F.J. Maarse, L.R.B. Schomaker & H.-L. Teulings (1988).

Automatic Identification of Writers

In: Gerrit C. van der Veer and Gijsbertus Mulder (Eds).
Human-Computer Interaction: Psychonomic Aspects.
New York: Springer, pp. 353-360.

1. Introduction

Using handwriting as a means of input to a computer has several advantages, currently not appreciated sufficiently. The use of pen (and paper) gives the user the opportunity of providing the computer with textual and graphic information in a “natural” fashion and it is expected that the keyboard will continue to be an obstacle for large-scale human-computer interaction. Equivalent arguments have been used by Zue (1985) for speech recognition, and speaker verification or recognition, but in spite of years of effort the performance of the available (commercial) speech recognition systems is still inferior to that of humans. Since the early 1960s efforts have been made towards computer recognition of handwriting. The disappointing results made it necessary to restrict the set of patterns to be recognized (e.g., to digits; Impedovo, Marangelli & Plantamura, 1976; Shridhar & Badreldin, 1985), use of standard character type (Apsey, 1978), and imposition of spatial restrictions (Spanjersberg, 1978; Suen, 1979).

[continued on the next pages, as raw scanned images]

panjersberg A.A. (1978). Experiments with automatic input of handwritten numeric data into a large administrative system. *IEEE Transactions on Systems, Man and Cybernetics*. SMC-8, pp. 286-288.

Suen C.Y., Berthold M. and Mori S. (1980). Automatic recognition of hand-printed characters - the state of the art. *IEEE Proceedings*, 68, pp. 468-487.

Suenaga Y. & Nagura M. (1980). A facsimile based manuscript layout and editing system by auxiliary mark recognition. *Proceedings of the 5th International Conference on Pattern Recognition, IEEE Computer Society*, pp. 856-858.

Tappert C.G. (1986). An adaptive system for handwriting recognition. In: *Graphonomics: Contemporary research in handwriting*. H.S.R. Kao, G.P. van Galen & R. Hoosain (Eds.), North-Holland, Amsterdam.

Teulings H.-L., Schomaker L.R.B. & Thomassen A.J.W.M. (1986). *Compatible software library for low-level processing of cursive script*. Esprit Report TK3-WP1-DI1.

Thomassen A.J.W.M., Keuss P.J.G. & Van Galen G.P. (Eds.). (1984). *Motor aspects of handwriting: Approaches to movement in graphic behavior*. North-Holland, Amsterdam.

Vredenbregt J. & Koster W.G. (1971). Analysis and synthesis of handwriting. In: *Philips Technical Review*, 32, pp. 73-78.

Chapter 21. Automatic Identification of Writers

Frans J. Maarse, Lambert R.B. Schomaker and Hans-Leo Teulings

1. Introduction

Using handwriting as a means of input to a computer has several advantages, currently not appreciated sufficiently. The use of pen (and paper) gives the user the opportunity of providing the computer with textual and graphic information in a "natural" fashion and it is expected that the keyboard will continue to be an obstacle for large-scale human-computer interaction. Equivalent arguments have been used by Zue (1985) for speech recognition, and speaker verification or recognition, but in spite of years of effort the performance of the available (commercial) speech recognition systems is still inferior to that of humans. Since the early 1960s efforts have been made towards computer recognition of handwriting. The disappointing results made it necessary to restrict the set of patterns to be recognized. Methods used in attempts to improve recognition results include limitation of the set of characters to be recognized (e.g., to digits; Impedovo, Marangelli, & Plantamura, 1976; Shridhar, & Badreldin, 1985), use of standard character types (Apsey, 1978), and imposition of spatial restrictions (Spanjersberg, 1978; Suen, 1979).

These methods may provide some results from the purely technical point of view, but the restrictions (e.g. writing within boxes or lines) proved to be unsatisfactory to users. Therefore, studies are being undertaken to develop methods that give the computer user the opportunity to use his personal cursive handwriting as a means of input without being disturbed by many restrictions on orientation, shape or vocabulary (Thomassen, Teulings, & Schomaker, 1987). Under these conditions, reduction of the recognition problem can only be achieved if the recognition system itself can reduce the set of patterns to be recognized. For instance, by estimation of an individual's handwriting parameter values the system can tune the recognition to a specific writer. Once the personal handwriting characteristics are known, they can be stored to enable the system to detect the identity of the user on later occasions. For each new user a description of his personal handwriting characteristics has to be added to the system, or the handwriting has to be classified as belonging to some general type of handwriting. Figure 1 shows the global flow chart of a handwriting recognition system with a writer-identification stage. In fact, the process of recognition is extended with an extra, less complicated recognition phase, the identification of the current writer, which facilitates the more complex phase of handwriting recognition itself.

