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**QUALITY EVALUATION APPROACHES OF THE FIRST GRADE CHILDREN'S  
HANDWRITING**

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**Abstract:** *The evaluation of early school-aged children's handwritten symbols is a challenging problem. The teaching of handwriting is still an essential skill in effective written communication. There is a need for an automatic quality evaluation of handwritten symbols in order to assess the progress of children ability to write nice letters or other symbols. In our case, the letters are positioned in a well defined two-dimensional space, similar to the special notebooks children use in school when learning how to write. For this study, a Wacom system composed of a tablet and a digital pen is used for collecting the data that will be sent to the analysis and evaluation module.*

*While the school-aged child writes a character, the pen transmits the (x,y) coordinates and the time t. Next, a normalization is needed in order to keep the same distance between neighboring pixels. Several approaches are investigated (e.g. normalization with/without interpolation). The coordinates sequence is transformed in a sequence of angles measured relatively to the X axis for each written character. They encode the changing directions during pen movement. An algorithm is used in order to detect if the overall shape of the written symbol is correct. Several parameters that characterise the written character are investigated (e.g. „centre of mass”, height over width ratio, alignment errors etc.). Their correlation with subjective scores is verified. Several metrics are proposed based on spatial and temporal measurements. Next, the handwritten quality using the legibility, form size and alignment of the letters or digits is investigated. It is shown that a rough discrimination between proficient and non-proficient handwriting can be obtained by considering the size and space parameters. Our simulations have revealed the importance of good handwritten reference samples. The goal is to develop a calligraphic handwriting learning system designed for first grade or pre-school childrens. Further research is needed in order to address other aspects of an intelligent tutor.*

**Keywords:** *Children handwriting; automatic evaluation; interactive pen display;*

## I. INTRODUCTION

The evaluation of early school-aged children's handwritten symbols is a difficult problem. Although the teaching of handwriting is not compulsory in all countries, it is still an essential activity for developing children's personality, basic coordination abilities and communication skills. An automatic quality evaluation of handwritten symbols is a useful tool for assessing the calligraphy skill progress of the children [1]-[9].

In [8] ten parameters based on spatial metrics computed from an x-y digitizing tablet and grip force patterns measurements were proposed. It was shown that the proposed parameters were statistically associated with the five handwriting quality primitives. In [1], a multimedia handwriting learning tool that incorporates audio, visual, and haptic modalities was proposed. The student performance was measured using the similarities between the test characters and the reference characters. It was shown that the learning ability was increased by incorporating the haptic modality [1]. All previously mentioned paper uses a lot of information beside that provided by the x-y and time coordinates. Our proposed method relies only on these available coordinates and the letters are

positioned in a well defined two-dimensional space, similar to the special workbook used by childrens when learning to write (see Fig. 1). Unlike in most previous works that considers straight vertical lines, in our case there is a vertical tilt between lines. A Wacom system composed of a tablet and a digital pen is used for collecting the data. A software program collects the time coordinates and the  $x$  and  $y$  coordinates. The pen-up and pen-down situation and the time are used by the tutor part to characterize the speed and proficiency of the pupil handwriting skills. Data analysis is performed off-line. All the writing sessions were supervised.

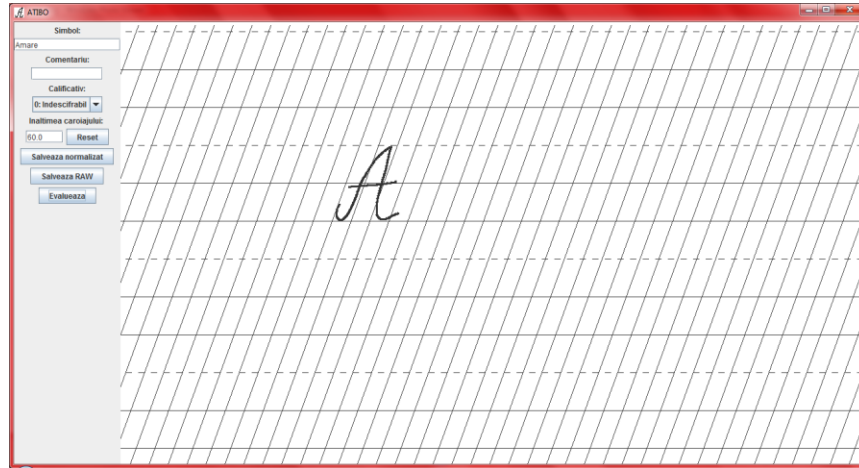


Figure 1 A snapshot of the handwriting acquisition.

