A novel multi-stage approach to the detection of visuo-spatial neglect based on the analysis of figure-copying tasks

R.M. Guest and M.C. Fairhurst
Department of Electronics,
University of Kent,
Canterbury, Kent, UK, CT2 7NT
+44 1227 823717
{rmg, mcf}@ukc.ac.uk

ABSTRACT
This paper examines a computer-based technique for the detection of visuo-spatial neglect from the responses of a simple geometric shape copying task. Defining pass/fail criteria based on the presence of drawn components, responses can be accurately and objectively assessed. More importantly, we show that by analysing novel dynamic performance features detailing timing and constructional aspects of each response, significant performance deficits can be noted in drawings made by clinically diagnosed neglect subjects that would have been classified as 'normal' using conventional static analysis, thus improving the sensitivity of the assessment.

Keywords
Drawing analysis, automated diagnosis, visuo-spatial neglect

INTRODUCTION
Visuo-spatial neglect (VSN) is a dysfunction typically caused by stroke [1] which causes subjects to fail to respond to stimuli in the opposite side of the visual field to the location of the lesion [2]. Diagnosis of the condition is critical for the selection of a rehabilitation process to compensate for the effects of VSN [3]. Inadequate detection of VSN at an early stage of therapy will result in performance deficit from the patient during rehabilitation and a failure to respond to treatment, prolonging the time-scale required for recovery and hence increasing associated costs [4].

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 VSN is the use of a series of pencil and paper based tests which can be used to quantify performance [5]. These tests typically involve the completion or drawing of a task printed on a sheet of paper which is placed directly in front of the patient. Using a pencil or pen, tasks such as the cancellation of printed targets [6], bisection of lines [7] or the drawing of simple geometric shapes [8] are widely used. The responses of these tasks are then evaluated by therapists or trained assessors. A typical implementation of a drawing task involves copying a series of simple geometric shapes or representational drawings (for example: a house, a man, and a tree).

Conventional assessment of figure copying tasks relies upon the subjective application of a set of marking criteria. The Rivermead Behavioural Inattention Test (BIT) [9] is commonly used within a clinical environment for the diagnosis of VSN. Assessment of figure copying drawings in this task (shapes used are a star, cube, flower and three simple geometric shapes) is based upon the presence of components within a response, resulting in a score between 0 and 4 awarded globally across all six drawings. The marks awarded are based on the individual assessor's interpretation of the quality of the drawing, preventing any standardisation between and within assessors, and this often leads to inconsistencies in application of the marking rules [10]. Various attempts have been made to rectify this [11,12,13], but a degree of subjective judgement from the assessor generally remains.

This paper seeks to assess the diagnostic capability of a set of “component-present” rule-based marking criteria for figure-copying tasks which can be applied automatically/algoritmically (for objectivity) in detecting VSN, and to demonstrate how by analysis of simple dynamic properties of task execution greater diagnostic resolution might be achieved.
METHODOLOGY

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. Test data from right CVA (cerebral vascular accident or stroke) subjects was collected by a single Occupational Therapist from four different hospital centres in East Kent. 30 VSN test subjects were identified using the Conventional battery of the Rivermead BIT [9], 17 male, 13 female with a mean age of 74.06 (SD=7.95, range 90-59). The mean BIT score obtained by the VSN group was 87.03 (range 41-129). Stroke subjects scoring above 129 in the Conventional BIT battery were included in the stroke control test group (SC). 58 subjects (33 male, 25 female) were included in this group with a mean age of 74.45 (SD=8.39, range 92-57) and a mean BIT score of 143.55. In addition, a series of 13 healthy age matched control subjects (AMC) with no known history of vascular disease were tested by the same assessor. 13 age matched subjects were assessed (5 male, 8 female) with a mean age of 72.77 (SD = 4.07, range 79-63).

