Modulating Population Granularity for Improved Diagnosis of Developmental Dyspraxia from Dynamic Drawing Analysis

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Abstract

In this paper, we describe a diagnostic tool for automated assessment of developmental dyspraxia among children using Beery's VMI test drawings. Various attributes extracted from the dynamic pen movements are used for this assessment. The test environment is exactly the same as that used in conventional VMI tests, except that the test population is partitioned into several age-bands. The population granularity significantly improved the diagnostic accuracy and also revealed interesting results despite limited data availability.

1. Introduction

Analysis of handwriting and drawings are often used to reveal physio-psychological states of a person. Researchers have used these for the diagnosis and/or assessment of severity of Parkinson's disease [1], stroke related problems [2], and so on. In this paper we present a tool for improved diagnosis of developmental dyspraxia in children by automated analysis of the copying of geometric shapes.

Dyspraxia is a neurological disorder which is associated with difficulty in planning and carrying out complex movements. Developmental dyspraxia is common among children and very little is known about its cause. Dyspraxic children often present with a range of difficulties including poor academic progress, speech delays and impairments, right-left disorientation, as well as emotional and behavioural difficulties due to rejection, frustration and low self-esteem [3]. Many children fail to have their difficulties recognized, and are often simply categorized as 'clumsy' [4]. An appropriate means of identifying and assessing such children is clearly therefore very important and, if automated in its implementation, can provide effective and efficient screening on a widely available basis.

The Visual Motor Integration (VMI) test [5] is a frequently used assessment procedure for dyspraxia among children. By judging children's ability to copy a set of geometric shapes, their developmental states are ascertained. The conventional VMI test procedure mainly concentrates on the finished quality of the copied shapes (e.g., completeness of the drawing, relative positioning of shape segments, etc.). We have already reported that a rich set of information can be extracted by examining the dynamic execution pattern of the drawings and a combination of standard static, dynamic, and execution strategy features can be effectively used as diagnostic indicators of developmental dyspraxia among children [6,7]. In this paper we argue that variability in the test population due to demographic attributes such as age, gender, etc. is significant and incorporation of these can lead to a superior discrimination. Empirical results support this hypothesis and significantly improved performance is achieved when age-based granularity is incorporated.

2. Developmental Dyspraxia

Dyspraxia is a neurologically based disorder of the functions associated with the planning and execution of movements to achieve a given task. It is one of the most common developmental disorders among children and may affect any or all areas of development – physical, intellectual, emotional, social, language, and sensory. Under normal circumstances, children with dyspraxia may appear no different from their peers. Only when new skills are tried or known ones taken out of context, do their difficulties generally become apparent. The World Health Organization (WHO) states that it affects 6% of all children, while other estimates vary between 10-20% [8].

Despite considerable research over the years, very little is known of its cause. It is believed this may be caused by a glitch of some kind at the foetal developmental period or at birth that damages some neuron cells. Dyspraxia is not the result of poor physical strength, impaired primary sensation, or anything that would show up on normal neurological examination.