A normalization step is needed in order to keep the same distance between neighboring pixels. We found that the normalization with interpolation gives the best results. A constant length of 500 pair of points are used in the following simulations.

It is known that the Euclidian distance between vectors is not suitable in case of handwritten letters. The Dynamic Time Warping (DTW) method is intuitively connected with the way people evaluate the handwritten text [9]-[11] and is used in our work.

The paper is organized as follows. Section II presents few details about the DTW method. In Section III, the proposed method and simulation results are presented. Finally, the conclusions are given and ideas for further improvements are proposed.

## II. DYNAMIC TIME WARPING

The DTW algorithm is a well known algorithm that computes the optimal alignment between two time series. It has been used in many applications such as speech recognition, gesture recognition, medicine etc [11].

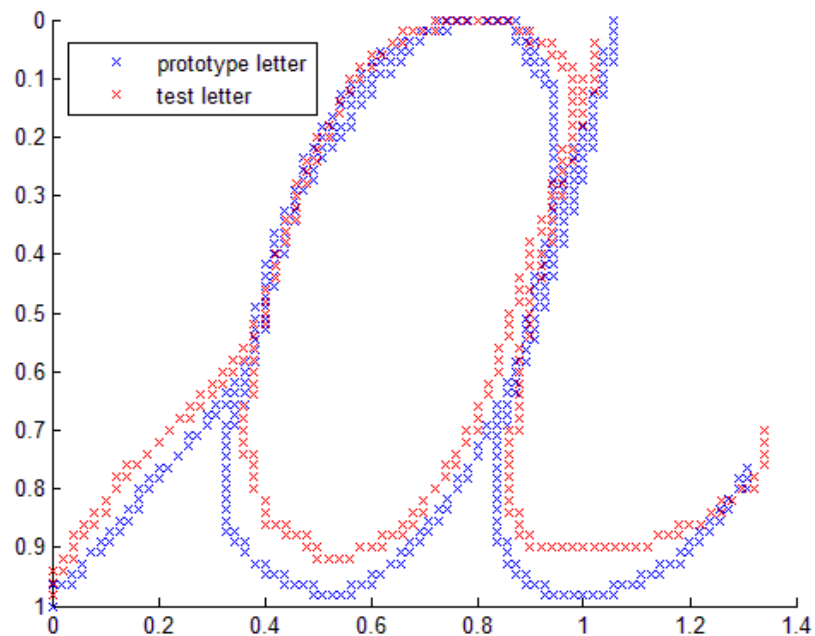
In the classical DTW algorithm, a two-dimensional cost matrix  $D(i,j)$  is formed by taking the difference between the values in the two time series  $X_n = x_1, \dots, x_n$  and  $Y_m = y_1, \dots, y_m$ . The matrix  $D(i,j)$  has a  $n$ -by- $m$  dimension and its elements are the minimum accumulated distances for the sequences  $X_i$  and  $Y_j$ . The algorithm finds the path traces with minimum-distance. The path with the least accumulated cost is chosen while the constraint that  $i$  and  $j$  being monotonically increasing is imposed. In order to reduce the computational load upper and lower bounds are imposed. The following optimization method is solved:

$$D(i, j) = \min \begin{cases} D(i-1, j) + d(i, j) \\ D(i-1, j-1) + 2d(i, j) \\ D(i, j-1) + d(i, j) \end{cases} \quad (1)$$

More information about the DTW algorithm can be found in [9]-[11].

