Journal of Universal Computer Science, vol. 12, no. 9 (2006), 1345-1357
submitted: 31/12/05, accepted: 12/5/06, appeared: 28/9/06 © *J.UCS*

Phasetransition-like Changes in Human Visual Information Processing

Péter Nagy
(Kecskemét College Faculty of Mechanical Engineering and Automation,
Sándor Kalmár Institute of Information Technology, Hungary
nagy.peter@gamf.kefo.hu)

Istvan Pintér
(Kecskemét College Faculty of Mechanical Engineering and Automation,
Sándor Kalmár Institute of Information Technology, Hungary
pinter.istvan@gamf.kefo.hu)

Mihály Bagány
(Kecskemét College Faculty of Mechanical Engineering and Automation,
Sándor Kalmár Institute of Information Technology, Hungary
bagany.mihaly@gamf.kefo.hu)

Abstract: For exact examination of human information processing ability we elaborated an information-theory-based model and a new measuring method. Starting from the theoretical background of the well-known Hick–Hyman law and analysing the data acquired during the Soyuz–Salyut space missions, an important fact was derived. When examining the model by reducing the $H(X)$ input entropy of the stimulus signals (symbols) and approaching to the 0 bit there was an interesting effect: through the reduction of $H(X)$ input entropy towards zero the ratio of (processed information)/(input entropy) was increasing and its value approached to 1, while at non-zero entropy this ratio was less than 1. Therefore a phase-change-like effect occurred below $H(X) = 1$ bit. Consequently the zero bit measurement could not be involved into the determination of Information Processing Ability (*IPA*) while the traditional measurements were performed only at two distinct values of entropy: at 0 bit and at a not too high $H(X)$ value (e.g. 2 bits/symbol).

Keywords: visual information processing, information processing ability, phase transition, artificial neural networks, associative memory

Categories: H.1.0, H.1.1, J.2, J.3, J.7

1 Introduction

Based on biomedical investigations of pilots' information processing ability and performance on an aircraft simulator the principles of measuring and evaluation of pre-flight, in-flight and post flight *IPA* and the concepts of the reaction time and cortical time spent on processing 1 bit of information have been elaborated. The method and the BALATON psycho-calculator device were first tested during pre-, in- and post-flight periods of real space flight in the Soviet-Hungarian joint mission, in 1979-80 [Hideg, 85]. Later on successful experiments were performed on the

Salyut–6 and Salyut–7 in the Soviet–Mongolian and Soviet–Romanian space missions. The results were published [Hideg, 82], [Remes, 83] and the relevant databases were constructed and ground-based experiments were carried out for reference. The classification of these databases was as follows: military fighter pilots (various groups of age, according to aircraft types and risk factors); airman staff, individuals working at commanders' observation posts, civilians, members of different expeditions (sportsmen and women), candidates for flight. For the results see [Nechaev, 85].

In the relevant psychological literature, Steven W. Keele [Boff, 86] summarizes the most important theoretical results concerning decision time. The applied mathematical models define the reaction time according to the Hick–Hyman law.

The problems connected with the law of Hick-Hyman are highlighted by S. Keele as follows: In the years since the Hick–Hyman law was formulated, psychologists investigating decision processes have come less and less to invoke formal information measurement. Information measurement has not been theoretically fruitful for understanding decision processes. Nonetheless, as a strictly empirical generalisation, the Hick–Hyman law still has important practical utility in drawing together under one formulation the effects of number of choice, probability of alternatives and speed-accuracy trade-off.

Our aim is to increase the safety of man-machine interaction and make more effective the work with exact examination of human information processing ability. For this reason we have elaborated an information-theory-based model and a measuring method, which provides reliable data.

The main features of the new method are the careful statistical design of stimulus signal set and the introduction of inter-stimulus time (depending on the previous reaction time and on a random variable). Experimental results show good match with the predictions of our mathematical model described in this paper.