Proceedings of the 9th Int'l Workshop on Frontiers in Handwriting Recognition (IWFHR-9 2004)
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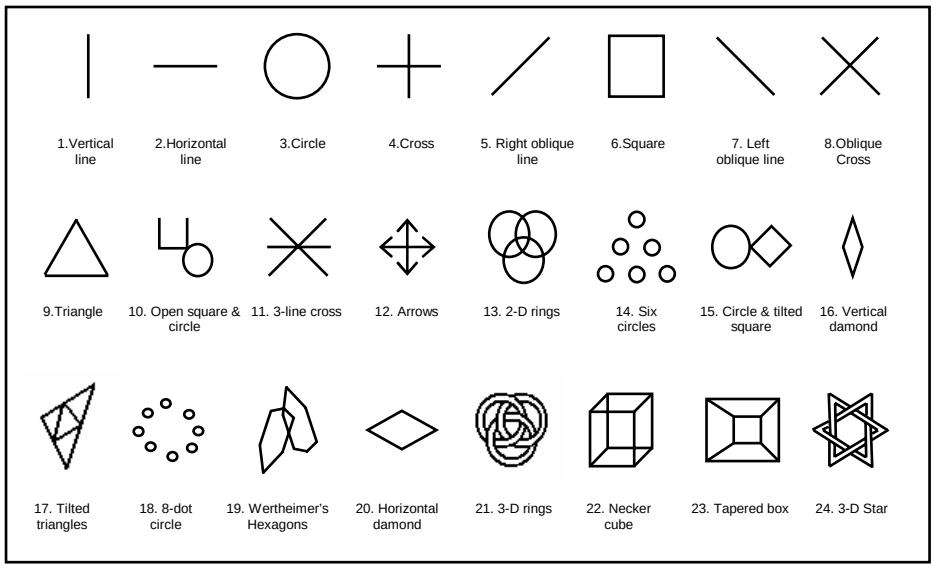

Figure 1. Shapes from the visual-motor integration (VMI) test.

The diagnosis of dyspraxia often involves a general screening carried out by a paediatrician, community medical officer, or clinical psychologist. In many cases the symptoms are not apparent until the impaired systems are overtaxed or the condition has severely deteriorated. There is no apparent clinical cure, and the treatment usually involves retraining the child (by specialist therapists) to overcome the observed difficulties.

3. The Visual-Motor Integration (VMI) Test

The Visual Motor Integration test (VMI), one of the standard tests adopted for assessing dyspraxia, is based on the observation that children's ability to copy geometric forms has a strong correlation with their academic achievements. The VMI test has had wide acceptability for use with children of varying background and cultures throughout the world.

The VMI test requires children to copy with pencil and paper a sequence of geometric shapes of increasing complexity. Figure 1 illustrates the 24 shapes used for the analysis in sequence. A smaller set is used for very young children. The VMI test procedure is generally not time-restricted, and not all children copy all the shapes. No feedback or encouragement is allowed except for some simple instructions which are essential for the proper conduct of the test. The test administrator compiles a raw-score which is then converted to other standardized metrics. The higher are the scores, the more competent the performance. The test is traditionally administered by an occupational therapist.

4. Proposed Diagnostic System

The proposed system for automated diagnostic/ screening is illustrated in Figure 2. It comprises a parallel combination of 24 classifiers, each committed to a particular VMI shape and acting independently. The children are categorized into a number of age groups and this information is passed both to the member classifiers and the combiner. The member classifiers, in our implementation, contain separate mathematical models for each age group. The classifier output is a hard decision (i.e., whether dyspraxia is or is not present) along with its relative confidence in that decision. These individual verdicts are then fed to a decision-fusion engine which, using standard multi-expert fusion protocols, reports the overall diagnosis.

The key to the scheme under consideration here is the capture of the execution mechanism of the drawings. The interface adopted for this collection is a standard computer-linked graphics tablet. The paper-based VMI test sheets are affixed to the tablet surface and the child copies the shapes directly on to paper using of a cordless digitizer pen. The experimental set-up is, therefore, made to parallel almost exactly the conditions prevailing when conventional manual testing is undertaken. In our automated testing, the pen movements and exerted pen-pressures are recorded as a time-stamped series of (x,y,p) vectors. Many systems may also record and utilize additional information such as the angle and tilt of the pen etc. It has already been shown that a range of interesting discriminatory metrics/attributes can be extracted from this data [6,7], which are subsequently used for our analysis.

