HUMAN RANDOM GENERATION AND ITS APPLICATIONS

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Abstract: Human Random Generation (HURG) is a psychological test meant to detect the degree of mental fatigue, or the level of concentration of individual subject, by testing the flexibility of thinking, without relying on any equipment(Wagenaar, 1977). In early days, HURG was practiced in clinical psychology in order to detect advanced level of schizophrenia. Later, the development of powerful computers made us possible to detect subtle irregularity hidden in HURG taken from normal subjects. We have been studying the possibility of utilizing HURG for self-detection of dementia at early stage, by using various information theoretical techniques over several years including the pattern classification by means of hidden Markov model (HMM), correlation dimension frequently used to identify chaotic time series, and selection of index suitable to characterize short sequences. In this paper, we report our recent progress in developing a novel method of HURG by using the pattern recognition and the randomness measured in the data taken from the Inverse-Ten-Key on the mobile phone keyboards (MPK).

1 INTRODUCTION

Human random number generation test (HURG) is a psychological test designed to check the flexibility of thinking in a simple manner. Usually, it takes a style of asking the subject to say or write numbers or letters as random as possible. In the early days when HURG was studied in the field of clinical psychology, ability to produce a reasonable amount of randomness was linked to the patients' mental state, since patients in advanced stage of a certain mental disease looses this ability considerably.

We interpret this test to detect small differences that distinguish mental conditions or personal characters of subjects. Our first investigation of HURG from 1996 to 1998 used 30 sets of data taken from 6 students at the age of 22 - 24. By means of hidden Markov models (HMM), we have barely succeeded in classifying those 6 subjects, and clearly classified them into two distinct groups.

We constructed an HMM model for each person by averaging over the learned values of parameters and found out that the models can recognize the correct persons with more than 50 percent of accuracy. Moreover, the correlation dimensions computed for each data split into the same two groups as classified by the HMM analysis.

Later we added more data taken from 7 male students of the same age as in the previous experiments and obtained consistent conclusion to the previous result mentioned above.

Recently we pay more effort on applying this method to design health-care products for early stage detection of dementia. However, we realize that the experimental method we used for students demands too much load on elderly people or patients.

In order to shorten the data series, we need novel methods suitable for such lengths. We first put our effort on searching for indices and selected 4 suitable ones. By using them, we have succeeded in classifying the data of different age categories correctly on the self-organized maps (SOM). Our second attempt was the introduction of a new direction of data-taking using the mobile phone keyboard (MPK) in order to keep the data length fixed to the shortest. We demand the subject to use nine figures 1-9 only once for each and put them in a random order. By doing this, we can keep the data length to be 9, although more concentration is required to produce data. This method can also be a good method of training the brain to keep it working.

The structure of the rest of this article is as follows. In Section 2, we introduce the methods of data collection and the results of statistical analysis.

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Section 3 is devoted to the results of HMM analysis. In Section 4, we examine indices suitable to characterize short data sequences. Finally, in Section 5, we report some result of our new direction using mobile phone keyboards for data-taking.

2 DATA COLLECTION AND STATISTICAL ANALYSIS

Various methods are used for data taking, such as oral, written, or keyboard-typing. In the old days, data were written on the paper. This method turned out obsolete nowadays since extra effort is required to convert the data into computer files. Moreover, it is more suitable to conceal the previously generated data from the eyes of the subjects in order to maintain the quality of the data. We used in our recent attempt the key-typing of the nine figures on the mobile phone keyboard only once in one attempt.

Commonly taken method is either to fix the length of strings or to fix the time to take data of one experiment. For example, the subjects are to say or write one digit number for 100 times for one experiment, or to say or write as many numbers as possible within one (three) minute(s), etc.

The immediately recognizable feature of HURG is the lack of repeats of the identical figures. Any subject exhibits this tendency. Although one can repeat the same figure one out of ten on purpose, this attitude requires extra effort on the subject thus can be easily lost as the subject gets tired and loose concentration.

Whether any particular figure is more likely to appear turned out to be negative. For the normal subjects in the age group of 20s, the probability of appearance of ten figures, 0,1,...,9 are almost equal so that the corresponding entropy is just as large as the case of machine random numbers. However, the entropy for elderly or patients of brain disease tend to be smaller than those of young normal subjects.

The patterns of two adjacent numbers in HURG data show some characteristics of individual subjects. However, the entropy of two-digit numbers is not a suitable measure for data sequence of length 100 or shorter, since not all the patterns appear in this length and the probability of appearance is meaningless.

Statistical method looses power for data sequences of length 50 or shorter, which we aim in order to reduce the burden of the subjects.

