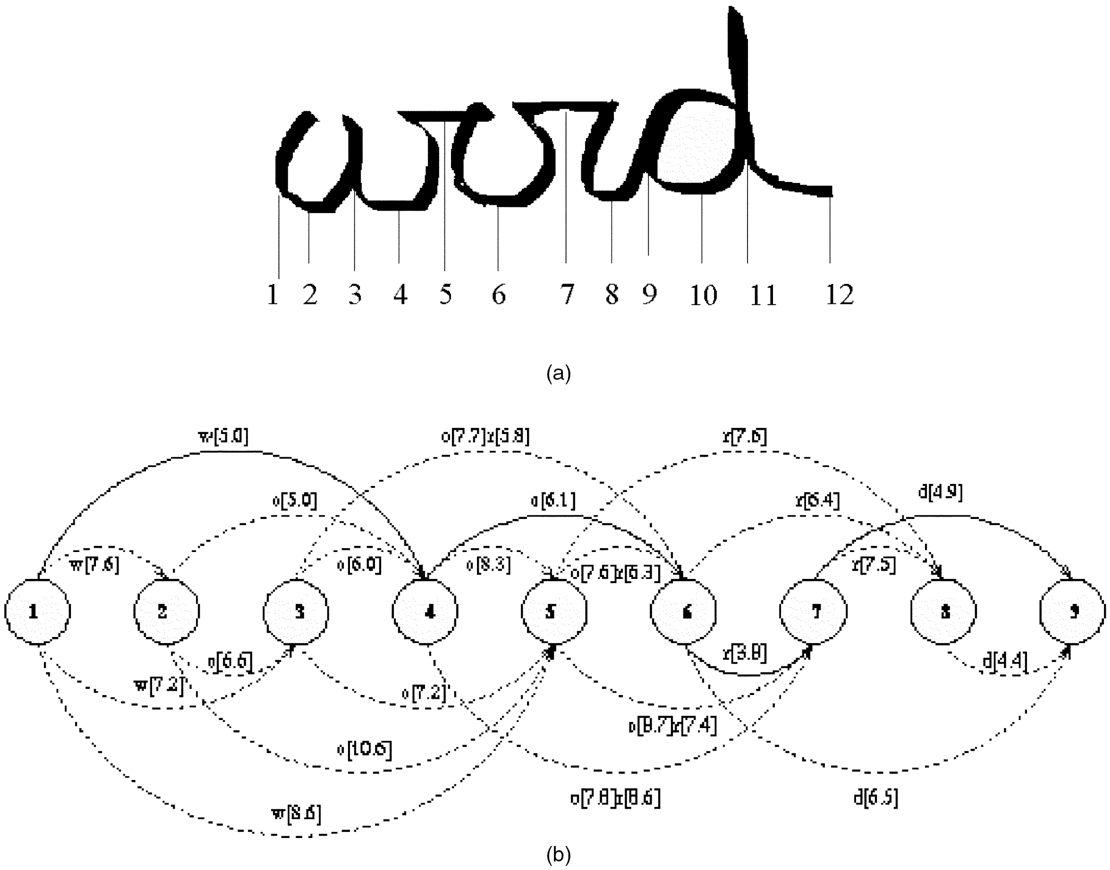


Fig. 7. Analytic word recognition: (a) word with pre-segmentation points shown, and (b) corresponding state transition diagram.

The most important of these has been in reading postal addresses, bank check amounts, and forms. We will describe the handwritten address interpretation task and the bank check recognition task in the following sections.

4.4.1 Handwritten Address Interpretation

The task of interpreting handwritten addresses is one of assigning a mail-piece image to a delivery address. An address for the purpose of physical mail delivery involves determining the country, state, city, post office, street, primary number (which could be a street number or a post office box), secondary number (such as an apartment or suite number), and finally, the firm name or personal name [31], [48].

A Handwritten Address Interpretation (HWAI) system uses knowledge of the postal domain in the recognition of handwritten addresses. The task is considered to be one of interpretation rather than recognition since the goal is to assign the address to its correct destination irrespective of incomplete or contradictory information present in the writing. This work has led to a system that recognizes handwritten addresses that is currently in use by the United States Postal Service (USPS) [220].