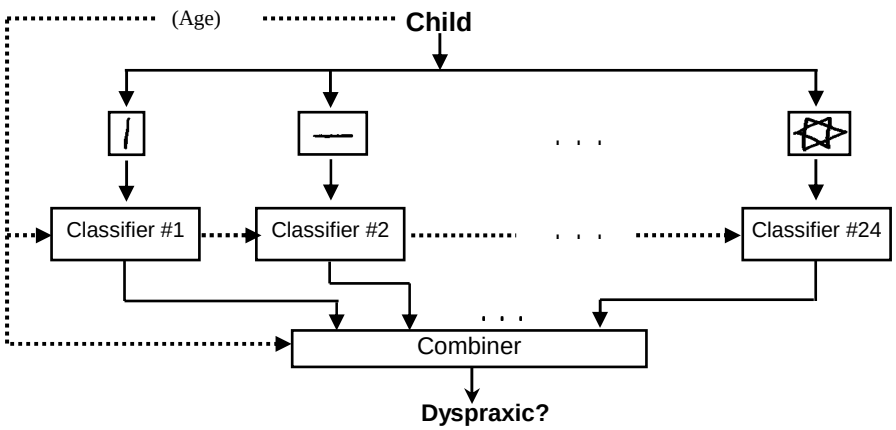

Figure 2. The proposed diagnostic system

5. Experiments and Results

A number of empirical investigations were conducted to assess the impact of granularity with respect to age banding on dyspraxia screening. Data for this evaluation trial were collected from two distinct test populations. The first group is from children with diagnosed dyspraxia and referred to a local Paediatric Assessment Centre. There are 75 dyspraxic children, 59 male and 16 female. The second group comprises non-screened children from a local primary school with no known disability. This group has 72 children of whom 32 are male and 40 female. 'Biological age' of both these populations ranged between 5 and 12 years. All these children underwent conventional VMI testing while their dynamic pen movement details were recorded as described previously.

Three types of features were extracted from the pen-dynamics: *static*, *dynamic* and *strategic*. The static features, such as width, height, etc., are indicators of the quality of the finished drawing. The dynamic features (e.g., velocity and pressure profile, various time intervals, etc.) provide insight into the mechanism of the drawing execution. The strategic features highlight aspects of drawings such as stroke sequencing, start/end locations, etc. In total, a 21-dimensional feature vector is extracted from each shape drawn. All measurements are normalized to a [0,1] scale and all the extracted features are used for the analysis irrespective of the shape complexities.

The first experiment focused on the ability of the member classifiers in identifying dyspraxia by using features from a single shape without incorporating any population granularity (i.e., all children are put into a single age group). Numerous classification techniques are available (e.g., statistical, AI, biologically-inspired networks etc.) [9]. We used a range of such algorithms and the observed error rates are presented in Table 1.

Table 1. Diagnosis error rates [irrespective of age].

VMI Shape #	Algorithm*							
	UDC	Parzen	Tree	LogLC	SVM	1-NN	Fisher	*Best*
Before fusion:								
1	43.8	44.5	51.4	**38.4**	39.0	51.4	41.1	LogLC
2	43.2	44.5	50.0	44.5	**42.5**	45.9	45.2	SVM
3	**32.2**	36.3	36.3	34.3	35.6	34.3	32.9	UDC
4	44.3	**32.2**	40.3	36.2	36.9	36.2	34.2	Parzen
5	55.7	**36.9**	49.0	43.0	41.6	45.0	45.0	Parzen
6	45.6	45.6	49.7	45.0	44.3	**40.3**	47.0	1-NN
7	47.0	45.0	53.7	**42.3**	42.3	50.3	42.3	LogLC
8	**41.9**	50.7	42.6	44.6	48.0	53.4	47.3	UDC
9	47.3	**39.2**	41.9	42.6	45.3	44.6	40.5	Parzen
10	50.3	43.6	49.7	**38.9**	47.0	52.4	40.3	LogLC
11	46.3	45.6	49.7	**38.9**	49.0	52.4	39.6	LogLC
12	38.9	49.7	49.7	**33.6**	39.6	51.7	37.6	LogLC
13	37.6	44.7	46.8	**36.9**	44.0	51.8	37.6	LogLC
14	36.9	41.1	48.2	36.9	**34.0**	43.3	36.9	SVM
15	42.9	**37.9**	48.6	39.3	44.3	44.3	39.3	Parzen
16	42.3	36.0	41.4	35.1	**32.4**	39.6	35.1	SVM
17	**40.5**	52.3	55.9	55.0	45.1	48.7	50.5	UDC
18	**36.9**	41.4	50.5	41.4	43.2	50.5	41.4	UDC
19	35.1	36.2	42.6	**31.9**	37.2	35.1	33.0	LogLC
20	**36.2**	44.7	43.6	40.4	38.3	38.3	39.4	UDC
21	43.0	44.1	46.2	50.5	60.2	**39.8**	50.5	1-NN
22	40.6	42.0	**31.9**	39.1	53.6	44.9	37.7	Tree
23	43.5	43.5	46.4	**26.1**	33.3	49.3	27.5	LogLC
24	59.7	41.8	53.7	50.8	44.8	**40.3**	52.2	1-NN
After fusion (by Mean rule):								
All 24 Shapes	30.9	29.8	31.8	26.9	34.0	30.1	27.4	**26.8**
Best 10 shapes	30.1	29.4	38.4	25.3	31.4	28.8	27.0	26.4
Best 5 shapes	30.6	27.0	33.2	26.4	29.3	27.7	25.2	28.9

