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Automatic analysis of the structuring of children's drawings and writing

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Abstract

The aim of this work was to build an objective tool for the detection of graphomotor difficulties involving disorders in the writing of children. We outline some characteristics of layouts, describing the automation level of the graphic activity. We have defined exercises, like copying figures or writing sentences under different conditions that allowed us to measure simple aspects of graphomotor skill up to complex ones. A tool was conceived which was able to automatically extract low-level and high-level primitives. Based on such descriptors, we focus on the analysis of the temporal structuring of two particular drawings. In the final part, we present the method we used to select features that can describe the automation level of the graphic activity and we show that, in most cases, these features allow to discriminate children with academic difficulties.

Keywords: Handwriting; Drawing; Learning; On-line segmentation; Feature selection; Classification

1. Introduction

Before handwriting becomes an additional and complementary way of expression for children, they will have to be familiarized with the use of a writing tool. This apprenticeship begins at the nursery school by the practice of drawing and continues at primary school mainly through copying tasks. Many early works have focused on the children's behaviour while copying drawings or while writing, e.g. Goodnow and Levine [1], Nino and Lieblich [2], Simner [3] or Smits-Engelsman et al. [4]. The interest in automating children's handwriting is to make them able to focus their attention on the linguistic dimension of their production. Studies have shown that some children labelled as presenting with "disorders of writing" saw their access to the written language strongly slowing down by graphomotor difficulties, e.g. Zesiger [5], Hamstra-Bletz and Blöte [6]. However, no objective tool allowing the detection of such difficulties is available. We outline here some spatio-temporal and kinematic characteristics of the layout, that we call descriptors, describing the automation level of the graphic activity, as pointed out by Rémi et al. [7]. Therefore, we have defined an experimental protocol, containing exercises, like copying figures or writing sentences under different conditions, to underline increasing evolved and complex aspects of graphomotor skill. The skills required during the layout production change according to the proposed task. All the layouts are realized on a digitizer tablet set under temporal mode and are on-line recorded as presented by Rémi et al. [7], and by Amara et al. [8]. Our objective is to

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process and analyse these layouts, from both a dynamic and a static point of view, using well-known image processing methods including the problem of reducing noise due to the digitizer (e.g. the work by Marquardt and Mai [9]), low-level features extraction and high-level descriptors identification. The latter is based on a phase of recognition of simple geometric elements and a clustering stage of the selected elements allowing the recognition of more complex patterns like circles, squares etc.

The remainder of this paper is organized as follows: Section 2 describes the experimental protocol. Section 3 discusses the analysis of the temporal structuring of two drawings: geometric elements identification, analysis of the grammar of action. Section 4 presents the feature selection process and results obtained in terms of school level recognition. Section 5 concludes the paper.

2. Experimental protocol and low-level features

The control of writing requires a specific training that is superimposed on the motor and perceptive development of the child. The school activities result in gradually automating the writing of the child. During this period of learning, noticeable changes occur on the strategies of writing. Such changes probably result from the modifications in the possibilities of planning the task, anticipation of gesture effects and control of the movement as pointed out by Thomassen et al. [10] or Ziviani [11]. In order to characterize these changes, we aimed to study layouts produced by children from a space-time point of view as well as from a structural one. The main interest of such approaches is to understand the behaviour of writing in terms of precision, speed, fluidity, strategy of execution and space structuring, and so the modifications of the concerned cognitive processes. To this end, we developed an experimental protocol, based on four different tests commonly used and recognized by psychologists to which we added a new one. The former aims at evaluating the level of learning of each basic skill necessary for the production of high level writings and are not used by the teacher to avoid bias due to the training effect. The latter, which consists in producing a sentence under various and unusual conditions, involves high level writing.

