Journal for Geometry and Graphics
Volume 6 (2002), No. 1, 99–109.

Predicting Academic Success of Engineering Students in Technical Drawing from Visualization Test Scores

Gerardo Prieto Adanez[1], **Angela Dias Velasco**[2]

[1]*Psychology Faculty, Salamanca University*
Avda. de la Merced, 109–131, 37005 Salamanca, Spain
email: gprieto@usal.es

[2]*Mechanics Dept., Engineering Faculty, Paulista State University*
Av. Ariberto Pereira da Cunha, 333, Guaratinquetá – SP – Brasil 12516-410
email: avelasco@feg.unesp.br

Abstract. While observing the difficulties of first-year engineering students toward learning technical drawing, taking into account the progressively reduced work time with them, and recognizing the importance of spatial aptitude in the engineering profession, we feel the necessity to improve the teaching methodologies in this subject. In our opinion, in order to effectively plan the didactic process, it is necessary to detect as early as possible those students who require more attention and support.

This study proposes an investigation of a visualization psychometric test that could facilitate an early diagnosis concerning the academic performance of technical drawing students.

To this end, a computerized version of the Mental Cutting Test (MCT) was carried out on a sample of Brazilian engineering students from the Paulista State University at Guaratingueta Campus (UNESP) and from the Polytechnic School of Sao Paulo University (EPUSP).

The test was analyzed by the Item Response Theory, with the Rasch model, a measurement model with optimal properties in order to estimate the level in spatial aptitude of the examinees. The results suggest that MCT can be useful in detecting those students with different performance levels in technical drawing.

Key Words: spatial aptitude, Rasch model, technical drawing

MSC 2000: 51N05

ISSN 1433-8157/$ 2.50

1. Introduction

The first year of engineering curricula presents great challenges and adaptation problems to the students. In some cases, these difficulties have negative consequences for the students' academic performance and can be the reason for leaving studies. This fact is not specific in Brazil, it appears in different countries [27]. The adaptation problems to a new curriculum are more serious in the subjects in which there is not a specific and wide work during high schools. Without any doubt, this is the case for technical drawing. We think that the activities in elementary and high schools do not promote sufficiently the development of spatial aptitudes. That is why teachers frequently have to attend students with limitations that could be improved with a distinct treatment. In our point of view, the teaching-learning process could have better support if it were possible early to detect the students with a low level of spatial aptitude in a way that allows to administer:

(1) a *distinct didactic treatment* or

(2) an *specific training program in spatial abilities.*

The first proposition is to apply the classic designs ATI (Aptitude $\times$ Treatment Interaction), that were proposed by Cronbach [7]. In his opinion, the analysis of the interactions between the students' aptitudes and the didactic methods allows one to adjust the teaching method to the aptitude level of a person. The second proposition is to use resources for training and the improvement of the spatial aptitude. Some of these resources have been used with success in samples of engineering students [12].

Spatial aptitude is one of the most studied abilities in the field of human cognition. It is very common to find a high level of spatial aptitude in people who work in activities related to engineering, architecture, piloting, air traffic control, just to pick out some of them [17]. Following the Carroll classification [5], currently in use, we can distinguish in spatial aptitude several subaptitudes, detaching the *visualization* and the *mental rotation.*

Mental rotation (MR) is defined by the speed in which one mentally rotates simple shapes. Visualization (Vz) is defined by the ability to mentally manage complex shapes.

Studies about the relation between spatial aptitude and the technical drawing performance are not in a great number as are the studies existent in others academic performance areas. The available data allows one to affirm that the Vz tests are moderately good predictors, while the MR tests do not have an impact on course performance [15, 19, 3, 23]. There are a few studies about these problems in the Brazilian population, mainly in the engineering field.

There are a great number of tests to evaluate Vz. An excellent compilation has been done by Eliot and Smith [8]. In this work we apply the Mental Cutting Test (MCT) because it has been used with success for samples of engineering students in many countries [23, 26, 25].

The objectives of this work are:

(i) to analyze the data with a psychometric model that has optimal properties to obtain a joint estimation of the MCT characteristics and the visualization capacity of the students,

(ii) to analyze the relations between MCT scores and qualification in technical drawing on the first exams of Brazilian engineering students in the first year, and

(iii) to determine the usefulness of MCT to detect those students that have a great probability of obtaining low levels of performance.