*****UDC-*Uncorrelated quadratic Bayes classifier*, PARZEN-*Parzen densities based classifier*, TREE-*Decision tree classifier*, LOGLC-*Logistic Linear Classifier*, SVM-*Support Vector Classifier*, 1-NN-*Nearest neighbour classifier*, FISHER-*Fisher's Least Square Linear Classifier*

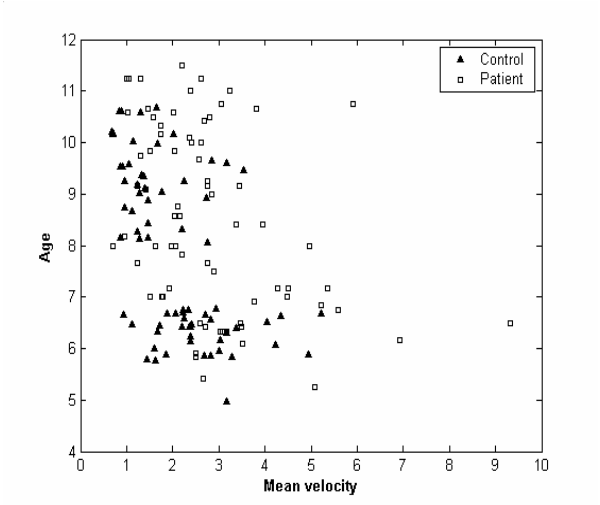

Figure 3. Behavioural shift with age (for shape 1)

Table 2. Diagnosis error rates for the Age Group I

VMI Shape #	Algorithm							
	UDC	Parzen	Tree	LogLC	SVM	1-NN	Fisher	*Best*
Before fusion:								
1	25.9	25.9	22.2	40.7	27.8	46.3	35.2	Tree
2	33.3	38.9	44.4	44.4	31.5	42.6	31.5	SVM
3	31.5	27.8	24.1	38.9	31.5	40.7	35.2	Tree
4	65.5	47.3	47.3	38.2	40.0	43.6	40.0	LogLC
5	41.8	50.9	49.1	52.7	32.7	50.9	47.3	SVM
6	32.7	32.7	50.9	38.2	32.7	40.0	40.0	UDC
7	36.4	41.8	36.4	45.5	36.4	52.7	45.5	UDC
8	38.9	37.0	51.9	35.2	33.3	38.9	27.8	Fisher
9	46.3	31.5	44.4	46.3	35.2	42.6	40.7	Parzen
10	30.9	29.1	45.5	32.7	29.1	38.2	27.3	Fisher
11	40.0	49.1	32.7	23.6	25.5	47.3	25.5	LogLC
12	25.5	29.1	38.2	36.4	21.8	30.9	25.5	SVM
13	29.2	43.8	41.7	45.8	27.1	41.7	35.4	SVM
14	31.3	39.6	39.6	37.5	27.1	43.8	29.2	SVM
15	54.2	35.4	39.6	41.7	31.3	41.7	41.7	SVM
After fusion (by Mean rule):								
All 15 Shapes	31.3	26.0	29.7	29.6	31.9	29.3	20.9	26.1
Best 10 shapes	30.1	25.7	28.6	22.2	31.3	27.4	22.5	22.3
Best 5 shapes	26.7	22.3	31.8	30.1	30.3	27.5	22.2	26.3