- *The test of understanding in reading* [12]
  Its objective is to evaluate the understanding of the language written by the child. Due to Khomsi, this test involves 22 boards each of them including one statement and four images. The task of the child is, for each board, to choose the image that corresponds to the presented statement. The boards of this test can be classified into three categories according to the syntactic structure of the associated sentences. The indication of the correct image requires processings of different complexity levels.
  The 3 usual notes are computed and new features like average times of response, full time, have been added.
- *The test of drawing*
  In this test, the child has to reproduce two drawings composed of geometrical shapes, known as *figure I of Bender and Figure of Meulenbroek.*
  - *figure I of Bender* [13]
    This drawing, which belongs to a series of tests used for the psychological examination of children of school age, contains a circle and a tangent square as in Fig. 1-(Up). This test was initially used to seek a possible defect of the grapho-perceptive organization in the children presented with a school delay. The model has to be copied on a sheet without any reference mark and no realization time requirement.
  - *Figure of Meulenbroek* [14]
    This drawing, shown in Fig. 1 - (Bottom), which is composed of four segments arranged so that its realization requires at least one rising of the pen, was conceived for adults. In our test, segments are longer according to the abilities of both the engine control of the young child and the linearity level of the straight lines. The production conditions are the same as Bender's figure one.
    Features describing the space organization (e.g. height, width, surface of the drawings) are retained. Others providing information about the regularity of the movement (e.g. mean and variance of the production speed) are computed as well as some features revealing the drawing strategy (e.g. number of pauses, duration, primitives sequencing). The extraction of symbolic features related to the sequencing (called high-level descriptors) is described in the next section.
- *The test of the crown* [15]
  It aimed at evaluating psychomotor abilities to control movement kinematics which may improve the spatial precision of writing. The child has to draw continuously two circles as slowly as possible. The circles must be traced in an area delimited by two concentric circles. A starting position (in the middle of the left half-circle) is indicated by the experimenter to the child without real point on the sheet.
  Realization times of part or the whole of each circle, pressure exerted on the pen and its orientation are features that can help in evaluating the control abilities.
- *Test of isolated words writing*
  This test consists of the child writing his first name with and then without visual feedback. Depending on the automation level of the writing, some characteristics of the writing would present significant variations with or without visual monitoring. In order to increase the validity of the test, the writing of the word "tintin" is

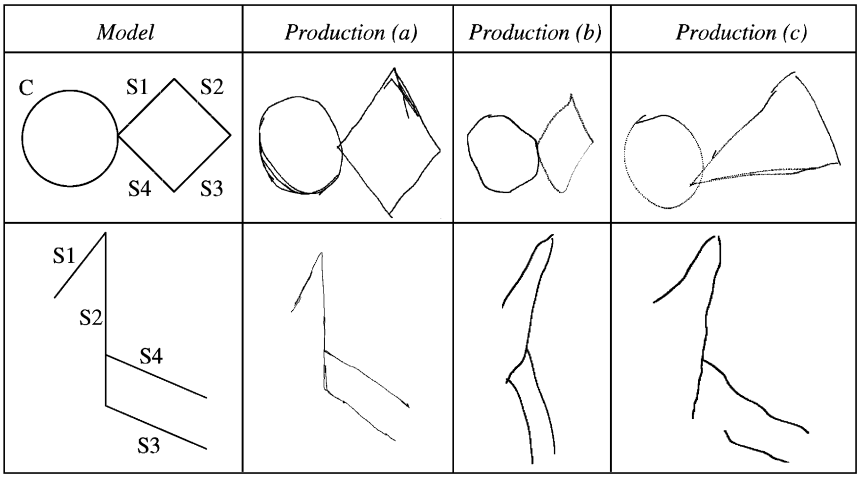

Fig. 1. Drawings. (Up) Bender's figure. (Bottom) Meulenbroek's figure.

Table 1
Summary of feature selection

Number of features	Khomsi	Drawing	Rey	Words	Sentence	Total	Ratio (%)
Before selection	6	22	27	126	60	241	
After exercise-based clustering	2	7	10	23	18	60	24.90
After global clustering	2	6	8	17	12	45	18.67
After forward selection	2	2	4	7	5	20	8.30

also required. This pseudo-name is well known by the children, and built with two familiar syllables.
Features describing spatial, dynamical variations between a production condition and another one are computed, e.g. some dimensions of the layouts, their orientation, the average size of letters, the number of pauses, full times of execution (not in the writing of the first name because of too much variability).