3 PATTERN CLASSIFICATION BY MEANS OF HMM

We adopted in our first experiment during 1996-1998 to take data from the subject orally by fixing the length of data to be 100 and the examiners input the data to the keyboard so that the input data are automatically styled into data files of prescribed format. We collected 30 sets of data files from each of 6 students, including 3 male students and 3 female students in the same department. By connecting 30 data sets, we used the data sequence of length 3000 as the input for learning the each student's HMM. We converted the original data sequence by the differences between adjacent numbers and coded them into 3 symbols, I for the case of identical figures, II for the case of the absolute values of the differences being 1 or 2, and III for the case of jumping more than 2. The learned parameters are the elements of two 3×3 matrices called A-matrix and B-Matrix, and one 1×3 matrix called π matrix. The A-matrix represents the transition probabilities between the hidden states, and the B-matrix represents the probability of appearance of those 3 symbols from 3 hidden states. The π matrix is the initial probability distribution among the hidden states. We have used Baum-Welch algorithm for EM learning. As shown in Table 1, the HMM can separate the 6 subjects into 2 groups. According to the patterns of two adjacent numbers appeared in data, those 2 groups correspond to the 2 types consisting of a group of people who tend to move to adjacent figures (absolute difference |d|=1, 2), and another group of people who tend to jump to distant figures (|d|>2) (Tanaka-Yamawaki, 1999).

Table 1: Six subjects are recognized by HMM.

HMM⇒	A	C	E	B	D	F
A(F) -data	23	3	3	0	1	0
C(F) -data	5	20	5	0	0	0
E(M) -data	3	6	20	0	0	1
B(F)-data	0	6	4	4	4	12
D(M)- data	1	0	3	4	14	8
F(M)- data	0	0	1	4	2	23

The correlation dimensions computed for the same data shows interesting correspondence to the above HMM result. As shown in Table 2 and Table 3, subject A, C and E, who belongs to the first group in HMM classification, have small numbers compared to subject B,D, and F who belong to the second group. This result confirms that the characteristics exist in HURG data and HMM together with the correlation dimensions can recognize those patterns. (Tanaka-Yamawaki, 1998)

Table 2: Correlation dimension of the differences between adjacent numbers ('rand' is machine-generated).

	dat1	dat2	dat3	Ave.	SDev
A	5.1	4.9	4.6	4.9	0.21
C	5.1	5.4	5.6	5.4	0.19
E	5.2	5.5	5.5	5.4	**0.15**
F	6.4	6.4	6.4	***6.4***	**0.04**
B	6.1	6.3	6.5	***6.4***	**0.17**
D	6.4	6.4	6.2	***6.3***	**0.11**
rand	6.3	6.4	6.2	***6.3***	**0.07**

4 INDICES FOR SHORT DATA

The immediate application of HURG that we can conceive is the self-diagnoses of dementia. Oral data of HURG generated without viewing the previously generated numbers should represent the memory of the subject of this experiment. The fact that the subject tends to avoid repeating the same figure reflects the memory effect. The memory toward more than one becomes less clear, and the memory goes blur for much longer past. However, the entropy of normal subjects being close to the maximum tells us that the HURG test is an easy task for young normal people.

For older age groups, however, it is not so easy to produce each figure evenly. For patients in the advanced stage of schizophrenia, it seems more difficult to generate random sequences. Some patients could not finish the test of generating 100 figures. This fact indicates the effectiveness of such test. At the same time, it tells us the necessity of reducing the burden of the subject having such tests. Thus we decided to shorten the length of data to 50, and searched more suitable indices to measure the randomness to be used for self-diagnoses.

We have selected 4 indices, the entropy (H), turning-point-index (TPI), adjacency (ADJ), and the repeat pattern (RP) defined as follows.

The entropy H is defined by using the probability p_i of appearance of the i-th figure.

$$H = -\sum_i p_i \log p_i \qquad (1)$$

The turning point index (TPI) measures how frequently the switch from ascending pattern to descending pattern, and vice versa, occurs in the data sequence. Defining the turning point (TP) as the letter after which the pattern changes, e.g., TP=2 for "135426", TPI is defined by dividing TP by its expected value, $TP_{ex} = (m-2)\times 2/3 = 32$, where m (=50) denotes the maximum data size.

$$TPI = TP_{obs} / TP_{ex} \qquad (2)$$

The TPI is highly vulnerable to the human brain condition. When the subjects is active, it tends to be larger than one, while for inactive subjects or patients in advanced stage of mental disease it tends to be smaller than one.

A remarkable feature of human generated random numbers is the lack of repeats of the same figures successively. Guided by this, we utilize the adjacency (ADJ) to characterize the data. Focusing on the difference between two adjacent figures (defined by d), we classify the data to the four types, d=0, |d|=1, |d|=2, |d|>2. All the data show the extremely low rate of d=0 in human generated data compared to computer generated random numbers. Also the rate of |d|=1 is a good measure of mental condition. For example, the data taken from the schizophrenia patients are characterized by an excess amount of |d|=1 compared to the data from normal subjects.