It is evident that a degree of diagnostic classification can be achieved from certain individual shapes, although in many cases, member classifiers failed to effectively discriminate between dyspraxic and normal children. Diagnostic accuracies are strongly dependent on the underlying classification algorithm. These relatively low accuracies may be attributed to the small size of the sample population.

In the second stage of our proposed system, the individual decisions are combined employing the 'Mean-rule' combination protocol [10]. In cases where a child did not draw some of the VMI shapes, the corresponding classifiers enforced decisions in favour of dyspraxia. The resulting global error rates are presented in the top row of the bottom section in Table 1. Note that identical classification algorithms were used for all the member classifiers. It is also evident that many shapes offered very low discriminatory information and their inclusion is unlikely to contribute towards an effective decision-fusion. Therefore, we attempted fusing only the best 10 or 5 decisions and the resulting error rates are shown in the bottom two rows of Table 1. We also observed that different member classifiers perform optimally under different algorithms (as indicated in the rightmost column of Table 1). So, we also combined member classifiers while using their most suited algorithm. Error rates thus achieved from the combination are shown in the rightmost column of the bottom three rows.

A general observation from this empirical study is that fusion of classifiers offered a more robust decision, although the combined performance is sometimes poorer than some of the fusing members. This is due to the adverse effect of combination with the non-discriminatory classifier outputs. Performance thus improved when only the best-N classifiers from the pool were combined. It is also noticeable that, for some of the combinations, the best-5 shapes generated less accurate decisions than best-10. This happened because the success of a combination not only lies in the individual superiority of the members but also depends on their mutual independence and diversity [11].

Another reason for the low accuracies of the member classifiers may be the high variability in the copied drawings introduced by the very wide range of child ages. Since the symptoms of dyspraxia can, to an extent, be ameliorated with increasing age, drawings of simple shapes of an older dyspraxic child may appear very similar to that of a healthy younger child. Figure 3 illustrates the change in behavioural trait with increasing age by plotting mean-velocity of all subjects tested across all biological age ranges with respect to their copying of Shape 1 (vertical line). This graph confirms the tendency of patients to draw faster than controls of a similar age, and also shows that older patients tend to develop a strategy of slower execution than their younger counterparts. This anomaly can be handled by categorizing children into a number of age groups so that children with anticipated similar ability are grouped together.

With this in mind, we created three heuristic groups where Group I included children below 7 years of age, Group II those aged 7 and 8 and Group III consists of children older than 8 years. We tested the system

performance with the population from one group only and the resulting error rates are shown in Tables 2, 3 and 4. In Table 2, VMI shapes only up to 15 are shown because very few children in this age group actually draw Shapes 16 or beyond.

We can readily see that the overall accuracy after fusion is significantly enhanced in most cases for all age groups. The relatively higher error rates found in Table 2 imply that Age Group I should be further split into smaller age bands.

In line with our previous observations, it is obvious that selection of an appropriate subset of shapes and corresponding classification algorithms can lead to the implementation of a superior diagnostic system. The choice of shapes and algorithms is related to the age of the child under consideration and it may even be worth exploring the possibility of incorporating non-VMI shapes into this automated diagnostic tool.

Table 3. Diagnosis error rates for the Age Group II.