- *Test of sentence writing*
The sentence used in this new test is composed of familiar words and is semantically and syntactically accessible even to the youngest children: *Le chien de la petite fille joue avec une grosse balle* (*The dog of the little girl plays with a large ball*). One can also note the presence of double letters, *ss*, and *ll*, that look like the arcades and garlands often used in the evaluation tests of the graphomotricity in Social Sciences, e.g. in Ref. [16]. It was decided that the child would write this sentence six times under the following conditions:

1. *With a model*, allowing to check if the child was able to read and write the sentence.
2. *Without the model*, testing the memory ability.
3. *Again without the model*, looking for performance improvement due to repetition.
4. *Without the model with the added task of counting irregular emitted sounds*, testing how a new task can interact with an automated one.
5. *Again without the model with the added task of counting irregular emitted sounds*, observing the repetition effect in a situation of overload.
6. *Without the model* (*as in* 2), offering another base-line of comparison with an added task: 3 with 5, 5 with 6 (to compensate for the effect due to the order of the two tests (simple recall, recall with added task).

Similar features to those of the isolated words writing are studied.

An overall number of 241 features are extracted (see Table 1, 1st row). The process we have conceived in order to select features that are relevant enough to characterize the school level is presented in Section 4. The experiments have been carried out in two primary schools in France (Mont-Saint-Aignan, Saint-Etienne-de-Rouvray); from now on, we will refer to both schools as classical schools. There are five school levels, starting at level one for the youngest children (six years old). We have considered that a child has a regular schooling if the child's age is in concordance with their school level,

Table 2
Distribution of tested pupils

Pupils	Classical schools	Specialized association	Total
With easiness	2	0	2
Regular	153	0	153
With difficulties	8	13	21

and it has never redoubled or jumped a class, and it does not have a proven problem in oral language or writing. In addition, layouts of children identified by experts as presenting speech and writing difficulties that have caused a school delay, were collected in a specialized association (ADEPA). For several reasons, e.g. missing values, about 27% of the recorded material has been discarded. Table 2 shows how the tested pupils are distributed with respect to proficiency in their scholarship.

3. Drawing strategy recognition based on high-level descriptors

Meulenbroek's figure contains four straight lines. Bender's figure is composed of a circle and four lines arranged in such a way that they form a pointed square. By visual observation of productions, e.g. in Figs. 1(a)–(c), we can immediately identify these patterns but we are not able to perceive the order in which they have been produced. To be reliable, an automatic analysis system must be able to simultaneously distinguish the spatial and temporal structuring of the layout. Even though it is easy to recognize lines or circles within an image, it is difficult to associate them with the strokes of a freehand layout produced in an unexpected order and described by an ordered points series. For example, during the realization of the drawing depicted in Fig. 1(a), the child has represented the four segments in 21 strokes (part of the drawing between two successive pen's raisings) in no particular order. The child has first produced segments S1 and S2 by numerous strokes. Then, he came back to complete already traced segments. For example, he sometimes gave up segment S4 to overlap segment S1. On the other hand, some strokes represent several segments of Meulenbroek's figure (Fig. 1(a): strokes S1 and S2), preventing to simply assign strokes to segments.

The purpose is to recognize the simple components of an on-line drawing such as lines or circles. From now on, we will denote them through models. The recognition then becomes a problem of feature clustering. Due to an important inter-writer differences in the production, we cannot use a priori knowledge about the presented model. So, for each processed layout, hence for each writer, it is necessary to identify a "germ" for each class based only on the description. These germs, determined using a Hough transform, as described by Illingworth and Kittler [17], Yuen et al. [18], will provide the parameters for the clustering initialization step. A germ will be a model considered as a potential starting point (kernel) during the clustering stage. The second difficulty lies in the possibly poor layout quality. For example, in Bender's figures, freehand circles sometimes present linear parts with a length similar to the sides of the square (Fig. 1(b)). To overcome this difficulty, all the features describing the circle must be first labelled.

Concerning strokes with several models, one can notice that model changes involve the most important angular variations occurring in a low speed part (valley in the speed curve). Consequently, an angular variation is significant only if the two following conditions are satisfied: it happens when the speed is low, and it has the greatest value in this part of low speed.

3.1. Segmentation

A segmentation method has been developed according to these conditions. It is based upon the determination of the eigenvector related to the principal axis of the set of points. In this method, the scatter matrix associated with the points between the last retained point and the currently processed point is computed. The eigenvector corresponding to the largest eigenvalue of this matrix is then determined. At each point, the method gives estimated parameters (a_T, b_T, c_T) defining the normalized equation of the optimal straight line describing all the points of each segment. Using a constant sampling frequency, local accumulations of points occur at low speed. We must introduce a weighting factor deriving from the distance of two consecutive points. Thus, the criterion to be minimized is

$$C_T \hat{=} \frac{1}{L_T}\sum_{t=1}^{T} p_t[a_T x_t + b_T y_t + c_T]^2, \tag{1}$$

where p_t is the distance between the two last points, and $L_T \hat{=} \sum_{t=1}^{T} p_t$ is the developed distance up to time T.