### III. THE PROPOSED METHOD AND SIMULATION RESULTS

Several parameters that characterise the written character were investigated. One of them is the centre of mass of both prototype and test letters. This parameter is computed as the mean value of  $X$  and  $Y$  vectors. The centre of mass can indicate if the written letter is not centered well with the prototype letter. Also, the minimum and maximum coordinates values can indicate some alignment errors. One example of a prototype and test letter for „a” is shown in Fig. 2. The centre of mass for the prototype letter is [0.7123 0.4874] while for the test letter is [0.7053 0.5223]. It can be noticed that the  $y$  coordinate of the test letter is higher than that of the prototype letter and confirms the visual evaluation of Fig. 3. Another useful parameter is the height over width ratio. The right value is specific to each small or capital letter. The distance of the written letter parameter from the prototype points to specific alignment or written errors.



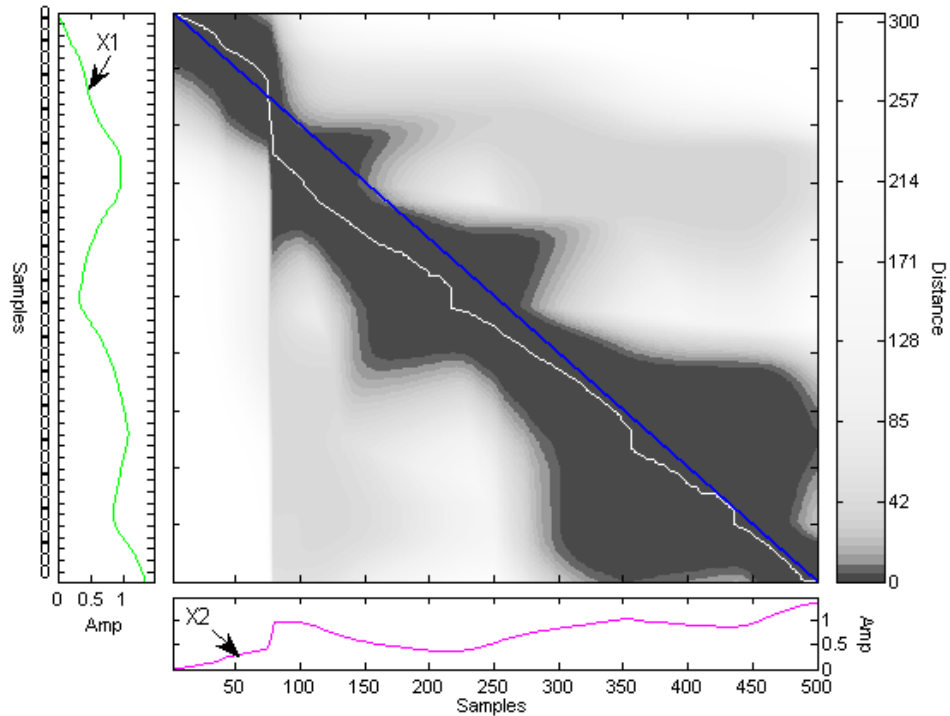
**Figure 2** The prototype and test letters.

Next, the DTW is used of both  $x$  and  $y$  coordinates between the prototype and test letter. One such example for the  $x$  coordinates is shown in Fig. 3. On the left side is one vector, while at the bottom of the figure is the second vector. The DTW computed path is shown by the white curve on the central plot. The blue line indicates no-warping and a one-to-one correspondence. The computed DTW distance is 0.12 for the  $x$ -coordinates time series. Figure 4 shows the DTW computed path for the  $y$ -coordinates. The computed DTW distance is 0.75 for the  $y$ -coordinates time series.