2. Method

2.1. Participants

In this study 163 first year students of engineering participated. 92 were from Paulista State University – Guaratingueta Campus (UNESP), and 71 from Polytechnic School of Sao Paulo University (EPUSP). The age mean was 19 years and 6 months and the standard deviation 2 years and 2 months. 19% of the sample were women.

2.2. Instrument

The Mental Cutting Test was applied to the students. It is an adaptation of a subtest of CEEB Special Aptitude Test in Spatial Relations, and is used in many countries to evaluate the spatial aptitude of engineering students [23, 26, 25, 6, 14].

Validation studies of MCT show that it is an excellent indicator of Vz [25]. In the MCT, the students are asked to determine true cutting views after being given pictorial views of objects and cutting planes. The test contains 25 multiple choice items with one correct option and four distracters. The time limit is 20 minutes. Saito, Suzuki and Jingu [23] propose that the items in the MCT are classified into two categories: pattern and quantity problems. In the first, the solutions are determined by identifying only the patterns of the sections. Nineteen items can be classified into this category. In the second, the solutions are determined by identifying not only the patterns of the sections, but also the quantities in the sections (e.g., the lengths of the edges). Six items can be classified into this category (Fig. 1).

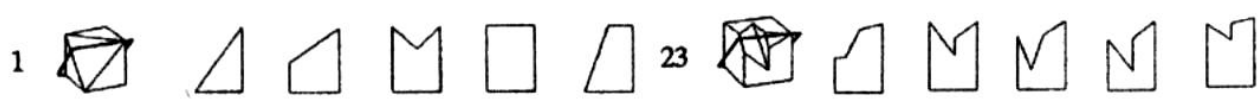

Figure 1: Pattern (left) and quantity (right) items

The technical drawing qualifications were obtained from the scores of the first exams. These exams were individual but with similar problems. The students at FEG-UNESP were supposed to make orthographic views of objects from pictorial views or other views of them. In EPUSP, they did practical problems about topographic surfaces. This difference was due to the different programs in both universities, but both exams were about basic themes of the basic engineering graphics area.

2.3. Procedure

The MCT was applied to each examinee in a single section in November 2000 by a computerized application made in MetaCard software [18]. The first exam of technical drawing was done in April 2000.

2.4. Measurement Model

The item response matrix was analyzed with the *Rasch model* [21], that provides measurement equivalent to that available in the physical sciences, because it synthesizes the key features of requirements for fundamental measurement (invariance, unidimensionality, and additivity) [24]. This model is known as a one parameter logistic model because the probability of a correct answer $P(X_{ij}=1)$ depends on the difference between the ability of the examinee (θ_j) and the item difficulty parameter (β_i): The greater the difference $\theta_j - \beta_i$, the greater the probability that the examinee answers the item correctly. The equation (1) describes the relation between both values.

$$P(X_{ij}=1) = \exp(\theta_j - \beta_i)/(1 + \exp(\theta_j - \beta_i)) \tag{1}$$

The advantages of the *Rasch model* against the Classical Test Theory (CTT) [11] have been widely spread [10, 2, 4]. We gave emphasis to the characteristics that are more important to psychological and educational measurement: conjoint measurement, specific objectivity, interval properties and specificity of the measurement standard error.

Conjoint measurement: This means that examinees and item parameters were expressed in the same units and were placed in the same scale. First, this property gives the *Rasch model* a more realistic character than CTT: it is not reasonable to maintain the idea that all items measure the same quantity of the construct. Second, this characteristic allows to analyze the interactions between examinees and items. Consequently, the score interpretations are not based necessarily on a normative group, but in identifying items that the examinee has a high or low probability of correct response. This characteristic gives to the *Rasch model* a great richness of diagnosis.

Specific Objectivity: A measure could be considered valid and general only if it does not depend on the specific conditions under which it is obtained. The difference between two examinees in an attribute does not depend on the specific items used to estimate it. Equally, the difference between two items does not depend on the specific examinees used to quantify it [10]. Important psychometric applications such as equating of scores obtained from distinct tests, construction of item banks and examinees' adaptive tests are based on this property.