An example of a mail-piece successfully scanned and interpreted by the HWAI system and physically delivered by the USPS is shown in Fig. 8. The interpretation result is represented in the form of a bar-code and sprayed at the

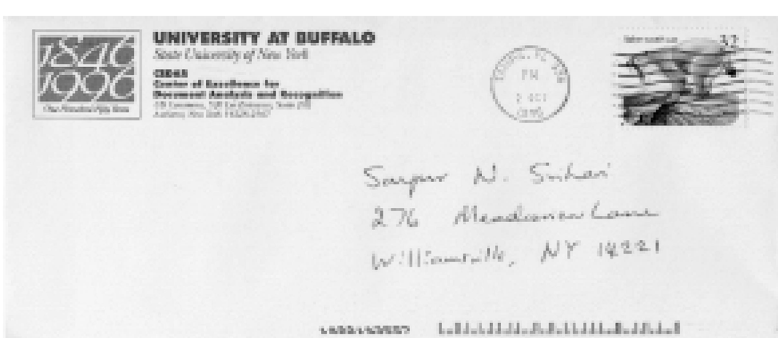


Fig. 8. Sample mail-piece.

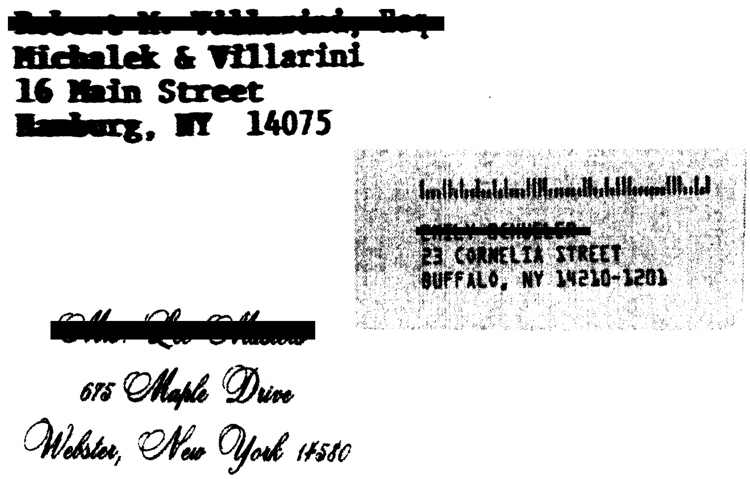


Fig. 9. Two-class discrimination (HW vs. MP). By determining whether an address is handwritten or machine-printed, appropriate recognition algorithms can be applied. Certain machine-printed fonts may have to be treated as handwriting.

bottom of the envelope so that subsequent stages of sorting can be made by a bar-code reader.

The HWAI task contains several well-formulated pattern recognition problems. Many of the techniques described in standard text-books of pattern recognition find a role in this task.

A gradation of class-discrimination problems is encountered. For example, a two-class discrimination problem is the following: handwriting vs. machine-print discrimination (Fig. 9). There are several multiclass discrimination problems: handwritten numeral recognition with 10 classes (Fig. 10), alphabet recognition with 26 classes (Fig. 11), and touching-digit pair recognition with 100 classes (Fig. 12). Word recognition with a lexicon is a problem where the number of classes is dynamically determined by contextual constraints. Another problem encountered is similar to the problem of object recognition in computer vision: determining the destination address in a cluttered background.

4.4.2 Bank Check Recognition

Bank check recognition presents several research challenges in the area of document analysis and recognition. The backgrounds are often colored and have complex patterns. The type and position of preprinted information fields as well as the guides that prompt patron information vary widely [62]. The handwritten components that are provided by the patron are: 1) legal (worded) amount, 2) courtesy (numeric) amount, 3) date, and 4) the signature [42].

Field layout analysis involves image filtering and binarization, segmentation of text blocks, and removal of guide lines and noise [124]. A complete bank check recognition system, including the layout analysis and recognition components, that are engineered for industrial applications is described in [41].

