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NOVEL RULE-BASED STATIC AND DYNAMIC FEATURE EXTRACTION FROM FIGURE COPYING TASKS FOR THE DETECTION OF VISUO-SPATIAL NEGLECT

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A series of static rule-based assessment criteria and dynamic constructional features are defined and used to analyse the hand-drawn responses from a geometric figure copying task. Assessment subjectivity is removed by the algorithmic definition of analysis criteria and test diagnostic sensitivity to the condition of visuo-spatial neglect is increased through the analysis of the novel dynamic features. This sensitivity increase is demonstrated by the identification of constructional performance deficits in test responses which appear 'normal' by conventional static assessment. The investigation is carried out with a population of stroke patients.

1 Introduction

The term *visuo-spatial neglect* describes a dysfunction caused by brain damage[1]. The main effect of the condition is to cause subjects to fail to respond to stimuli in the visual field on the opposite side to the location of the lesion[2]. Diagnosis of the condition is critical for the selection of a rehabilitation process specially devised to compensate for the effects of neglect[3]; inadequate diagnostic data may result in a failure to respond to treatment. Traditional testing has exploited the visual inattention effect by measuring the identification of objects within all areas of the visual field.

A standard neuropsychological technique for the assessment of neglect is the use of a series of writing and drawing tests which can be used to *quantify* performance. Tasks such as the cancellation of printed targets[4] or the drawing/copying of simple geometric shapes[5] on a sheet of paper which is placed directly in front of the patient are widely used. The responses of these tasks are then evaluated by therapists or trained assessors. Conventional assessment of figure copying tasks relies upon subjective evaluation, often leading to inconsistencies in application of the marking criteria [6]. A number of attempts have been made to standardise the assessment of geometric drawings[7] devising criteria based on drawing accuracy, positioning and the number of image components drawn[8].

The use of *dynamic* features – features relating to the constructional aspects of test performance such as drawing time and pen velocity - from straight line (rather than figure copying) drawing tests[9] has been shown to produce significant differences within a population of neglect subjects. The constructional aspects of drawings made by other clinical populations have been examined through the use of computer-based recording of pen movements[10]. In this study both accuracy and

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consistency in static assessment were obtained and dynamic features revealed differences between test populations which were previously unobtainable.

The aims of the study described in this paper are:

- to assess diagnostic capability of a set of component-related rule-based marking criteria applied to the responses from a figure copying task for the detection of neglect, in an attempt to define an objective scheme of assessment.
- to establish the dynamic properties of figure copying task execution

The data presented in this paper have been extracted using a computer-based test infrastructure, whereby the drawings are made on a sheet of paper (*test overlay*) which is placed on a graphics digitisation tablet. The increased positional resolution of the tablet enables the accuracy and fine-movement dynamics to be assessed with consistency. Applying algorithmically-defined feature extraction routines to the responses removes subjectivity. The time-stamping of positional data enables the computation of the dynamic or constructional features of test performance hitherto unobtainable from conventional assessment of pencil-and-paper tasks.

2 Methodology

30 neglect test subjects were included in the trial, identified using conventional clinical assessments. Stroke subjects without neglect were included in a stroke control test group (SC). 58 subjects were included in this group. In addition, a series of 13 healthy age matched control subjects (AMC) with no known history of vascular disease were also assessed. Three geometric shapes (a square, cross and cube) were used as models for the figure copying task. The cross and the cube have been found to give the best separation between neglect and non-neglect RCVA subjects based on judged performance characteristics[11]. The square was selected for its simplicity, signified by the small number of components (sides), thereby providing a basic performance screening task. The shapes were printed individually in the top horizontal centre of three separate test overlays. The test subject was required to copy the shape directly below the printed image. Position data was captured using a Wacom WD1212 graphics digitisation tablet (spatial accuracy of 6.25 lines/mm) sampled at a rate of 100Hz. The test overlays were placed individually on the surface of the tablet and the test subject asked to copy the image using a cordless biro ink pen.