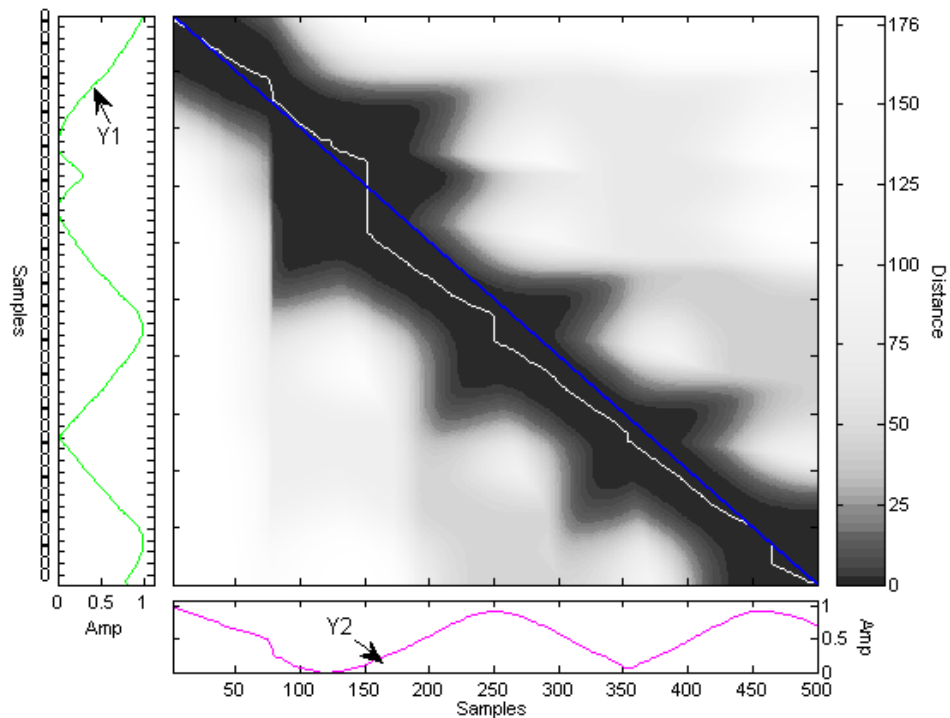
In Fig. 5 the  $x$ -coordinates vectors of prototype and test letters are shown on the same plot and a 3-D correspondence found by DTW between them is also shown. In Fig. 6 a similar figure that shows the  $y$ -coordinates vectors and their 3-D correspondence found by DTW is plotted.

Each symbol is also represented by a sequence of angles in degrees measured relative to the  $x$  axis. The angle vector describes the shape of the symbol. It is not really necessary to compute this sequence for each pixel. In Fig. 7 the angles are computed between consecutive 10 points. The sequence of the template letter and the test one are compared by using the DTW technique and a normalized distance is computed. It is assumed that very similar angles should be obtained if the written letter is close to the reference letter.

We found a good correlation with the subjective assessment as shown in [12]. The normalized DTW distance for the angles is rather high when the shape of the letter does not match the shape of the reference letter, i.e. 2.75. A warning is issued that the general shape of the test letter should be improved by the pupil.