Hidden Markov Models are used for the recognition of both the legal and courtesy amounts in [68], [70], [153].

A check-reading system that recognizes both the legal and courtesy amounts on French checks in real-time with a read rate of 75 percent and an error rate of 1 in 10,000 is described

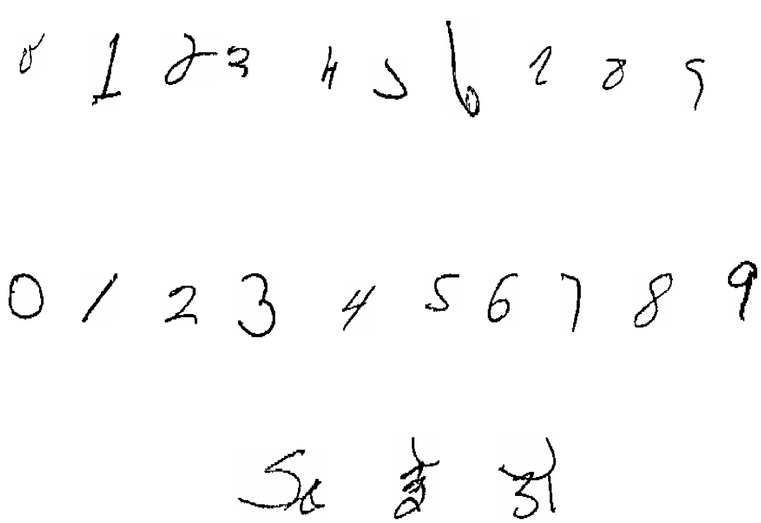


Fig. 10. Ten-class discrimination (digits). Three sets of images are shown. The top row consists of difficult-to-read numerals. The middle row consists of fairly standard ones. The bottom row has nondigits supplied to a digit recognizer which must be rejected.

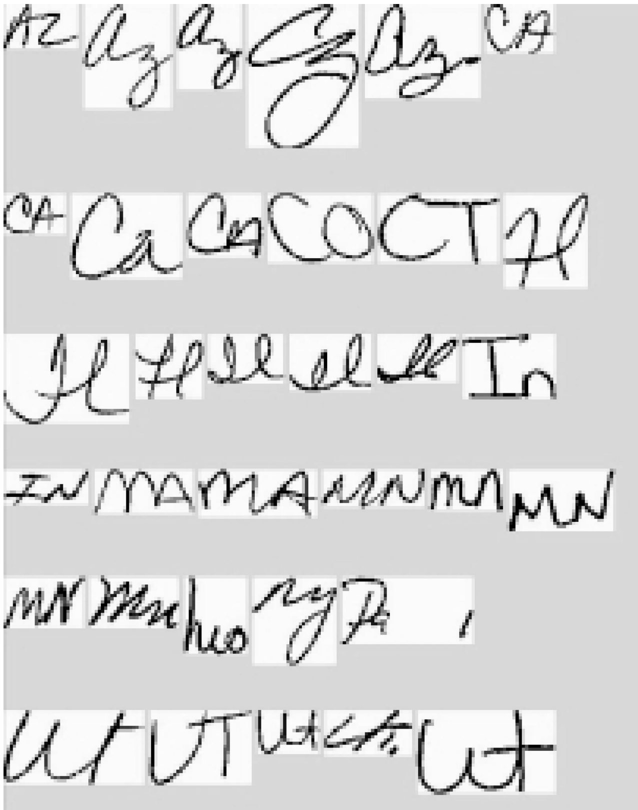


Fig. 11. State abbreviations recognition with 66 classes. The valid abbreviations are: AA, AE, AK, AL, AP, AR, AS, AZ, CA, CM, CO, CT, CZ, DC, DE, FL, FM, GA, GU, HI, IA, ID, IL, IN, KS, KY, LA, MA, MD, ME, MH, MI, MN, MO, MP, MS, MT, NC, ND, NE, NH, NJ, NM, NV, NY, OH, OK, OR, PA, PR, PW, RI, SC, SD, SQ, TN, TX, TT, UT, VA, VI, VT, WA, WI, WV, WY. The figure shows image snippets containing two-letter abbreviations collected from actual mail.