Interval Properties: The meter to score jointly persons and items (usually the *logit scale*) has interval properties. The interval property is based on interpretations originated from the specific objectivity: similar differences between people have the same meaning throughout the continuous scale. The location of the point zero on the scale is arbitrary. In the Rasch tradition, it is situated in the difficulty mean of the items. In this case, the interpretation of the persons' parameters is simple (values of θ_s greater than 0 means that these persons have a probability of success greater than 0.50 on items that have a mean difficulty). Although the logit scale can adopt values between $\pm\infty$, in the majority of cases it is situated between ± 3. The interval property has a great importance because it is a necessary condition to precisely use the parametric analysis methods which are most frequently used in social sciences (ANOVA, regression, etc.) and moreover, guarantees the invariance of differences of scores all through the continuous scale (a necessary requirement in the analysis of the changes due to development or training).

Specificity of the Measurement Standard Error: It is supposed in CTT that the tests have the same reliability in all regions of the variable. The *Rasch model* does not assume this supposition that is so improbable. In contrast, it allows

(i) to quantify the measurement error in each point of the continuous scale and

(ii) to select items that permit increasing the reliability in previously specified trait regions.

Generally the measure precision increases adjusting the item difficulty to the person level [10].

The advantages of the *Rasch model* can only be obtained if the raw data fits to the model. According to the equation (1), the probability of a correct response only depends on the difference between persons and items in the trait (unidimensionality). Presence of aberrant responses like people with low trait levels correctly answer difficult items, indicates that the person and item parameters are only numerals without theoretical meaning. The misfit could be due to many factors: multidimensionality, biased items, lack of precision on the item formulation, guessing, lack of motivation or cooperation, errors in pointing the answer, copying of the right answer, etc. [13]. The analysis can detect items and persons that misfit the model. Several statistics to evaluate the model fit have been proposed [13].

The most employed statistic is called *Infit*, which is an information-weighted sum. The statistical information in a Rasch observation is its variance. To calculate *Infit*, each squared standardized residual value is weighted by its variance and then summed. *Infit* statistic is reported as mean squares divided by their degrees of freedom, so that they have a ratio scale form with an expected value of 1 and a range from 0 to positive infinity. In this form, the mean squared fit statistics are used to monitor the compatibility of the data with the model. Traditionally it is considered that values greater than 1.3 shows maladjustment [2, 4, 13]. The softwares bring graphical representations that facilitate the interpretation. In this work we analyzed the data with the *Quest* [1] software. The answers were codified dichotomously: 1 = correct, 0 = incorrect or no reached. The presence of no reached items was very low (91.4% of the students answered all items).

3. Results and Discussion

3.1. Adjustment of MCT to estimate the students' capacity in Vz

First, we show the results of the fit model analysis for items and examinees. As we have commented, the fit is crucial. If it does not exist, the values does not have a theoretical meaning and the *Rasch model* advantages disappear. We used the *Infit* statistic as an indicator of the global fit. The descriptive statistics of *Infit* values are shown in Table 1.

Table 1: Item and person fit. Descriptive statistics of *Infit* values

Object	*Mean*	*Std. Dev.*	*Maximum Infit*	*Percentage with Infit* > 1.3
Items	1.00	0.90	1.17	0
Persons	1.00	0.19	1.59	6.13

The statistics reveal a good fit-model data. On one hand, the means and standard deviations of values are those that are expected when there are not substantial divergences between the model predictions and the raw data. On other hand, no items and only 6.13% of the students present values greater than 1.3.

Table 2: Descriptive statistics of item and person distributions

Object	*Mean*	*Std. Dev.*	*Maximum logit*	*Minimum logit*
Items	0.00	1.16	2.57	-2.72
Persons	0.15	0.98	2.88	-2.05