Inside each stroke of Bender's figure, the model change is based on the estimation of the circle parameters computed using all the points from the last retained one. The circle parameters, i.e. the centre (x_{0T}, y_{0T}) and the radius r_T, is processed using a least-squares method minimizing

$$C_T = \frac{1}{L_T}\sum_{t=1}^{T} p_t[(x_t - x_{0T})^2 + (y_t - y_{0T})^2 - r_T^2]^2, \tag{2}$$

where p_t is another weighting factor.

The estimation-detection process is initialized using the three first points of each new segment. The centre coordinates and the radius are analytically computed from these points and are used as initial parameters values.

For the two patterns, the model change is decided by thresholding the local speed (less than), the angle

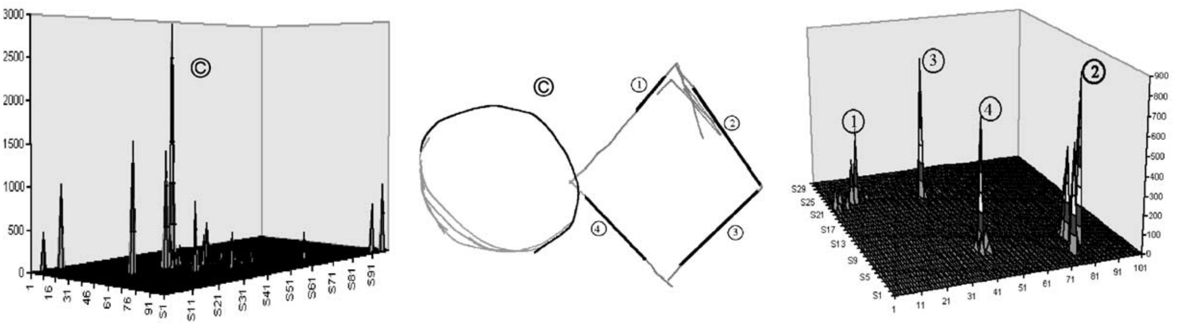

Fig. 2. Searching for germs in Bender's figure. (Left and Right) Hough spaces. (Centre) Identified models in the drawing.

variation (greater than) and the distance from the last retained point (greater than).

3.2. Straight lines identification

We obtain from the segmentation stage, a drawing coded by a list of segments. We then have to select a list of germs for the clustering step. This selection uses a Hough Transform to identify the four main directions in the drawing. In this context, each accumulator in the Hough space is incremented by the length of each corresponding segment and depends on the sum of lengths of all the related segments.

The parameters (ρ, θ) of the four main directions are iteratively identified, neglecting an area around each already obtained peak, avoiding the use of a Fuzzy Hough Transform proposed by Han [19]. When several segments have incremented an accumulator, we choose as germ the longest segment. Fig. 2 (right) shows the peaks obtained in the Hough space and the four identified germs, from the child's production presented in Fig. 1(a). In Bender's figure, the method is applied for the four lines of the square, when the circle has already been identified. The non-labelled segments in the drawing must be associated with one of these classes. Due to the small number of segments, a non-supervised clustering is performed using the k-means algorithm, as described in Ref. [20].

To compute the dissimilarity between two segments s_i and s_j we define the following distance:

$$d(s_i, s_j) = \sqrt{(\rho_i' - \rho_j')^2 + (\theta_i' - \theta_j')^2} \quad (3)$$

where $\theta' = \theta^2$ and $\rho' = \rho \arctan(\theta'^2 + \pi\theta')$ allowing to decrease within class variance.

The four germs are taken as kernel for the initial classes. Each segment is then assigned to the class minimizing the distance d. In the following iterations, centres of gravity of classes are chosen as kernels.

This method has been tested on a set of 111 children's drawings for Meulenbroek's figure. In 110 drawings (99.09%), the segment models have been correctly identified inside the drawing. In the only case of failure, only a segment, describing a small stroke added by the child to join S3 to S2, was misclassified (in S4 class instead of S3).