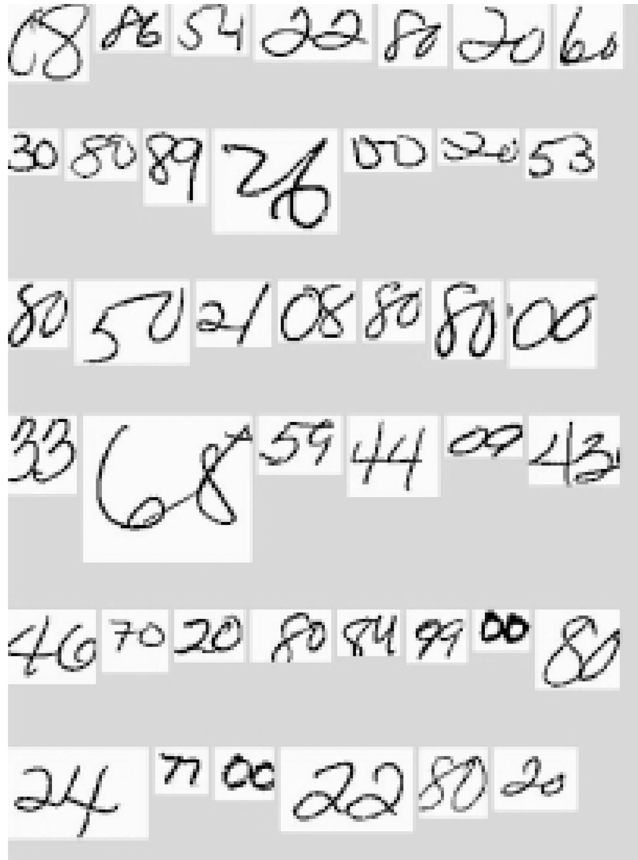


Fig. 12. Hundred-class discrimination (digit pairs). Touching digit pairs can be hard to separate and it may be preferable to treat them as a single unit consisting of 100 classes. The figure shows touching digit image pairs extracted from zip codes.

in [100]. They use a segment and recognize paradigm. Recognition involves a combination of multiple classifiers.

The approach of first recognizing the legal amount to drive the recognition of the courtesy amount is used in [103]. A lexicon of numeric words is generated from the independent recognition of the legal phrases. Experiments were conducted on checks written in English. They have reported a 44 percent read-rate with no error.

4.5 Signature Verification

In a typical off-line signature verification system, a signature image, as scanned and extracted from a bill, a check or any official document, is compared with a few signature references provided, for example, by a user at the opening of his account. Opposite to on-line systems, there is no time information directly available and the verification process relies on the features that can be extracted from the luminance of the trace only.

Although the extraction of a signature from a document background is already a very difficult problem in itself, particularly for checks (see, for example, [44]), most of the studies published to date assume that an almost perfect extraction has been done. In other words, the signature specimens used in these studies are generally written on a white sheet of paper.

A few survey articles have summarized the state of the art in this field up to 1993 [114], [171], [190]. We will partially update these surveys in this section by describing some approaches that have been added to the list of still unsuccessful attempts to solve this difficult problem.

Since 1993, a focus has been made on neural networks. Most of these studies use conventional approaches: multilayer perceptrons [4], [38], [90], cooperative architecture neocognition [22], [60], and ART network [61]. Other conventional approaches are minimal distance classifier [187], nearest neighbor [189], dynamic programming [76], and threshold based classifier [121], [188], [205]. Approaches based on multiple experts [34] and HMMs [182] have been recently described. The major differences between these studies are in the features used to represent a given signature. Simple, direct description based on fixed window [182], geometric primitives [60], [76], [90], [179], or form factors and descriptors like extended shadow code [187], [188] have been used, as well as more complex algorithms based on pattern spectrum [49], [61], [189] and wavelets transform [205].

They produce Type I and II errors of a few percentage points; and the signature databases generally are too small, both in terms of the number of signers and the number of specimens per signer.