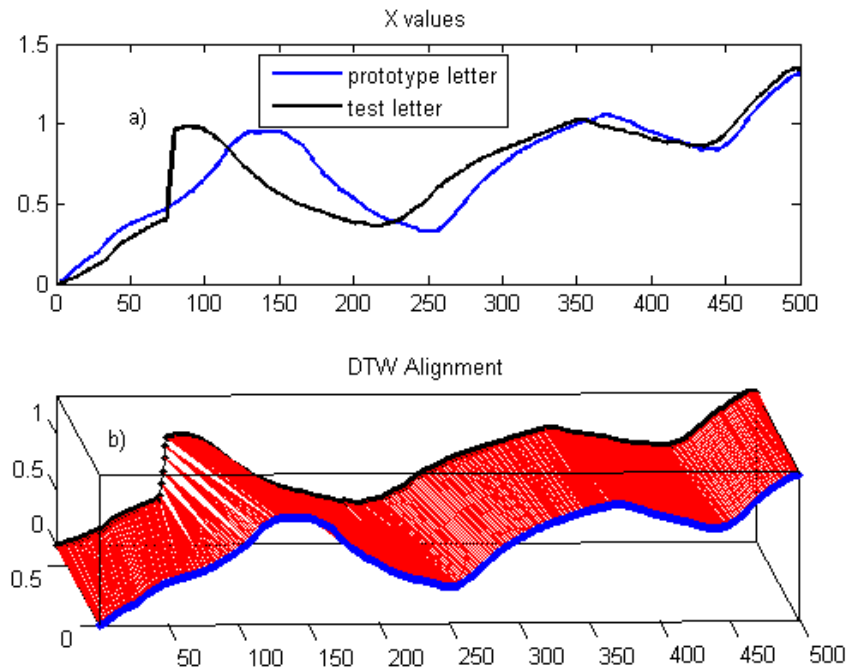


**Figure 3** The DTW applied to the  $x$ -coordinates of the prototype and test letters.

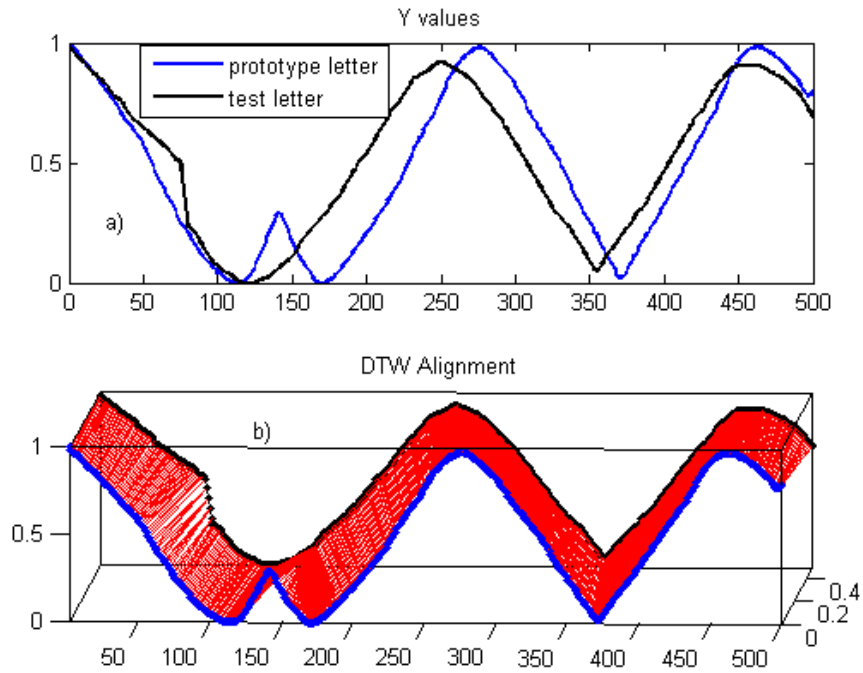


**Figure 4** The DTW applied to the  $y$ -coordinates of the prototype and test letters.

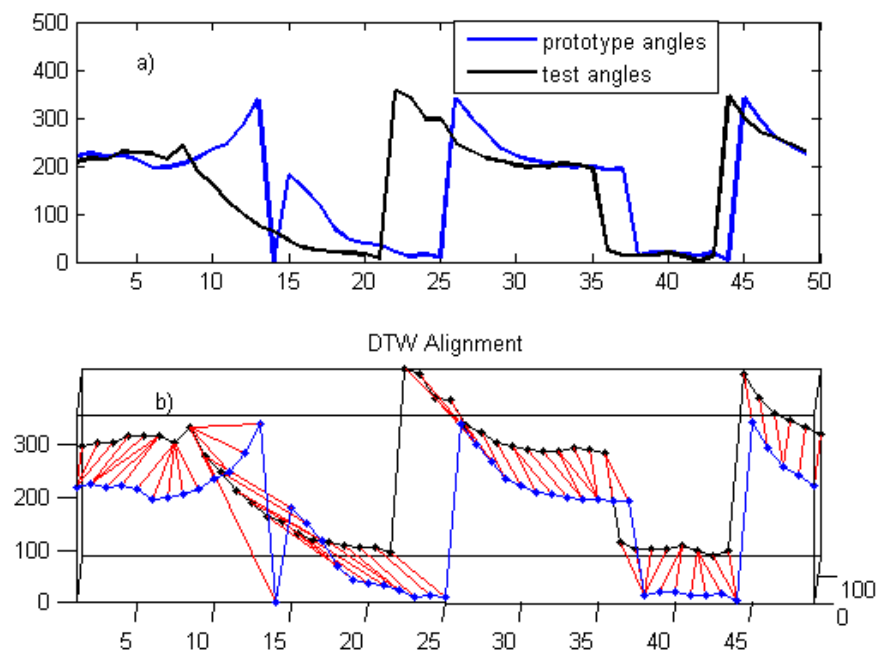
Another useful approach to determine handwriting errors is to use the projection on horizontal and vertical axis of bitmapped letters. Examples of bitmapped “t” letter are shown on the left side of Fig. 8. The horizontal and vertical projections are computed on the bitmap images.