Compared with CTT, the greatest advantage of *Rasch model* is the property of conjoint measurement: the items' and persons' parameters are on the same scale. In Fig. 2 and in Table 2, a graphical representation and descriptives data of the conjoint scaling are shown.

```
Students (each X represents 1 student )      Items (identification number)
-------------------------------------------------------------------------------
 3.0                             |
                          XXX    |
                                 |
                                 |
                                 |    25
                                 |
                            X    |
                                 |
                                 |
 2.0                      XXXXXXX    |
                                 |
                                 |
                        XXXXX    |
                                 |
                         XXXX    |
                                 |    23
                                 |
                      XXXXXXX    |
 1.0                             |    24
                      XXXXXXX    |
                                 |    13
                     XXXXXXXX    |    22
                   XXXXXXXXXX    |    20
                                 |    14      21
          XXXXXXXXXXXXXXXXXXX    |    10      19
                                 |     7       9      17      18
              XXXXXXXXXXXXXXX    |     1      15
  .0                             |
               XXXXXXXXXXXXXX    |    12
                                 |     6      16
                     XXXXXXXX    |
                                 |
                  XXXXXXXXXXX    |
             XXXXXXXXXXXXXXXX    |     2
                                 |
                                 |     4
                    XXXXXXXXX    |
-1.0                             |
                    XXXXXXXXX    |
                                 |    11
                     XXXXXXXX    |
                                 |
                                 |
                            X    |
                                 |
                                 |
-2.0                        X    |     3
                                 |
                                 |
                                 |
                                 |
                                 |     5
                                 |     8
                                 |
                                 |
-3.0                             |
-------------------------------------------------------------------------------
```

Figure 2: Conjoint measurement of items and students

We can observe a conjoint representation of students and items on a scale that goes between -3 and 3 logit. The majority of items is grouped on a mean difficulty level, as well as the students on the ability mean level. This indicated that the test is much convenient to evaluate the visualization level on the students majority (it is neither so easy nor so difficult).

A small students group (12.3%) shows high values on the variable measured by MCT

($\theta > 1.5$). Nevertheless, the students group with low values of ability (1.2% with values lower than -1.5) is smaller.

In Fig. 2 we can observe that there are a few items in the extreme ranges of the measured trait. This characteristic conditioned the MCT precision in these ranges. For example, the measurement standard error (*MSE*) of students with higher ability is much greater ($\theta = 2.88$; $MSE = 0.77$) than that of students with a mean ability ($\theta = 0.15$; $MSE = 0.44$). With the purpose of improving the test reliability in the extreme regions of trait, it would be convenient to include items with extreme difficulty values in future versions of MCT. As we pointed out before, the procedures to increase the reliability are based on adjusting the items' difficulty to peoples' capacity (e.g., we can not estimate with precision the level of the examinees with much capacity with easy items for them).

3.2. Construct validity of MCT scores

In this work, we analyzed the relationship between the difficulty and complexity of items as a way to question about the construct validity of MCT scores. Embretson [9] has proposed a two-part distinction for construct validation: *construct representation* that involves the identification of cognitive components underlying task performance, and *nomothetic span*, which concerns the specification of the network of test scores correlations with other instruments or constructs. The traditional methods of construct validation involve only nomothetic span, whereas new advances in cognitive psychology suggested that the meaning of measures can also be established by the understanding of the operations involved in problem-solving behavior for individual items (construct representation). An important aspect of construct representation is the determination of item complexity. This involves the identification of skills related with item performance and item characteristics that poses a demand on these skills [20].

From this approach, we look for answering some questions about MCT. First, we have analyzed if there are differences in difficulty between items of distinct forms (quantity and pattern problems).

As we have mentioned previously, Saito, Suzuki and Jingu [23] propose that the items in the MCT could be classified as pattern and quantity problems. Firstly, the solutions are determined by identifying only the patterns of the sections. Secondly, the solutions are determined by identifying not only the patterns of the sections, but also the quantities in the sections (e.g., the lengths of the edges). If this task form has an impact in its difficulty, it could be inferred that the resolution of each type of item demands distinct aptitude level. We analyzed the mean difficulty of quantity and pattern problems to infer if this task form influences the cognitive complexity.

In Table 3 the results of a variance analysis are shown in which the item difficulty estimations were the dependent variable (β) and the form task, the independent one.

Table 3: ANOVA for item difficulty. Effect: pattern or quantity problems

Modality	*Pattern*	*Quantity*	*F*	*DF*	*P-value*
Mean	-0.12	0.38	0.83	1	0.37
Std. Dev.	1.26	0.77	–	–	–
Count	19	6	–	–	–

As it can be observed, the difference in the mean difficulty of both types of items is not statistically significant. Nevertheless, due to the low number of quantity items, the results can not be considered conclusive. A new analysis would be necessary after introducing a greater number of this type of items in future versions of the test.