From a practical point of view, most researchers agree now that a solution to their problem will rely on the extraction from a signature of pseudodynamic features reflecting, for example, some specific characteristics used by a forensic document examiner, as well as the automatic recovery of the stroke sequence in the signature image.

While the number of potential applications for on-line signature verification systems is expected to be growing with the development of various forms of an electronic penpad, the specific use of off-line systems, if they are commercialized on time, is not even sure. With the decreasing use of checks, paper bills, etc. in many countries, these systems will have to adapt to the new requirements of electronic commerce to become a reality [234].

4.6 Writer Identification

Handwriting identification deals with comparing *questioned writing* with known writing *exemplars* and determining whether the questioned documents and exemplars were written by the same or different authors.

Two issues of concern in this procedure are the variability of handwriting within individuals, which are *individual characteristics* and between individuals, which are *class characteristics*. The extraction of distinctive individual traits is what is relied on to determine the author of the questioned document.

Information about these two classes of variability are gathered based on the features for characterizing handwriting [17] , [154]. Some of the elements of comparison are: alignment (reference lines), angles, arrangement (margins, spacing), connecting strokes (ligatures and hiatuses), curves, form (round, angular or eyed), line quality (smooth, jerky), movement, pen lifts, pick-up strokes (leading ligatures), proportion, retrace, skill, slant, spacing, spelling, straight lines, and terminal strokes.

Several of these features are readily computable based on existing techniques for handwriting recognition. For instance, handwriting recognition procedures routinely compute baseline angle and slant so that a correction can be applied prior to recognition.

The result of applying these procedures is then used to cluster different samples of handwriting in a multidimensional feature space. The authorship of the questioned document is then established from its proximity to the exemplars.

Most handwriting identification experts today almost entirely on manually intensive techniques. Although some literature is available on prototype toolsets for document examination [11], [117], [191], there does not exist any tool that has completely automated the handwriting identification process.

5 Language Analysis and Processing

5.1 Language Models

Whatever the approach for recognition, on-line or off-line, language models are essential in recovering strings of words after they have been passed through a noisy channel, such as handwriting or print degradation [172]. The most important model for written language recognition is the lexicon of words. String matching algorithms between candidate words and a lexicon are used to rank the lexicon, often using a variant of the Levenshtein distance metric that incorporates various edition costs into the ranking process [109]. String matching methods are often improved by incorporating dictionary statistics in the training data [67]. Lexical subsets, in turn, are determined by linguistic constraints [30], e.g., in recognizing running text, the lexicon for each word is constrained by the syntax, semantics, and pragmatics of the sentence. The performance of a language model is evaluated in terms of the text perplexity which measures the average number of successor words that can be predicted for each word in a text. The performance of a recognition system can thus be improved by incorporating statistical information at the word-sequence level. The performance improvement derives from selection of lower-rank words from word recognition output when the surrounding context indicates such selection makes the entire sentence more probable. Lexical techniques, such as collocational analysis [214], can be used to modify word neighborhoods generated by a word recognizer. Modification includes reranking, deleting, or proposing new word candidates. Collocations are word patterns that occur frequently in language; intuitively, if word A is present, there is a high probability that word B also is present.

Methods to apply syntactic knowledge include: *N*-gram word models, *N*-gram class (e.g., part-of-speech) models, context-free grammars, and stochastic context-free grammars. N-Gram word models seek to determine the string of words that most probably gives rise to the set of output words that has been digitized or scanned [78]. The problem with this approach is the difficulty of reliably estimating the parameters as the number of words grows in the vocabulary. A few alternatives to avoid this problem have been proposed: smoothing back-off models [29] and maximum entropy methods [185]. N-Gram class models [92], [99] map words into syntactic or semantic classes. In the first case, also referred to as the part-of-speech approach, for each sentence that has to be analyzed, a lattice of word/tag assignations is created to represent all possible sentences for the set of possible word candidates. The problem is to determine the best path through the lattice. The semantic approach [184] relies mainly on machine-readable dictionaries and electronic corpora; it uses word definition overlaps between competing word candidates to select the correct interpretation. Other approaches that involve collocations are cooccurrence relations [213] and the use of semantic codes that are available in some dictionaries.