**Figure 5** a) The  $x$  coordinates of the prototype and test letter; b) The DTW alignment between prototype and test letter  $x$  coordinates.



**Figure 6** a) The  $y$  coordinates of the prototype and test letter; b) The DTW alignment between prototype and test letter  $y$  coordinates.



**Figure 7** a) The angles of the prototype and test letter; b) The DTW alignment prototype and test letter angles.

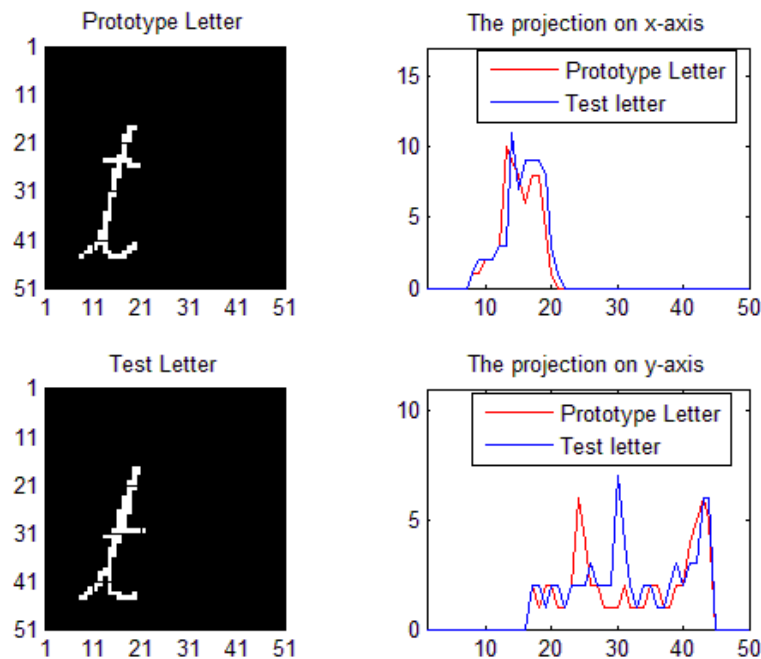
These projection vectors are compared in order to identify differences from the prototype letters. For example, the following common mistake regarding the letter “t” can be easily detected by examining the projection on y-axis.

A threshold imposed on the projection vector can detect that the upper line of “t” is placed lower than it should be. The peaks correspond to the horizontal lines of the letter. The sharpness of the peaks indicates if the line is parallel with the horizontal baseline or not. If the line is tilted, the peak width is increased due to spread of bits on the vertical projection vector. This mistake also modified the centre of mass of the letter. It can be noticed from right part of Fig. 8 that both letters are well placed on both axis. A similar procedure can be applied for other letters such as “A”, “F”, etc. The displacement between projection vectors indicates the improper placement of the test letter on the designed 2-D space if compared with the prototype letter. This displacement can be easily computed using known techniques from image processing [13].

The total accumulated errors is calculated and compared to a threshold. If the error goes beyond the threshold, a message is displayed. Also, the mean and variance of these distances provide a measure of the child’s proficiency in replicating the prototype letter. This spatial-temporal variability in handwriting reveals small deviations of each individual consistency in letter writing. A histogram of the DTW distances can show the specific letters where the child encounters writing problems. The sum of the division between all the DTW distances and the number of letters of the corresponding bin is computed. In the initial phases of the learning process, this computed parameter has high values; afterwards, when the child turns to a proficient writer, it becomes much smaller. This confirms previous studies about the letter writing variability variation during the learning process [2], [7], and [8]. We found that the most common features of poor writing were wrong letter proportions and form errors. Also, we’ve noticed that, in these cases, the number of pen up/pen down is typically larger than the required number of strokes to trace the letter. It also indicates the difficulty of the letter and its shape. This is also in agreement with previous works [2], [8].