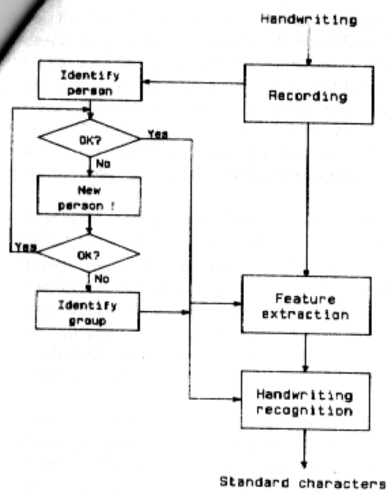

Figure 1. Flow diagram of a pattern recognition system for handwriting extended with a system for identification of the individual (left).

The left part of the figure shows the possible steps in identification of the individual. On the basis of the result of the identification, parameters are selected that apply to the given (type of) handwriting. Important individual characteristics of handwriting are cursive vs block print, handwriting slant, individual choice of letter and symbol shapes and their variants, relative size of handwriting constituents, time-dependent changes in stroke size within words, and pen speed. Figure 2 shows two examples of ambiguity in handwriting that could be solved if writer-dependent knowledge were available in the recognition system. In the first example, the first three letters are the same in both patterns, but the interpretation is determined by the fourth letter. If the recognition system knew that the user writes smaller at the end of a word than at the beginning it would recognize the word correctly. In the second example it is clear that in "normal" handwriting the word *clip* has to be read. If the recognition system uses the knowledge that the sample is produced by a writer who uses a large X progression, the pattern will be correctly recognized as *dip*. These examples indicate in what ways identification of individuals may be useful in handwriting recognition. Here we will concentrate on this identification stage. Central issues are the choice of handwriting material and methods of determining the values of relevant parameters.

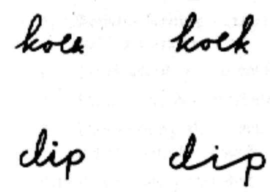

Figure 2. Some handwriting samples that are especially prone to cause errors in automatic handwriting recognition.

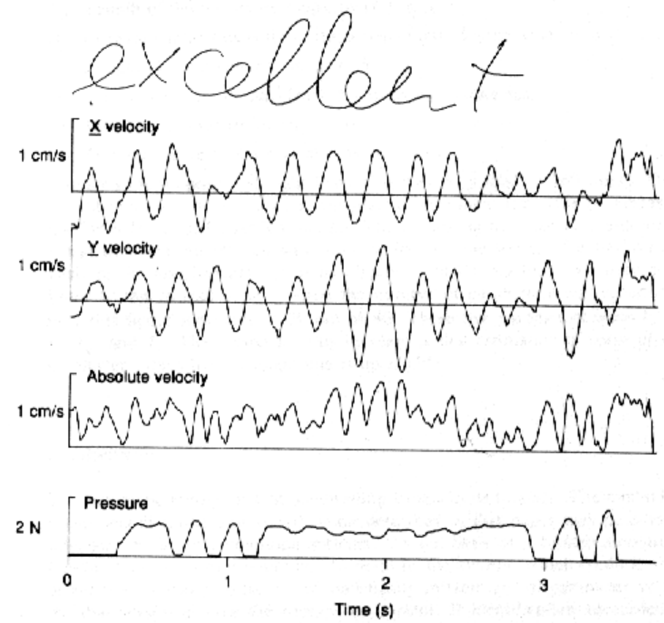

Figure 3. A handwriting sample with x and y velocities and pen pressure vs time, which are used in the determination of the personal handwriting characteristics.

n the literature on this subject, essentially three methods have been described. In the first method, a recording of a handwritten signature is used. Crane and Ostrem (1983) achieved 95%-99% correct classification in a group of 58 individuals, using 14 spatial and temporal parameters of the handwriting trace. Parameters used were stroke size, total writing time, etc. However, this method only works for users known to the system, and a disavantage is that the writer has first to identify himself. However, we are searching for a procedure whereby the system itself can recognize the user.

A second method, described by Azari (1977, 1983) and Duvernoy (1976), is based on pages of handwritten text. The parameters used here concern the layout, word length, and vertical spacing on a page. Recording is done by spatially digitizing a page of text within a field of about 1000 × 1000 pixels. This density is unfortunately not enough to obtain relevant information about the shapes and sizes of individual letters. Temporal information cannot be evaluated either. On the other hand, parameters that can be determined easily from spatially digitized pages are "ink" density and handwriting slant.