3.3. Circle and square identification

The circle is not always drawn by a single stroke but is generally described by several bows. So, we have chosen to define a germ in order to simplify the circle recognition. This germ is also determined using a Hough Transform. The m to 1 Hough Transform increments the cell (x_0, y_0, r) containing the current tree points, where (x_0, y_0) are centre co-ordinates of the circle returned by the segmentation step for each bow and r its radius. Each cell is incremented by the length of the current segment. The longest segment corresponding to the highest peak is selected as a germ. Fig. 2 (left) shows the Hough space and the circle germ identified from the layout of Fig. 1(a). In order to determine the bows belonging to the class defined by the germ, we use a set of rules based on both spatial and temporal information of the drawing.

Once the features describing the circle are isolated, the segments models (S1, S2, S3, and S4) that define the square sides of Fig. 1 (model) have to be recognized. The method described in the previous subsection has been used. Fig. 2 shows a drawing, the peaks obtained in the Hough space and the identified germs: circle C, square composed of S1, S2, S3, and S4. This method has been tested on a set of 120 children's drawings for Bender's figure. In 95% of cases, the components of the drawing have been correctly identified within the layout. The method failed only for six drawings. Three failures were due to the quality of the layout, e.g. the child drew a triangle rather than a square as shown in Fig. 1(c). Three other cases of failure were caused by too small features, preventing to locate the junction between the circle and the square. Two difficult but correctly recognized drawings are shown in Fig. 1(a) and (b). In Fig. 1(b), the drawing was realized in two strokes: one for the circle

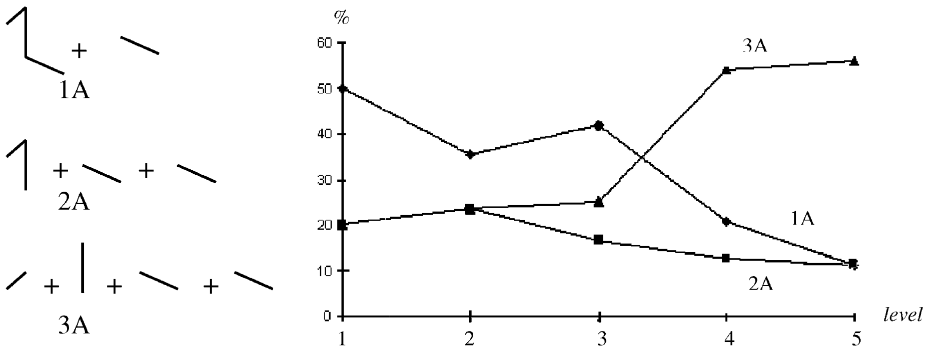

Fig. 3. Meulenbroek's figure. (Left) Main observed strategies. (Right) Percentage of children adopting the strategies by school level.

and another one for the square. In this case, five items were enough to describe the layout. The production of Fig. 1(a) required 20 features including 9 for the construction of the square and 11 for the circle. During the description phase, this drawing was coded with 58 items.

3.4. Analysis of the grammar of action

The adopted order to draw components of a layout is relevant from the psychologist's point of view. It is assumed to show the strategy followed by the child during his drawing. Numerous works in Social Sciences attempted to characterize the strategies employed by children to copy some relatively simple geometrical figures (e.g. Goodnow and Levine [1], Ninio and Lieblich [2], Simner [3], Thomassen et al. [10], or Vinter [21]). Most of the authors, who have focused on this problem, refer to the term "grammar of action". This expression was defined to describe some motor production rules that would be generally used when producing drawings or first letters. These rules determine a priori probabilities of action alternation or action sequences. So, they allow the prediction of the starting point location, the order and the direction of the strokes construction.

As part of validating the automatic analysis system, we have tried to determine if such rules would govern the way of constructing the figures suggested in the protocol, and if they must be retained as features for the following work. For example, three main strategies are employed to draw Meulenbroek's figure, as depicted in Fig. 3 (left). The percentage of children adopting each of these strategies, is shown in Fig. 3 (right) according to the school level. The use frequency of strategy 2A is relatively stable. 1A is the main strategy for youngest children. It is then replaced by 3A with a drawing segment by segment, in more than 50% of cases.

The inversion of the tendencies for the prominent strategies is observed in the vicinity of the level three, which corresponds to children being eight-nine years old. Surveys have shown that radical changes on the level of the graphomotricity would occur during this period, e.g. in Ref. [5]. The same analysis has been done with Bender's figure for the drawing of which four main strategies are identified, showing that the proposed descriptors have to (and will) be taken into account.