Second, we questioned what are the characteristics of representative tasks of a low and a high ability. This aim is not free of difficulties because, what occurs at many classical tests, the MCT construction was not based on an explicit cognitive model that could be derived from the task conditions associated to cognitive abilities. Consequently, we limited ourselves to a rational analysis of item characteristics with extreme values on the difficulty continuous scale.

As it could be seen in Fig. 2, the easier items (with values $\beta \leq -2$) are 8, 5 and 3, the harder are 23 ($\beta = 1.38$) and 25 ($\beta = 2.57$). The easier and harder item format can be seen in Fig. 3.

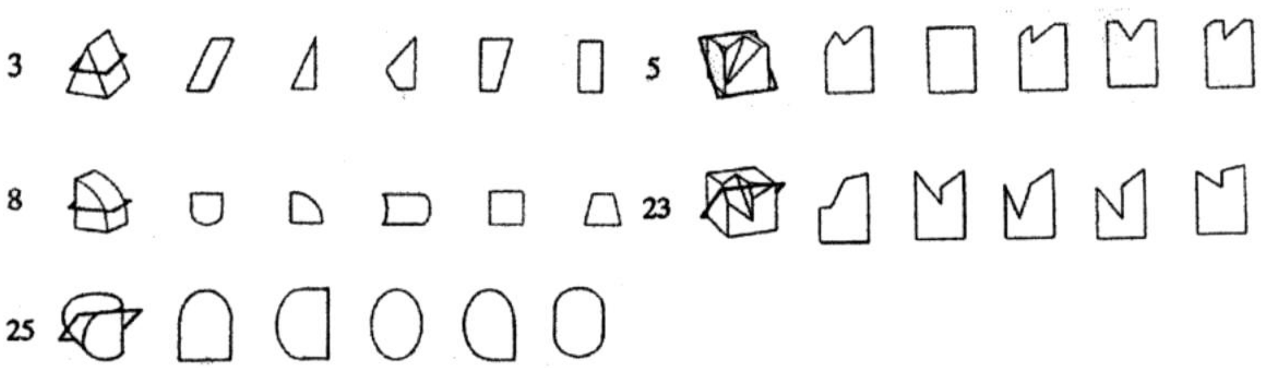

Figure 3: Easier and harder MCT items

It could be observed that in the easier items the sections were merely rectangles, similar figures of the cut planes presented, e.g., not only were they pattern items but the visualization of the cutting plane already brings the desirable form. Consequently, the task resolution does not requires very complex mental transformations of the figure.

Since the presence of no reached items was so few, the difficulty values obtained to items 23 and 25 are not due to lack of time for the students to have answered the last items of the test. In our point of view, on item 23, the difficulty could be due to the fact that the frontal face shown in the picture view has the same feature of the required section but, logically, does not present the same proportions between its edges, working as a distracter in the final evaluation of those measures, e.g., in the visualization of the section real largeness. In the item 25, it could be due to the fact that the required section is the result of the intersection of an inclined plane with two curved surfaces, which does not occur with other test items, moreover the fact that the section is half covered by the object presented. In our judgement, the task complexity is determined by the difficulty in rotating the section in a way to reach visualization of the real feature and largeness, as well as imagining the invisible elements of features. Therefore the capacity to solve those kind of problems demands the capacity to represent and manage precisely the invisible elements of features.

In our point of view, the analysis of sources of item difficulty allows one to extract convergent conclusions as well as those obtained from other validation methods. For example, the construct validity of MCT had been analyzed by means of the exploratory factor analysis [25], from analysis of verbal protocols and recorded eye fixations during the resolution process [16] and from error analysis done by experts and novices [22]. The authors of those studies concluded that MCT score reflects the students' ability to make and manipulate mental images of three-dimensional objects from pictorial views. The main reasons of errors are difficulty in recognizing a cutting plane's position, difficulty in transforming a section to a true size view and difficulty in reading a view synthetically. These conclusions and those obtained in this work, reinforce the idea that MCT is an excellent indicator of the visualization construct.

3.3. MCT usefulness to foresee the technical drawing performance

The main objectives of this work were:

(i) to analyze the relationship between MCT scores and the technical drawing performance of the first year engineering students and

(ii) to determine the utility of MCT to detect those students with a high probability of obtaining a low level of performance.