Rule-based assessment criteria are used to standardise the static assessment of the drawn shapes. Simplifying the scoring process to award a 'pass' (normal response) or 'fail' (neglect response) to each drawing enabled the definition of the requirements for a particular shape drawing to be classified as being from a normal population. Furthermore, this removed the subjectivity inherent within conventional assessment techniques. Retaining the 'component present' elements used in the existing drawing score methodologies[8], the following rules were defined along with the number of constituent assessed components within each shape:

- **Square** - 4 edge components with no perseveration (multiple drawing of a single component). Edges need not form corners and opposite sides need not be perpendicular as these are assessed by additional static features described elsewhere. Number of components: 4 edges.
- **Cross** - Drawings are excluded if the 5 sub-boxes that form the cross are not present in a response. The sides of each box need not be perpendicular. The boxes, however, must form a cross shape. Each box must comprise 4 sides. Number of components: 5 sub-boxes.
- **Cube** - the drawing must contain 7 vertices; 4 forming the 'square' section of the cube (the square formation rules defined above are applied) and 3 others forming the top left, top right and bottom right of the three-dimensional section of the drawing. Number of components: 7 assessment vertices.

Components are assessed by analysing the static drawn image using standard line extraction image processing techniques, generating a list of positional and size data for each component within the drawing. Analysis of these lists can determine the location and the number of components detected within each drawing. Two main strands of dynamic feature are extracted from the test responses detailing timing and pen kinematic aspects of the drawing performance. The timing features extracted from the test responses are: *Drawing time (sec)* - the time period when the pen is drawing on the surface of the tablet, *Movement time (sec)* - the time during which the pen is removed from the surface *during the drawing process* and *Movement to drawing time ratio* - giving the ratio between amount of time spent with the pen drawing and removed from the tablet (a larger proportion of movement time indicates a disjoint approach to drawing construction). This ratio is calculated by dividing *movement* by *drawing* times. *Overall execution time (sec)* is defined at the sum of the *drawing* and *movement* times.

Two additional dynamic features are also extracted: *Mean velocity (mm/sec)* - Pen velocity across the surface of the tablet is calculated by taking the first derivative of the coordinate pair displacement against time (Velocities are calculated only when the pen is on the tablet surface) and *Pen lifts* - The number of times the pen is removed from the tablet *during* the drawing time (not including the final pen lift at the end of the drawing). This quantifies the number of movement segments within the drawing. Significant differences between test groups for each extracted feature are calculated using a one-way analysis of variance (ANOVA) with a significance level of 0.05. t tests were used to identify significant differences between individual test groups.

3 Results

Table 1 shows the percentage of each group failing the *rule-based pass/fail* evaluation of the static drawings. It can be seen how the increasing complexity of the shape causes a proportional error rate in drawings with the cube causing the largest proportion of failures in all test groups. The biggest difference between the SC and the Neglect group (and also between the AMC and Neglect group) is produced from the cross drawing task. Table 2 details the mean and standard deviation *number of features* (as defined by the assessment criteria) located in each of the drawing tasks. It can be observed that the neglect group consistently draw fewer of the defined features.

Table 1 : Percentage of group excluded from analysis using rule-based exclusion

	Neglect	**SC**	**AMC**
Square	36.6 %	14.1 %	0 %
Cross	53.3 %	21.1 %	0 %
Cube	70.0 %	56.1 %	30.7 %

Table 2 : Mean number (and standard deviation) of components drawn.

	Neglect	**SC**	**AMC**
Square	3.55 (1.83)	4.02 (0.81)	4.0 (0)
Cross[1]	3.43 (1.85)	4.23 (1.57)	5.0 (0)
Cube[2]	4.90 (2.20)	5.68 (1.62)	6.46 (1.20)

[1] Significant between AMC and Neglect Group (p=0.013)
[2] Significant between AMC and Neglect Group (p=0.043)

Table 3 : Square Copying Results

Square Copying	**Neglect**		**SC**		**AMC**	
	Mean	SD	**Mean**	SD	**Mean**	SD
Dynamic Features						
Number of Pen Lifts	**4.16**	5.68	**2.61**	3.15	**3.54**	1.56
Total Movement Time (Sec)	**3.23**	3.55	**2.21**	2.49	**2.53**	1.26
Total Drawing Time (Sec)	**5.31**	3.76	**5.44**	2.86	**3.28**	1.39
Movement to Drawing Time Ratio[1]	**1.54**	2.30	**0.54**	0.43	**0.86**	0.44
Overall Execution Time (Sec)	**8.95**	4.90	**7.86**	4.26	**6.17**	2.26
Mean Pen Velocity (mm/sec)[2]	**2.88**	1.67	**2.90**	1.89	**4.82**	3.50

[1] SC vs Neglect: p=0.017, [2] AMC vs Neglect: p=0.046, AMC vs SC: p=0.018

Following the exclusion of drawings that fail the drawing criteria, a range of dynamic features are extracted from the remaining drawings. Any significant differences detected between groups in these features (using an ANOVA) indicate differences which would not be noted in conventional assessments as all responses included in this further analysis are considered 'normal' by static component-based analysis. The results shown in Tables 3 to 5 show the mean and standard deviation of the feature results within the individual test groups. These results indicate the overall performance trend of each group. Any significance between two identified populations (when $p<0.05$) within a feature is detailed at the foot of each table.