Figure 1 shows the cumulative distribution of the BIT marks awarded to test subjects. It can be noted from this chart that VSN is not an 'all-or-nothing' condition: the wide variation in BIT marks awarded to members of the VSN group shows the range of performance variability caused by the condition. The continuous range of scores extracted from the test indicates that the defined threshold provides an arbitrary division of performance. No significant differences were found in gender, age and the number of days post-stroke that testing was performed between test subject groupings.

This paper focuses on the “cross” target shape shown in Figure 2, which has been shown to be effective in this type of task [14]. The size of the cross was 42mm by 42mm (maximum height/maximum width), and subjects were required to copy the shape in a space directly below a displayed “target” or model shape.

Rule-based assessment criteria were used to standardise the static assessment of the drawn shapes. Simplifying the scoring process to award a 'pass' (normal response) or 'fail' (VSN response) to each drawing enabled the definition of the requirements for a particular shape drawing to be classified as being from a normal population. The rules used to assess the drawn cross were defined such that the drawing should be excluded if:
Figure 2: The target “cross” shape to be copied

- The 5 sub-boxes that form the cross are not present in a response and, though the sides of each box need not be perpendicular, the boxes must form a cross.

- Each box must comprise 4 sides - the 4 internal corners of the cross are used as spatial model comparison points.

A subject who failed to produce a drawing which met these conditions would be deemed to have “failed” the test, in the sense that, with respect to this piece of evidence, the detection of VSN is indicated.

We also wished to extract a variety of other features from the drawing, and the complete list of static features extracted from the drawn image is as follows:

**Width and height model differences** - calculated from the maximum and minimum drawn coordinates in the y and x axis respectively. Deviations from the actual model width and height provide a copying accuracy measure.

**Total drawing distance** - the total travel distance of the pen in mm. Perseveration (multiple repetition of a single line) is usually represented by an increased travel distance.

**Mean reference positional error** - calculated using the Euclidean distance between pairs of adjacent reference points located on the drawings. Reference points are located at corners within the model image, so corners within the drawn image are defined at the intersect or an interpolation of the intersection point if lines do not cross. A mean is taken of the differences between the model and the calculated distances to produce a value (mm) describing the drawing formation accuracy.

**Mean angle error** - computed by comparing the angles at each of the reference points against those defined in the model and dividing by the number of reference points.

However, a particularly novel aspect of this work is to exploit the availability of dynamic information about drawing execution (timing and kinematic aspects), and a number of dynamic features are therefore also extracted from the test responses, as follows:

**Drawing time (sec)** - time when the pen is drawing on the tablet surface.

**Movement time (sec)** - the time during which the pen is removed from the surface during the drawing process. In this way movement times are ignored a) before the pen initially marks the overlay and b) when the pen is finally removed from the tablet surface at the end of the drawing process.

**Movement to drawing time ratio** - gives the proportion of the overall task execution time with the pen removed which usually represents a planning and movement phase to the next drawing component, and is calculated as movement time divided by drawing time. A larger proportion of movement time indicates a disjoint approach to drawing construction.

**Overall execution time (sec)** – is drawing time + movement time

**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. Third order, four coefficient polynomial modelling is used to obtain a derivative of displacement at each coordinate point [15]. The mean velocity is obtained by summing the velocities at individual points within the drawing and dividing by the number of samples taken. Velocities are calculated only when the pen is on the tablet surface.

**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). Quantifies the number of movement segments within the drawing.

Significant differences between test groups are calculated using a one-way analysis of variance (ANOVA) [16] with a significance level of 0.05. t tests were used to identify significant differences between individual test groups. Any significant differences detected between groups in these dynamic features 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.

**RESULTS**

Using the simple rule-based assessment described in Section 2, 53.3% of true VSN subjects failed the test (and are hence correctly identified as VSN subjects), compared
with 21.1% of the stroke control group. These groups correspond to subjects nominally diagnosed as suffering from VSN based on the rudimentary static analysis described, and this therefore indicates the deficiencies of using the component-based assessment alone.