Related to the first aim, we obtained a Pearson correlation of 0.34 ($p < 0.0001$) between MCT Rasch-scores and the qualifications on the technical drawing first exam. It reveals a moderate association, similar to that obtained by Suzuki et al. [23, 26] in samples of Japanese students.

To reach the second aim, we classified the students in four categories from the following technical drawing qualification groups (G): insufficient ($G < 5$), acceptable ($5 \leq G < 7$), good ($7 \leq G < 9$) and excellent ($G \geq 9$). The significance of differences between the means of these four groups on the MCT Rasch-scores was contrasted, using ANOVA and Fisher's a posteriori contrasts.

The results are shown in Table 4 and Fig. 4.

Table 4: ANOVA for MCT-score. Effect: Technical drawing performance. The means with different letters have a significant difference in a Fisher's contrast

MCT	*Insufficient*	*Acceptable*	*Good*	*Excellent*	*F*	*DF*	*P-value*
Mean	-1.69a	0.27b	0.50b	0.62b	3.85	3	0.01
Std. Dev.	0.85	1.04	0.90	0.90	–	–	–
Count	32	47	37	17	–	–	–

It could be observed that the F-value was significant. The posteriori contrasts reveal that the mean on MCT of the students with an insufficient performance in technical drawing is significantly lower than the means of the others groups.

In this way, it could be affirmed that MCT can be an appropriate instrument of diagnosis to identify early those students with low capacity to have a good performance in technical drawing. The diagnostic usefulness could be increased if the test, in its future versions, incorporates new items with extreme difficulty values.

In summary, we consider that the incorporation of visualization psychometric tests in the learning-teaching methodology certainly facilitates the gain of important data in planning it, optimizing its development by the way of new and different didactic strategies that allow one to surpass the obstacles that currently would be presented.

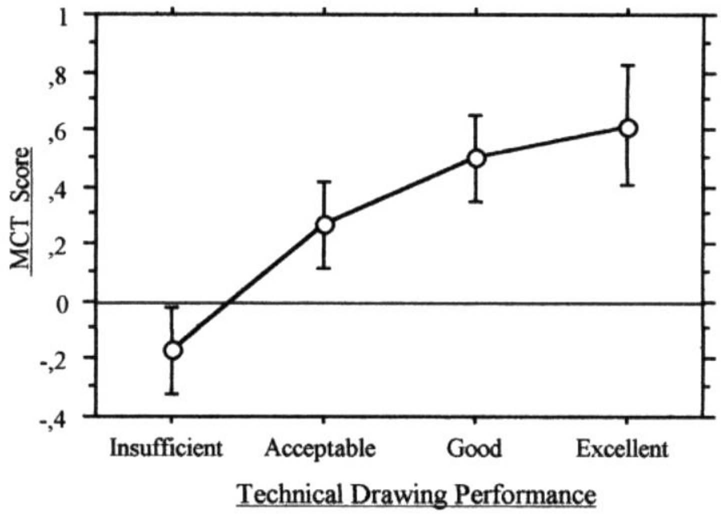

Figure 4: Interaction line plot for MCT-score.
Effect: Technical drawing performance. Error bars: ±1 Standard Error(s)

Acknowledgements

- To the Engineering Faculty of UNESP, Guaratingueta Campus, and the Polytechnic School of the University of Sao Paulo,
- to the students who did the tests,
- to CAPES.

References

[1] R.J. Adams, S. Khoo: *Quest: The Interactive Test Analysis System*. HACER, Victoria 1996.

[2] D. Andrich: *Rasch Models for Measurement*. Sage, Newbury Park 1988.

[3] M. Besterfield-Sacre, C.J. Atman, L.J. Schuman: *Characteristics of Freshman Engineering Students: Models for Determining Student Attrition in Engineering*. Journal of Engineering Education **86**, 139–149 (April 1997).

[4] T.G. Bond, C.M. Fox: *Applying the Rasch Model: Fundamental Measurement in the Human Sciences*. LEA, Mahwah, NJ, 2001.

[5] J.B. Carroll: *Human Cognitive Abilities. A Survey of Factor-analytic Studies*. Cambridge University Press, New York 1993.