4. School level recognition

In order to validate the whole procedure, we present in this section the process which led to the classification of children. We recall that we have mixed pupils coming from two classical schools and one specialized association where children with known writing difficulties are placed. There are five school levels, starting at level one for the youngest children (six years old). Table 2 shows how these pupils are distributed with respect to proficiency in their scholarship. We have used the 153 regular children with no particular difficulties in a process of feature selection as well as in the design of a classifier aiming at detecting a school level.

4.1. Feature subset selection

In spite of the fact that most of the 241 processed features are either not useful or redundant for the characterization of the school levels, we and the psychologists did not want all the processed features of the same to be discarded. That is the reason why we have decided to select the most pertinent features in three different steps.

4.1.1. Test-based clustering

The first step consisted in performing five different correlation analysis of the features to make sure that every test will be represented in the reduced feature space. Since the age of the children could be an hidden factor which characterizes the school level, we have first standardized each feature P_i with respect to the levels as follows:

$$P'_i(x) = \frac{P_i(x) - E(P_i \mid C(x))}{Var(P_i \mid C(x))^{1/2}}, \tag{4}$$

where $C(x)$ represents the school level of a child x, $E(|)$ and $Var(|)$ the conditional expected value and the conditional variance, respectively.

Then, a hierarchical clustering method, e.g. Jain and Dubes [22], has been applied according to:

- an agglomerative measure for groups: the unweighted pair group method averages (UPGMA)
- a dissimilarity index between individual features: the Euclidean distance which has been chosen because it is known to be related to correlation between features

  $$d^2(P'_i, P'_j) = 2n(1 - Corr(P_i, P_j)), \tag{5}$$

  where n is the dimension of each feature vector, namely the number of children.

For each obtained hierarchy, a partition of compact clusters of features is chosen with respect to the increase of the agglomerative measure and common sense as well. The nearest feature of each cluster centre is selected as a pertinent one and the other ones are discarded. Fig. 4 shows the clustering results obtained in the case of the Rey exercise: 10 compact clusters of features are detected, therefore 10 features are selected from the 27 original ones. At the end of this test-based step, only 60 features have remained from the 241 original ones representing a compression rate of more than 75% (see Table 1 for details).

4.1.2. Global clustering

The same clustering method has been applied to the remaining features in order to check whether some features from different tests are similar or not. It occurred for some features of same nature, e.g. the pen pressure, whatever the test: Drawing, Words or Sentence writing. As we could expect, according to the agglomerative measure we used, this global clustering also has resulted in grouping features issued from the same test but at a lower level than the one obtained in the previous phase. 45 features have been selected from this step. Every test is still represented by several features (see details in Table 1). The remaining features relate to: spatial structure, pen angle and pressure, production strategy, speed, movement accuracy.

4.1.3. Forward selection

Next, we aimed at finding the most relevant subset of features to separate the five school levels. Different approaches (e.g. Fukunaga [23]) allow to find the best combination of features according to a class-separation criterion generally based on within-class, between-class and mixture-class covariance matrices. We have chosen the Wilks criterion, to be minimized, defined as

$$Wilks = \det(W)/\det(V), \tag{6}$$

where W and V are the within-class and the mixture-class covariance matrices, a class being a school level.

Instead of performing an exhaustive search of the optimal subset of features, with respect to the chosen criterion, or using branch and bound approach as proposed by Narendra and Fukunaga [24] we rather use a stepwise search known as forward selection, e.g. Devijver and Kittler [25]. The values of the Wilks criterion we obtained for the 45 ordered subsets of features are plotted in Fig. 5 (left). For 20 features, one can notice a change in curvature and the Wilks criterion value falls down under 0.05; so it seemed to be a good choice. As a final result of feature selection, we performed again hierarchical clustering on the 20 selected features. The resulting hierarchy is shown in Fig. 5 (right). It can be seen that no grouping occurs below a relatively high value (13.5) of the agglomerative measure and all the features were grouped in the same cluster below a value which is close to the former (17.5). Therefore, the selected features are clearly different and our choice was relevant. It is worth noting that every kind of exercises (Khomsi, Drawing, Rey, Words, Sentence writing) is represented in the last set of selected features by more than one feature, see Table 1. This confirms the psychologist's point of view, claiming that every type of exercise is useful.