Table 4 : Cross Copying Results

Cross Copying	Neglect		SC		AMC	
	Mean	SD	**Mean**	SD	**Mean**	SD
Dynamic Features						
Number of Pen Lifts[1]	**11.21**	8.48	**5.84**	4.19	**7.54**	2.79
Total Movement Time (Sec)[2]	**16.30**	16.07	**7.12**	5.93	**5.78**	2.86
Total Drawing Time (Sec)[3]	**14.61**	5.60	**12.17**	7.01	**7.11**	3.13
Movement to Drawing Time Ratio	**1.22**	1.69	**0.71**	0.69	**0.92**	0.41
Overall Execution Time (Sec)[4]	**30.91**	17.34	**19.35**	10.05	**13.12**	5.14
Mean Pen Velocity (mm/sec)	**2.77**	1.16	**2.82**	1.78	**4.67**	3.14

[1] SC vs Neglect: p=0.003, [2] AMC vs Neglect: p=0.009, SC vs Neglect: p=0.002
[3] AMC vs Neglect: p=0.016, [4] AMC vs Neglect: p=0.001, SC vs Neglect: p=0.003

Table 5 : Cube Copying Results

Cube Copying	Neglect		SC		AMC	
	Mean	SD	**Mean**	SD	**Mean**	SD
Dynamic Features						
Number of Pen Lifts[1]	**14.33**	9.15	**9.21**	3.30	**8.60**	3.13
Total Movement Time (Sec)	**12.74**	8.57	**10.82**	6.13	**7.23**	3.20
Total Drawing Time (Sec)	**14.61**	6.30	**11.39**	6.54	**7.63**	3.82
Movement to Drawing Time Ratio	**0.92**	0.50	**1.28**	0.97	**1.09**	0.61
Overall Execution Time (Sec)	**27.88**	12.43	**22.26**	10.30	**15.23**	7.00
Mean Pen Velocity (mm/sec)	**3.04**	1.77	**3.50**	2.32	**5.95**	6.66

[1] SC vs Neglect: p=0.034

4 Discussion

The results from the study have shown that it is possible for dynamic features to distinguish between neglect and control populations based on responses which would conventionally be classed as 'normal'. In this way, the sensitivity of a figure copying task is improved. Static-based analysis of the drawing responses have also been standardised by the introduction of assessment rules. The classification results obtained using these rules correspond with previous studies of neglect-based drawings[15] in that the cross shape provides the best diagnostic separation between a neglect and control population.

In analysing the features that produce significant differences between neglect and control populations, the *pen movement* and *overall task execution time* during the drawing process are significantly greater for the cross and star shapes. The number of *pen lifts* is also significant for the cross, star and cube, which indicates a disorganised component-based approach to task execution. Neglect subjects perform differently from brain-damaged control patients by drawing each component separately with an extended planning (*pen up and movement*) phase between individual drawing phases. Analysis of individual features reveals mean differences which, although not significant, show that performance trends are distinct from control populations. An improved automated diagnostic conclusion may be obtained by assessing the outcome of a series of features and selecting the decision fusion which provides the best classification rate. Performance progress over time can be monitored by assessment of the quantitative values obtained from the algorithmic implementation of the dynamic and static features. The simplification of the rule-based assessment to a 'pass/fail' analysis enables a high-level (or instant) evaluation of performance. Specific performance details can be inspected using a quantitative algorithmic assessment of the dynamic and static features.

5 Conclusions

This paper has shown that by capturing drawing responses from a series of figure copying tasks using a computer and graphics tablet it is possible to standardise the assessment of drawings using a series of static rule-based 'pass/fail' marking criteria and algorithmically defined static and dynamic features. It has been shown that performance differences do exist with respect to novel dynamic features, providing an important insight into the constructional aspects of test performance.

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