[6] CEEB: *Special Aptitude Test in Spatial Relations, Developed by the College Entrance Examination Board*. USA 1939.

[7] L.J. Cronbach, R.E. Snow: *Aptitudes and Instructional Methods: A Handbook for Research on Interactions*. Irvington P., New York 1981.

[8] J. Eliot, I.M. Smith: *An International Directory of Spatial Tests*. NFER-Nelson, Windsor 1983.

[9] S.E. Embretson: *Construct Validity: Construct Representation versus Nomothetic Span*. Psychological Bulletin **52**, 179–197 (1983).

[10] S.E. Embretson, S.P. Reise: *Item Response Theory for Psychologists.* LEA, Mahwah, NJ, 2000.

[11] H. Gulliksen: *Theory of Mental Tests.* Wiley, New York 1950.

[12] S. Hsi, M.C. Linn, J.E. Bell: *The Role of Spatial Reasoning in Engineering and Design of Spatial Instruction.* Journal of Engineering Education **86**, 151–158 (April 1997).

[13] G. Karabatsos: *A Critique of Rasch Residual Fit Statistics.* Journal of Applied Measurement **1**, 152–176 (2000).

[14] C. Leopold, R. Górska, S. Sorby: *Experiences in Developing the Spatial Visualization Abilities.* J. Geometry Graphics **5**, no. 1, 81–91 (2001).

[15] D.F. Lohman: *Spatial Ability.* In R. Sternberg: *Encyclopedia of Human Intelligence.* McMillan, New York 1994, pp. 1000–1007.

[16] K. Makino, T. Saito, K. Shiina, K. Suzuki, T. Jingu: *Analysis of Problem Solving Process of a Mental Cutting Test by the Use of Eye Fixations Data.* Proc. 5th ASEE International Conference ECGDG, Melbourne, Australia, 1992, pp. 398–402.

[17] M. McGee: *Human Spatial Abilities: Sources of Sex Differences.* Praeger, New York 1979.

[18] MetaCard Corporation: *MetaCard Users Guide.* Boulder, USA, 1997.

[19] M. Peters, P. Chisholm, B. Laeng: *Spatial Ability, Student Gender, and Academic Performance.* Journal of Engineering Education **84**, 69–73 (1995).

[20] R. Primi: *Complexity of Geometric Inductive Reasoning Tasks. Contribution to the Understanding of Fluid Intelligence.* Intelligence **30**, 41–70 (2002).

[21] G. Rasch: *Probabilistic Models for Some Intelligence and Attainment Tests.* Danish Institute for Educational Research, Copenhagen 1960.

[22] T. Saito, K. Makino, K. Shiina, K. Suzuki, T. Jingu: *Causes of Error in a Mental Cutting Test — Analysis of Problem Solving Process by the Use of Eye Fixations Data.* Proc. 6th ICECGDG, Tokyo, Japan, 1994, pp. 815–819.

[23] T. Saito, K. Suzuki, T. Jingu: *Relations between Spatial Ability Evaluated by a Mental Cutting Test and Engineering Graphics Education.* Proc. 8th ICECGDG Austin, USA, 1998, pp. 231–235.

[24] I. Styles: *The Study of Intelligence — The Interplay between Theory and Measurement.* In M. Anderson: *The Development of Intelligence*, Psychology Press, Hove 1999, pp. 19–42.

[25] Y. Sugai, K. Suzuki: *Comparison of Problem Solving Process between a Mental Cutting Test and Other Spatial Tests.* Proc. 4th China-Japan Joint Conference On Graphics Education, Dunhuang, China, 1999, pp. 105–110.

[26] K. Suzuki, K. Shiina, K. Makino, T. Saito, T. Jingu, N. Tsutsumi, S. Kashima, M. Shibata, H. Maki, E. Tsutsumi, H. Isoda: *Evaluation os Student's Spatial Abilities by a Mental Cutting Test.* Proc. 5th ASEE International Conference ECDGD, Melbourne, Australia, 1992, pp. 277–281.

[27] S.R. Ting: *Predicting Academic Success of First-Year Engineering Students from Standardized Test Scores and Psychosocial Variables.* International Journal of Engineering Education **17**, 75–80 (2001).

Received March 14, 2002; final form July 4, 2002