The third method uses findings from psychomotor research concerning movement grammars and trajectory formation (Thomassen et al., 1988; Dooijes, 1983). Typical findings are that some writers tend to reduce the size towards the end of a word, that there are specific relations between height, width, and slant (Maarse & Thomassen, 1983), and that handwriting is executed at a specific pace (Teulings & Maarse, 1984; Maarse, Schomaker & Thomassen, 1986). Figure 3 shows a typical sample of handwriting, recorded with a digitizer, together with the corresponding velocity and pen pressure time functions. As can be seen, spatial as well as temporal characteristics can be derived from such a recording. Findings from psychomotor research have indicated in what way the signals can be segmented. The psychomotor approach can be compared with the technical approach used in speaker identification and recognition (Doddington, 1985), where "low-level" dynamic acoustic features are used. These features include characteristics of the speech signals such as pitch frequency, spectral amplitudes, bandwidth, and characteristic voicing aperiodicities.

2. Experiment

In an experiment described in Maarse, Schomaker & Teulings (1986), we searched for specific parameters that could be used to identify subjects. We defined 13 parameters. From earlier handwriting studies, the most of these parameters were known to be relevant with respect to this type of psychomotor behavior:

- T_r Relative writing duration: this is total pen-down duration divided by total writing duration
- v Mean absolute pen velocity in pen-down segments
- P Mean axial pen pressure
- ϕ Handwriting slant, determined from the mean direction of long, downgoing strokes (Maarse & Thomassen, 1983)
- Rnd A roundness measure: this is the mean length of the long up- and downstrokes divided by the mean length of the short strokes going from left to right and from left to right
- Z_c Z transform of the Pearson coefficient of correlation between velocities in x and y directions
- H_d Length of the descender loops, as in *j, g, y*
- H_c Corpus height: this is the vertical size of letters such as *m, n, a*
- H_a Length of the ascenders, as in *b, h, k, l*
- W_x Width of letters, derived from the horizontal stroke size
- dP Increase of pressure during words
- dH Decrease of vertical stroke size during words

Twenty subjects produced eight lines of text each (a total of 160 lines). One-half of this material was used to calculate discriminant functions by means of the SPSS DISCRIMINANT program. The remaining 80 lines were entered in a test in which an attempt was made to identify the writer of a line on the basis of the discriminant functions obtained. Of the 80 lines, 77 were attributed to the correct writer. When the number of parameters was reduced to five, this figure increased to 79 out of 80. These five parameters were P, ϕ, v, W_x, and T_r. The reason for this increase is that estimation of some of the parameter values from a single line is unreliable.

3. Discussion

The automatic recognition of handwriting is still in its infancy. The method of writer identification and classification described in this paper may be a valuable tool in future recognition systems. On the basis of a limited amount of handwriting, the writer could be identified by the system, which could in turn select from a database the set of statistically reliable global parameter values for that person to tune the recognition system. If identification succeeded, a set of writer-specific letter descriptions could also be selected. The determination of the identity of the writer could be based on a minimum certainty of 95%. The results described here indicate that this probability can be reached fairly easily, although replication of the study is necessary.

It can be argued that successful automatic recognition of handwriting depends to a large extent on knowledge concerning the production mechanisms. Availability of the temporal information helps to disambiguate many segments of handwriting that are virtually impossible to recognize on the basis of spatial information only. In future handwriting recognition systems, however, it should be possible to infer some temporal characteristics from the spatial handwriting trace. Until then, more success is to be expected from handwriting recognition systems that make use of temporal or at least sequential information to be interpreted in terms of production mechanisms, and spatial information.

What is needed here is knowledge of handwriting production mechanisms (handwriting being a type of human motor behavior) and of handwriting grammar. Individual handwriting is chararacterized by idiosyncratic letter shapes, motor dynamics and degree of variability. Similarly, in speech recognition, knowledge of speech mechanisms is being used to improve speech recognition and speaker identification (see Leung, 1985).

Another potential application of the procedure is person identification by cursive script rather than by signature. The person could be asked to write some words or sentences randomly selected by the system, thus making forgery even more difficult than in identification systems based on signature. In this application, however, much higher reliability figures than 95% would be necessary. Improvement of the reliability of the identification procedure requires a search of parameters that are independent of rotation, size, and content. In speech recognition the "fixed-text" approach has been more successful then the "free-text" approach (Doddington, 1985). Which is more useful for handwriting recognition is a question that should be the subject of further studies.