Following the exclusion of drawings that fail to pass the drawing criteria, a range of static and dynamic features are extracted from the remaining drawings (i.e. from subjects in whom VSN was not diagnosed). Table 1 lists relevant data. A range of dynamic features provide a separation between the SC and VSN groupings which again show the component-based drawing strategy of the VSN group (pen lifts and total movement time). Related to this strategy for the VSN subjects is an increased overall execution time for the drawing (which encompasses slower drawing phases).

The results from this preliminary study show that it is possible for dynamic based features to distinguish between responses from VSN and control populations which would conventionally be classed as 'normal', improving the sensitivity of figure copying tasks. We have also highlighted other features which, although not statistically significant, do indicate performance trends showing clear differences between the test populations. Static analysis of the drawing responses has also been standardised by the introduction of assessment rules which can be implemented algorithmically.

In analysing the features that produce significant differences between VSN and control populations, the pen movement and overall task execution time during the drawing process are important. The number of pen lifts is also significant, which indicates a disorganised component-based approach to task execution. VSN 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 reveal mean differences which, although not significant, show performance trends which 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.

<table>
<thead>
<tr>
<th>Cross Copying</th>
<th>VSN Mean</th>
<th>SD</th>
<th>SC Mean</th>
<th>SD</th>
<th>AMC Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dynamic Features</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of Pen Lifts</td>
<td>11.21</td>
<td>8.48</td>
<td>5.84</td>
<td>4.19</td>
<td>7.54</td>
<td>2.79</td>
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<tr>
<td>Total Movement Time</td>
<td>16.30</td>
<td>16.07</td>
<td>7.12</td>
<td>5.93</td>
<td>5.78</td>
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<td>Total Drawing Time</td>
<td>14.61</td>
<td>5.60</td>
<td>12.17</td>
<td>7.01</td>
<td>7.11</td>
<td>3.13</td>
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<td>Movement to Drawing</td>
<td>1.22</td>
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<td>0.71</td>
<td>0.69</td>
<td>0.92</td>
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<td>Overall Execution Time</td>
<td>30.91</td>
<td>17.34</td>
<td>19.35</td>
<td>10.05</td>
<td>13.12</td>
<td>5.14</td>
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<tr>
<td>Mean Pen Pressure (0-255)</td>
<td>115.82</td>
<td>61.85</td>
<td>144.81</td>
<td>48.73</td>
<td>147.65</td>
<td>55.67</td>
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<td>Mean Pen Velocity</td>
<td>2.77</td>
<td>1.16</td>
<td>2.82</td>
<td>1.78</td>
<td>4.67</td>
<td>3.14</td>
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<tr>
<td><strong>Static Features</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Width Model Difference</td>
<td>10.38</td>
<td>6.73</td>
<td>8.41</td>
<td>7.83</td>
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<td>5.14</td>
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<tr>
<td>Height Model Difference</td>
<td>9.31</td>
<td>10.14</td>
<td>4.82</td>
<td>4.51</td>
<td>7.10</td>
<td>4.73</td>
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<td>Mean Ref. Positional</td>
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<td>Mean Angle Error</td>
<td>9.37</td>
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<tr>
<td>Total Drawing Distance</td>
<td>123.69</td>
<td>60.55</td>
<td>146.10</td>
<td>60.44</td>
<td>164.32</td>
<td>58.11</td>
</tr>
</tbody>
</table>

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

Table 1 : Cross Copying Results
CONCLUSIONS
This paper has shown that by capturing drawing responses from a simple figure copying task 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 within novel dynamic features providing an insight into the constructional aspects of test performance.

The figure copying task is part of a wider computer-assessed battery of neuropsychological tests for VSN which have been used in a clinically-based trial. The combination of accurate and objective assessment of static features and the novel dynamic measurements both aid the diagnosis of VSN but also further the understanding of the condition with respect to constructional and timing aspects of test performance producing a clearer indication of rehabilitation progress.

ACKNOWLEDGMENT
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REFERENCES