4.2. Classification

Based on the $p = 20$ selected features, a classifier can be designed. We have chosen to present here the simplest geometric classifier derived from linear discriminant analysis. It consists in classifying an unknown p-dimensional pattern vector x to the closest class according to the following distance measure:

$$d^2(x, \omega_i) = (x - m_i)^t W^{-1}(x - m_i), \tag{7}$$

where m_i is the mean vector of class ω_i and W represents the within-class covariance matrix. The classifier design simply consists in learning these parameters from a reference set, here regular pupils.

For classifying regular pupils, a leave-one-out or one-fold cross-validation procedure has been implemented. It consists in classifying each of the n samples by a classifier that has been designed with the other $n - 1$ samples. Thus, every sample is classified without contributing to the classifier's parameters. Another advantage of such a scheme lies in the use of a maximum number of samples for each classifier. Classification results are given in Table 3 in terms of a confusion matrix that is close to be a band-matrix. In addition, it gives the correct classification rates P_c obtained for each

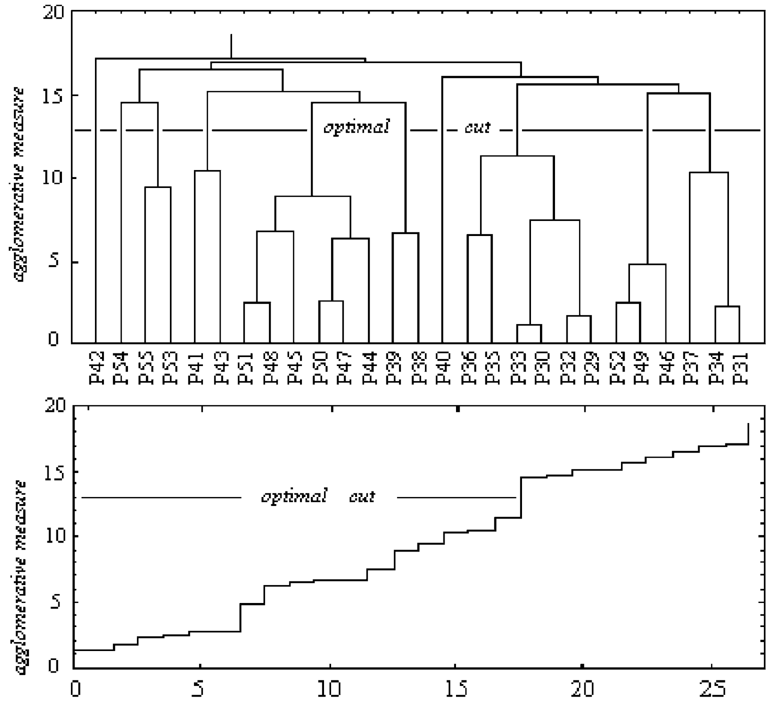

Fig. 4. Crown of Rey features clustering. (Top) Hierarchy. (Bottom) Marginal increase of the agglomerative measure.

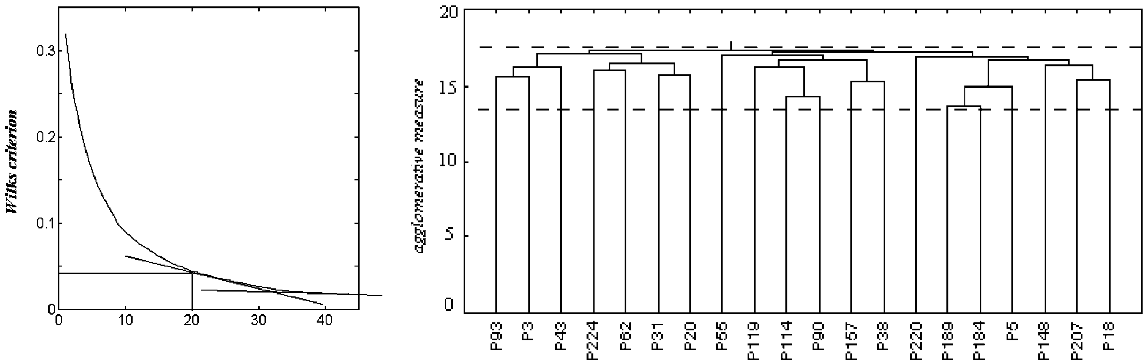

Fig. 5. Features subset selection. (Left) Forward selection. (Right) Selected features clustering attempt.