It should be noted that several methods and techniques used in speech recognition are also suitable for handwriting recognition. In some respects, however, handwriting recognition is less complicated. For example, the lower storage requirements make the use of time-costly data compression techniques virtually unnecessary. In other respects, solving the problems of the handwriting recognition requires the development of specific methods from both signal-processing theory and artificial intelligence.

Successful use of handwriting recognition depends largely upon the ergonomics of the devices used for recording the handwriting. Before the digitizer can become a standard peripheral for computers, the shortcomings of the existing pens for them must be dealt with. Many of the commercially available pens are too large and thick, and often the pen tip cannot be seen by the user at all. Moreover, the cord connecting the tablet and pen is a nuisance, although this could be overcome by building a transmitter into the pen. A final problem to be solved is the spatial dissociation between the action on the tablet and the result on the CRT screen. The solution to this problem would be an integrated liquid-crystal flat panel with digitizer. Such a system would combine all the advantages of the writing pen and the mouse, and avoid the disadvantages of the mouse and the light pen (Thomassen et al., 1988).

References

Apsey R.S. (1978). Human factors of constraint handprint for OCR. *IEEE Transactions on Systems, Man and Cybernetics*, 8, pp. 292-296.

Azari B. (1977). Handwriting identification by means of run-lenght measurements. *IEEE Transactions on Systems, Man and Cybernetics*, 12, pp. 878-881.

Azari B. (1983). Automatic handwriting identification based on the external properties of the samples. *IEEE Transactions on Systems, Man and Cybernetics*, 12, pp. 878-881.

Crane H.D. & Ostrem J.S. (1983). Automatic signature verification using a three-axis force-sensitive pen. *IEEE Transactions on Systems, Man and Cybernetics*, 13, pp. 329-337.

Doddington G.R. (1985). Speaker recognition - Identifying people by their voices. *Proceedings of the IEEE*, 73, pp. 1651-1664.

Dooijes E.H. (1983). Analysis of handwriting movements. *Acta Psychologica*, 54, pp. 99-114.

Duvernoy J. (1976). Optical pattern recognition and clustering: Karhunen-Loeve analysis. *Applied Optics*. 15 pp. 1584-1590.

Impedovo S., Marangelli B. & Plantamura V.L. (1976). Real-time recognition of handwritten numerals. *IEEE Transactions on Sytsems, Man and Cybernetics*, 6, pp. 145-148.

Leung H.C. (1985). *A procedure for automatic alignment of phonetic transcriptions with continuous speech*. Thesis, MIT, Cambridge, MA.

Maarse F.J. & Thomassen A.J.W.M. (1983). Produced and perceived writing slant: Differences between up and down strokes. *Acta Psychologica*, 54, pp. 131-147.

Maarse F.J., Schomaker L.R.B. & Teulings H.-L. (1986). Kenmerkende verschillen in individueel schrijfgedrag: Automatische identificatie van schrijvers. *Nederlands tijdschrift voor de psychologie*, 41, pp. 41-47.

Maarse F.J., Schomaker L.R.B. & Thomassen A.J.W.M. (1986). The influence of changes in the effector coordinate systems on handwriting movements. In: *Graphonomics: Contemporary research in handwriting.* H.S.R. Kao, G.P. van Galen, & R. Hoosain (Eds.). North-Holland, Amsterdam. pp. 33-46.

Shridhar M., & Badreldin A. (1985). A high-accuracy syntactic recognition algorithm for handwriting numerals. *IEEE Transactions on Systems, Man and Cybernetics*, 15, pp. 152-158.

Spanjersberg A.A. (1978). Experiments with automatic input of handwritten numerical data into a large administrative system. *IEEE Transactions on Systems, Man and Cybernetics*, 8, pp. 286-288.

Suen C.Y. (1979). A study on man-machine interaction problems in character recognition. *IEEE Transactions on Systems, Man and Cybernetics*, 9, pp. 732-736.

Teulings H.-L. & Maarse, F.J. (1984). Digital recording and processing of handwriting movements. *Human Movement Science*, 3, pp. 193-217.

Thomassen A.J.W.M., Teulings H.-L, & Schomaker L.R.B. (1988). Real-time processing of cursive writing and sketched graphics. In: *Human-Computer Interactions: Psychonomic Aspects.* G.C.v.d.Veer & G.Mulder (Eds.). Springer-Verlag, Heidelberg.

Zue V.W. (1985). The use of speech knowledge in automatic speech recognition. *Proceedings of the IEEE*, 73, pp. 1602-1615.