The null score quotient (NSQ) measures the degree of deviation from the even generation of pairs (array of length 2). It is defined by

$$NSQ = NS/(a^2 - 1) \qquad (3)$$

where NS denotes the numbers of pairs not appearing in the sequence and a denotes the size of letters used. In the case of using decimal figures {0,…,9}, a=10 (Towse, 1998) .

We propose a new index to be used in place of NSQ for the case of short HURG. Since the subjects of HURG try to generate the next letter based on their memory of the last generated letter, NSQ is a good measure for the memory capacity of the subjects. However, the problem is that the value of NSQ ranges from 51.5 to 100 for the case of data sequence of length 50. We need a better index for short data (Mishima, Tanaka-Yamawaki, 2008).

Consider the case when the generated data is "1358763" so far, and 5 is about to come out next, one would make an effort to avoid 5, by considering the previously generated 35. Human would pay all the effort to improve the randomness (complexity, in fact). Guided by this thought, we define a new index

$$RP = 1 - \frac{NRS}{m-(n-1)} \qquad (4)$$

which represents the frequency of repeated pairs. Here NRS denotes the number of unrepeated pairs, m (=50) denotes the length of the sequence, and n denotes the length of array (n=2 for pair). The more the repeated pairs, the larger the value of RP, indicate the deterioration of the memory capacity of the subject. Since the case of n=3 did not show much difference from that of n=2(pair), we stick to consider only pairs (n=2). Note that RP ranges [0:100] in percent, irrelevant to the size of the data sequence unlike NSQ. We show in Figure 1 that the data are separated to 4 distinct regions according to the age groups by using RP, TPI, ADJ, H for indices.

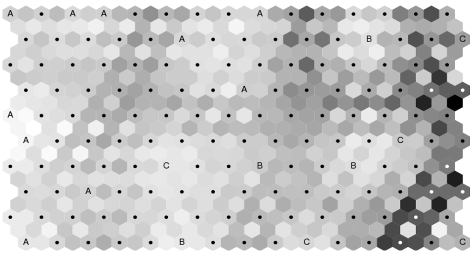

Figure 1: The SOM representation of 20 subjects in RP, TPI, ADJ, H. showing separation of different age groups: A(20s), B(30-49), C(50-79), D(80-).

5 MOBILE PHONE KEYBOARD

HURG-on-MPK (Mobile Phone Keyboard) is designed to reduce the length of data sequence, which asks subjects to type 9 numerical keys on the mobile phone keyboard once per each key in a random order. In this scheme of HURG, the length of data is fixed to 9, which is far shorter than the previously studied HURG. Moreover, this is effective to train the flexibility of brain, demanding high level of concentration to the subjects.

This new method requires a new set of analytical tools. Since all the 9 figures (1-9) are used in one data only once, the randomness measure used for the standard HURG such as entropy becomes useless in this case. The randomness for HURG-on-MPK lies in the order of those 9 figures.

We have developed a classification method of such data by using a 3-layered feed-forward neural network (3NN). The location the 9 figures plus the total length of the path that the finger travels over the keyboard are put into the 10 units of the first (input) layer. Those are sent to the second (middle) layer that consists of 3 nonlinear units, which convert the weighted sum of the information from the 10 input units into 1 (if it exceeds the threshold) or 0 (if it is below the threshold). The outputs from the 3 units of the middle layer are sent to the output layer of the same kind of nonlinear structure and they are compared with the teacher signals. We have used the back-propagation learning algorithm for training this 3NN. By using this, we have successfully classified the 7 subjects. The rate of recognition of 7 subjects (A-G) are shown in Table 3, where the result with and without the 10-th unit are compared. Note that the information of the total path that the finger travelled put into the 10-th unit plays an important roll.

Table 3: Recognition Rates [%] for 7 subjects (A-G).

Subject	A	B	C	D	E	F	G	ave
1-9 units	90	73	53	0	57	53	60	55
1-10 units	100	93	97	33	70	80	90	80

6 CONCLUSIONS AND BEYOND

We have presented in this article various ways of pattern recognition of HURG, such as HMM, correlation dimensions, etc., and the efforts to shorten the length of data sequence. In this regard, we discussed analytical techniques to extract patterns from HURG, in particular, the identification of the four indices, RP, TPI, ADJ, H to characterize short sequences.

We have also introduced HURG-on-MPK and presented the effectiveness of the 3 layered neural network system (3NN), using the locations of 9 figures appeared in the data sequences and the path length that the finger travels.

Our future work is to collect more data and test the effect of HURG including the new method proposed in this article. Other tools of pattern recognition are to be considered.

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