Table 3
Classification of regular pupils

From/To	Level 1	Level 2	Level 3	Level 4	Level 5	P_c–1st (%)	P_c–2nd (%)
Level 1	10	2	1	0	0	76.92	76.92
Level 2	2	24	3	1	0	80.00	90.00
Level 3	0	3	25	7	2	67.57	89.19
Level 4	0	0	8	22	6	61.11	94.44
Level 5	0	0	5	6	26	70.27	83.78

Table 4
Classification of children having difficulties. Classical schools—specialized association

From/To	Level 1	Level 2	Level 3	Level 4	Level 5
Level 1	0	0	0	0	0
Level 2	1–0	1–0	0	0	0
Level 3	0	0–2	0	0	0
Level 4	0	0	1–0	2–1	0
Level 5	0–1	0–6	1–1	1–0	1–2

level when the right level has been selected in the first position or in the second one. We obtained a satisfactory overall rate of correct classified children as 69.93%, respectively, 88.24%. The rates range from 61.11% to 80% in the first case, whereas they range from 76.92% to 94.44% in the second one. The gain particularly occurs for medium-level, confirming that so-aged children face noticeable changes in their graphomotricity levels as pointed out by Zesiger [5]. It is worth noting that misclassified pupils have been either up classified or under classified in relatively same proportion. Unfortunately, it has not been possible to discuss the discordant assignments with the teachers or psychologists for confidential considerations.

Results obtained for the 21 children with well-known difficulties are given in Table 4. Let us emphasize that no child has been up classified. 66.67% of them have been under classified and 33.33% have been classified in the level they really were. Most of these pupils were coming from the classical schools, representing half of the eight children coming from these schools to be classified. Does this mean that the classifier is less reliable for classical schools or that the difficulties a child might have in a classical school are not so severe? The other half of such children have been classified, as expected, in a lower level: three in an immediate lower level and one by two levels. This is a good result because it must be rare, in classical schooling, that a pupil of a particular school level could have so many difficulties that it would be considered as a child being in a two or more lower level. Only three of the thirteen pupils (# 23%) coming from the specialized association have been assigned to the level they were. Let us underline that this is a lower number than in the case of classical schools. Three pupils have been under classified by one or two levels, i.e. having a regular behaviour. The other seven (55%) have been assigned to a lower level with a higher difference. Since such a specialized association follows up children with so many difficulties that they are placed out of classical schooling, it is not surprising that most of them are so under classified.

The two children with particular easiness were issued from level three and five, respectively. They both have been successfully assigned to the upper level (level five).

5. Conclusion

This paper presents a contribution to the detection of graphomotor difficulties involving disorders of the writing in children. It is based on the analysis of geometrical layouts and textual production by schoolchildren, from both a space-time and a structural approach. We aimed at objectifying and standardizing the methodology adopted for such an analysis. In order to underline some properties of layouts, describing the automation level of the graphic activity, an experimental protocol has been defined. Containing exercises, like copying figures or writing sentences under different conditions, this protocol results in a large amount of acquired data. Therefore, we aimed at building a tool for the automatic extraction of high-level descriptors and the selection of relevant features.

For the first objective, we have presented a method allowing the analysis of the spatio-temporal structuring of drawings. It first consists in modelling the layout with simple geometric elements like segments of straight lines or bows of circles. Then, a clustering step allows the identification of more complex patterns like circles or squares. We have shown that the temporal structuring of drawings (Bender and Meulenbroek's figures) can help in estimating the handwriting skill level children have reached. Let us emphasize that the method allows to quickly have dynamic information which the human being cannot reach during a simple visual monitoring of the children production. A medium-term objective is to extend these methods on a production of writing.

The second purpose was to determine which features can help to distinguish between the children having writing difficulties and others. An exploratory analysis of the data, using an ascending hierarchical clustering and a sequential forward selection procedure, enabled us to identify a significantly reduced number of relevant features (about 8%). These features describe the automation level of the children graphic activity. A very simple classification test showed that these primitives, in most of cases, provide the school level of the children having a regular schooling. Furthermore, assignments of children, having difficulties, to their level seldom occur, and to higher one never occur. These results are promising. The resulting tool could be very helpful to the early detection of children presenting difficulties, the follow-up of their progression in order to prevent school failures.

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