Future work is needed to assess this parameter effect on the DTW distance mean and distribution. A much larger and comprehensive database with different writing styles is needed for a

comprehensive statistical analysis. Future work will be focused in extending the work with the help of the teachers and include many other typical errors.



**Figure 8** (left side) The bitmap images of the prototype and test “t” letters; (right side) The horizontal and vertical projection vectors of the prototype and test letters respectively.

#### IV. CONCLUSIONS

The assessment of children’s handwriting is mostly based on tutor subjective judgment. We present a preliminary work that tries to combine the advantages of a computerized based objective evaluation with a conventional measure. We found that the DTW technique can provide objective information about the letter shape and some of the shape inconsistencies typically found in the first grade workbooks.

One of the measured parameters is the distance from the prototype letter that uses not only the spatial coordinates but also the angles coding the shape of the letter. An interesting insight is obtained on the learning process of the new letter form. The dynamic time warping is a promising tool in the investigation of handwriting quality and allows an objective evaluation of the overall letter form. It complements the investigated temporal-spatial parameters. All the described techniques improve our understanding towards an intelligent tutor end-product.

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## Reference Text and Citations

- [1] Mansour, M., Eid, M. and El Saddik A., "A Multimedia Handwriting Learning and Evaluation Tool", in *Proc. Intelligent Interactive Learning Object Repositories (I2LOR)*, Montreal, QC, Canada, November 2007
- [2] Stefansson, T., and Karlsdottir, R. "Formative evaluation of handwriting quality", *Perceptual and Motor Skills* 2002, 97, 1231-1264.
- [3] Tappert, C.C., Suen, C.Y., Wakahara, T. , "The State of the Art in On-Line Handwriting Recognition", *IEEE Trans. On Pattern Analysis and Machine Intelligence*, vol. 12, Issue 8, 1990
- [4] Plamondon, R. and Srihari, S.N., "On-Line and Off-Line Handwriting Recognition: A Comprehensive Survey", *IEEE Trans. On Pattern Analysis and Machine Intelligence*, vol. 22, Issue 1, 2000.
- [5] Doster, W. and Oed, R., "Word processing with on-line script recognition", *IEEE MICRO*, vol. 4, pp. 36-43, Oct, 1984.
- [6] Powers V. Michael, "Pen Direction Sequences in Character Recognition", *Pattern Recognition*, Pergamon Press 1973, Vol. 5, pp. 291-302.
- [7] Palluel-Germain, R., Bara, F., Hillairet de Boisferon, A., Hennion, B., Gouagout, P., and Gentaz, E., "A visuo-haptic device - telemaque - increases kindergarten children's handwriting acquisition. *Second Joint EuroHaptics Conference and Symposium on Haptic Interfaces for Virtual Environment and Teleoperator Systems (WHC'07)*, 2007.
- [8] Falk T.H., Tam C., Schellnus H., Chau T., "On the development of a computer-based handwriting assessment tool to objectively quantify handwriting proficiency in children", *Comput Methods Programs Biomed.* 2011;104, (3):e102-11.
- [9] Kruskal, J. and M. Liberman, "The Symmetric Time Warping Problem: From Continuous to Discrete", In *Time Warps, String Edits and Macromolecules: The Theory and Practice of Sequence Comparison*, pp. 125-161, Addison-Wesley Publishing Co., Reading, Massachusetts, 1983.
- [10] Keogh, E. and Pazzani, M., "Derivative Dynamic Time Warping", In *Proceedings of the First International Conference on Data Mining*. Chicago, Illinois. 2001.
- [11] Senin P., "Dynamic Time Warping Algorithm Review", *Technical Report* - University of Hawaii at Manoa, 2008.
- [12] S. Rosenblum, A. Y. Dvorkin, and P. L. Weiss, "Automatic segmentation as a tool for examining the handwriting process of children with dysgraphic and proficient handwriting", *Human Movement Science*, 25:608–621, 2006.
- [13] K. Sauer and B. Schwartz, "Efficient Block Motion Estimation Using Integral Projections", *IEEE Trans. Circuits, Systems for video Tech.*, vol. 6, No. 5, pp. 513-518, October 1996.