VMI Shape #	Algorithm							
	UDC	Parzen	Tree	LogLC	SVM	1-NN	Fisher	*Best*
Before fusion:								
1	64.7	47.1	38.2	50.0	32.4	44.1	52.9	SVM
2	20.6	41.2	32.4	50.0	29.4	38.2	44.1	UDC
3	29.4	32.4	26.5	35.3	38.2	29.4	38.2	Tree
4	67.7	32.4	29.4	23.5	23.5	29.4	35.3	LogLC
5	67.7	29.4	41.2	47.1	38.2	41.2	50.0	Parzen
6	26.5	41.2	20.6	26.5	23.5	41.2	26.5	Tree
7	67.7	47.1	55.9	50.0	32.4	41.2	50.0	SVM
8	32.4	32.4	32.4	47.1	32.4	29.4	41.2	1-NN
9	41.2	58.8	41.2	41.2	38.2	52.9	29.4	Fisher
10	47.1	41.2	23.5	17.7	38.2	50.0	29.4	LogLC
11	50.0	41.2	41.2	47.1	32.4	50.0	32.4	SVM
12	44.1	58.8	50.0	44.1	32.4	64.7	50.0	SVM
13	33.3	30.3	30.3	39.4	36.4	33.3	21.2	Fisher
14	42.4	48.5	33.3	57.6	33.3	33.3	33.3	SVM
15	30.3	36.4	21.2	27.3	36.4	33.3	30.3	Tree
16	40.9	31.8	54.6	54.6	36.4	31.8	45.5	Parzen
17	50.0	45.5	59.1	4.6	77.3	50.0	4.6	Fisher
18	36.4	45.5	54.6	45.5	50.0	50.0	45.5	UDC
19	33.3	22.2	55.6	55.6	16.7	33.3	55.6	SVM
20	33.3	33.3	61.1	22.2	27.8	38.9	27.8	LogLC
21	35.3	52.9	76.5	23.5	47.1	70.6	23.5	LogLC
22	61.5	61.5	61.5	46.2	46.2	61.5	53.9	LogLC
23	15.4	38.5	30.8	69.2	53.9	38.5	53.9	UDC
24	7.7	38.5	30.8	69.2	61.5	30.8	76.9	UDC
After fusion (by Mean rule):								
All 24 Shapes	27.3	18.4	17.1	17.8	21.4	19.0	21.3	**15.1**
Best 10 shapes	25.9	13.2	18.4	19.3	11.4	15.9	21.1	10.3
Best 5 shapes	33.6	10.3	19.1	24.7	12.4	13.6	18.9	15.6

Table 4. Diagnosis error rates for the Age Group III.