So far, these approaches have been limited to proof-of-concept and no large-scale experiments have been reported to demonstrate the effectiveness of semantic information in resolving ambiguities, although real-life analysis of human behavior suggests that this is very often the only way to proceed. An example of a handwritten sentence together with recognition choices produced by a word recognizer and grammatically-determined correct paths is shown in Fig. 13. An increase in the top choice word recognition rate from 80 percent to 95 percent is possible with the use of language models [214].

6 Conclusion

Research on automated written language recognition dates back several decades. Today, cleanly machine-printed text

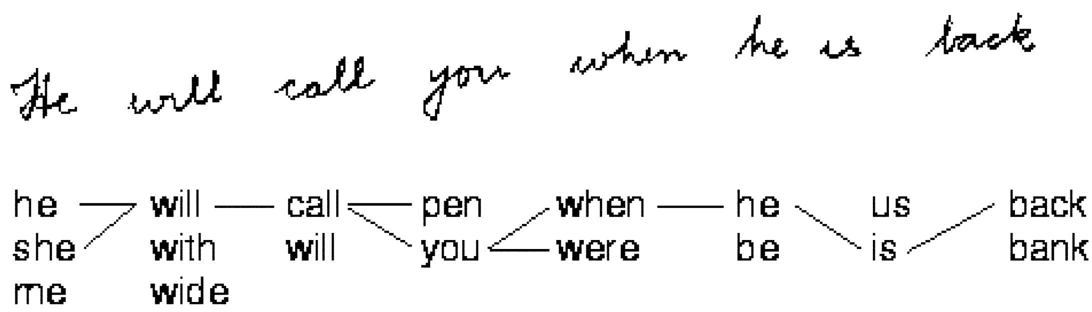


Fig. 13. Handwritten sentence recognition. The path through top word choices is determined using part-of-speech tags.

documents with simple layouts can be recognized reliably by off-the-shelf OCR software. As we have seen throughout this paper, there is also some success with handwriting recognition, particularly for isolated handprinted characters and words. For example, in the on-line case, the recently introduced PDAs have practical value. Similarly, some on-line signature verification systems have been marketed over the last few years and instructional tools to help children learn to write are beginning to emerge. Most of the off-line successes have come in constrained domains, such as postal addresses [31], bank checks, and census forms. The analysis of documents with complex layouts, recognition of degraded printed text, and the recognition of running handwriting continue to remain largely in the research arena. Some of the major research challenges in on-line or off-line processing of handwriting are in word and line separation, segmentation of words into characters, recognition of words when lexicons are large, and the use of language models in aiding preprocessing and recognition. In most applications, the machine performances are far from being acceptable, although potential users often forget that human subjects generally make reading mistakes [5].

In an e-world dominated by the WWW, the design of human-computer interfaces based on handwriting is part of a tremendous research effort together with speech recognition, language processing and translation to facilitate communication of people with computer networks. From this perspective, any successes or failures in these fields will have a great impact on the evolution of languages. Indeed, as the next century will probably confirm the supremacy and convenience of English, "the Latin of the third millenium," the survival of other languages and cultures will necessarily go through their "computerization."

Although we have mostly focussed on the processing of English in this paper, there are numerous projects going on in many countries to process and recognize specific languages. It is hoped that many of these projects will succeed to maintain the diversity and richness of the global human experience.

Acknowledgments

This work was supported by grants RGPIN915-96, STR-0192785, FCAR-ER1220, and FCAR NT-0017 awarded to Réjean Plamondon; and grants awarded to Sargur Srihari from the United States Postal Service and the National Institute of Justice. The authors would like to thank Drs. Wacef Guerfali, Salim Djeziri, and Alessandro Zimmer for their contribution to Sections 3.2, 3.3, and 4.5, respectively, Dr. Venu Govindaraju and Hina Arora for their contributions to Sections 4.1, 4.4, and 4.6. The authors are also grateful to Hélène Dallaire and Kristen Pfaff, secretaries at Laboratoire Scribens and CEDAR, respectively, for their kind help in preparing and integrating the manuscript. Finally, the authors thank the reviewers for their fruitful comments and suggestions.

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