VMI Shape #	Algorithm							
	UDC	Parzen	Tree	LogLC	SVM	1-NN	Fisher	Best
Before fusion:								
1	37.9	50.0	29.3	34.5	43.1	43.1	41.4	|Tree
2	37.9	46.6	53.5	44.8	43.1	34.5	44.8	1-NN
3	34.5	41.4	22.4	37.9	39.7	37.9	36.2	Tree
4	40.0	33.3	48.3	40.0	40.0	41.7	38.3	Parzen
5	36.7	36.7	38.3	48.3	41.7	50.0	55.0	UDC
6	31.7	30.0	45.0	38.3	31.7	31.7	38.3	Parzen
7	45.0	46.7	35.0	36.7	48.3	55.0	40.0	Tree
8	35.0	46.7	36.7	40.0	35.0	51.7	38.3	UDC
9	35.0	40.0	28.3	26.7	33.3	35.0	30.0	LogLC
10	40.0	30.0	36.7	38.3	35.0	38.3	38.3	Parzen
11	50.0	46.7	41.7	41.7	45.0	46.7	30.0	Fisher
12	58.3	33.3	45.0	31.7	28.3	46.7	30.0	Fisher
13	58.3	46.7	56.7	40.0	43.3	48.3	48.3	LogLC
14	33.3	40.0	35.0	26.7	56.7	41.7	40.0	LogLC
15	35.6	30.5	33.9	32.2	28.8	33.9	30.5	SVM
16	32.2	35.6	33.9	37.3	33.9	37.3	40.7	UDC
17	37.3	44.1	45.8	44.1	40.7	40.7	40.7	UDC
18	33.9	42.4	45.8	32.2	44.1	50.9	23.7	Fisher
19	39.3	58.9	46.4	39.3	48.2	33.9	46.4	1-NN
20	33.9	25.0	44.6	32.1	35.7	30.4	33.9	Parzen
21	41.1	39.3	30.4	35.7	42.9	33.9	42.9	Tree
22	41.7	27.1	56.3	39.6	31.3	27.1	45.8	Parzen
23	35.4	41.7	45.8	39.6	31.3	52.1	29.2	Fisher
24	55.3	40.4	36.2	48.9	46.8	40.4	38.3	Tree
After fusion (by Mean rule):								
All 24 Shapes	32.2	26.6	26.8	24.2	24.9	23.6	24.7	**13.4**
Best 10 shapes	29.7	15.6	25.0	18.3	24.5	21.9	26.1	22.0
Best 5 shapes	30.7	20.5	24.2	21.9	21.9	19.0	24.2	20.4

Table 5 shows the error rates for the whole population. These values can now be compared with those shown in the bottom 3 rows of Table 1. By considering all the children as belonging to one age group we obtained error rates around 26%. However, by introducing just three separate age categories, the error rate achieved improves to around 19%. This is indicative of a very fruitful avenue to explore for improved assessment of dyspraxia in the future.

6. Conclusion

This paper has outlined an approach, based on classifier combination techniques, to the design of an automated system for screening dyspraxia in children. The potential of the proposed system has been discussed in the context of the established VMI test. Population granularity was introduced by categorizing children into several age groups which subsequently lead to a 26% improvement in its diagnostic ability.

Table 5. Overall diagnosis error rates of the population (Age Groups I, II and III).

VMI Shape #	Algorithm							
	UDC	Parzen	TREE	LogLC	SVM	1-NN	Fisher	*Best*
After fusion (by Mean rule):								
All Shapes	30.6	24.3	25.4	24.6	26.7	24.6	22.4	**18.7**
Best 10 shapes	28.9	18.8	24.7	20.1	23.8	22.5	23.5	21.9
Best 5 shapes	29.9	18.6	25.8	25.8	22.7	20.9	23.1	20.1

It is apparent that error rates reported here can nevertheless be considered rather high. However, such figures are not uncommon when dealing with a small population with very high variability.

Dyspraxia is a general categorization of a range of diverse symptoms and phenomena, and dyspraxic children often also suffer from other neuro-psychological abnormalities such as dyslexia, attention deficit hyperactivity disorder (ADHD), etc. [12]. These complex mixtures of variables make it nearly impossible to introduce a common-platform solution and point towards the need for a greater degree of granularity in population specification. The initial results of this study strongly support this notion.

Granularity may be introduced in many forms. We investigated the impact of population granularity on our system performance. Despite heuristic age-based partitioning, the improvements are noticeable and point towards the necessity of more sophisticated clustering of the subjects. Similar granularities may be introduced based on gender, handedness, and so on.

Despite the embryonic stage of the investigation reported here, it is apparent that an automated system for dyspraxia screening may be developed based on the pattern analysis paradigm. Furthermore, a subset of the VMI shapes is capable of producing superior diagnostic decision.

Acknowledgement

The authors gratefully acknowledge the support of the UK Engineering and Physical Sciences Research Council, and the help of their clinical collaborators Mrs Wendy Clark, Dr Roger Bradford and Mrs Marian Bond. The authors also acknowledge the support of the staff and children from Blean School and the Mary Sheridan Centre, Canterbury, UK.

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