2 Phenomenological model

It is necessary to take into consideration the recently accepted and used neurone-dynamic models for the correct description [Amari, 80]. When processing visual information, a temporally increasing potential distribution caused by external signals occurs in the pre-synaptic cell space (receptors). The temporal formation of the stimulus can be characterised by the activation time t_a which is an average time between the occurrence of the stimulus and the time when the average of the potential distribution rises above the activation level. The pre-synaptic pattern creates the post-synaptic potential distribution in the post-synaptic cell space (in the cortex) via the synapses. Gradually it converges to a potential distribution characterising an element of the previously fixed pattern set as the cortical processing time t_c increases. After this time, determined by the subject's tactics, the classification of the external signals is carried out by comparing the two potential distributions. The time needed for the physical reaction is represented by the parameter t_b. The full reaction time (CCRT) is the sum of the three time data: $t_r = t_a + t_b + t_c$. The simple reaction time, or sensory-motor reaction time *SMRT* is the sum of the activation time and the physical reaction time ($t_a + t_b$). This sum is not easy to separate.

The concept of *IPA* was introduced for the quantitative description of the above-mentioned process in the cortex. *IPA* is the ratio of the processed information I_p, and the mean time (cortical time t_c) spent on decision-making:

$$IPA = \frac{I_p}{t_c}, \quad [IPA] = \frac{\text{bit}}{\text{s}}. \tag{2.1}$$

Measurement of *IPA* was based on the formula

$$t_r = t_s + \frac{I_p}{IPA}\ , \tag{2.2}$$

the so-called Hick−Hyman law, where:

t_s the sensory-motor reaction time (SMRT),
t_r the complex (choice) reaction time (CCRT),
I_p the quantity of processed information,
IPA the so-called information processing ability, characterising the subject's actual psychic condition concerning decision-making.

The tasks can be characterised by the simultaneous, optimal performance of two cross requirements depending on events, according to a decision scheme. On the basis of conscious decision, the action (motoric response) should be carried out

at the lowest possible percentage of error,
at the highest possible speed.

Let the cortical time be a monotone increasing function of the tactical parameter τ, and input entropy H, since the more reliable decision is to be made and the more complex problems are to be solved the more time is required. The simplest form of the $t_c(\tau, H)$ function fulfilling the above-mentioned requirements is

$$t_c(\tau, H) = \tau \cdot H. \tag{2.3}$$

Let the processed information be a finite, monotone increasing function of the tactical parameter since longer time, i.e. safer tactics results in a better classification. If the subject chooses tactics of highest possible speed, there is no information processing. The information processed is equal to the input entropy if having the lowest speed:

$$I_p(\tau{=}0) = 0, \qquad I_p(\tau{=}\infty) = H. \tag{2.4}$$

Let the transmission speed (bit/sec) be introduced as

$$R(\tau) = \frac{I_p(\tau)}{t_c(\tau)}. \tag{2.5}$$

So let the transmission speed $R(\tau)$, be a non-negative, continuous, differentiable function having one maximum. At the two extreme tactics, it has the values

$$R(\tau{=}0) = 0, \qquad R(\tau{=}\infty) = 0. \tag{2.6}$$

Under these conditions, it follows that

$$\left[\frac{dI_p}{d\tau}\right]_{\tau=0} = 0. \tag{2.7}$$

Experiments show that there is an optimal tactics (it depends on the input entropy H) if the transmission speed is maximum:

$$C(H) = R(\tau_{opt}) = \max\left[R(\tau)\right]. \tag{2.8}$$

This maximum transmission speed is called as channel capacity. We suppose that in a small (a couple of bits/symbol) range of input entropy the channel capacity can be considered as constant, i.e. the entropy-dependence of $C(H)$ is negligible. Let this constant be called as maximum speed of information processing (MSIP). It characterises the information processing ability of the subject using optimal tactics. According to the model above, and to experience, human brain is a highly non-linear system and, during its operation, it has no steady state. It keeps a dynamic balance that occurs in our model in such a way that the actual tactic fluctuate around the working point $\tau = \tau_{opt}(H)$. Thus the tactical parameter is a stochastic variable, which implies that the measured values I_p and t_r are also stochastic variables. Based on the ideas above, the Hick–Hyman law can be modified as follows. The processed information I_p and the average reaction time t_r calculated on groups of signals are stochastic variables which are in a non-linear connection with each other through the tactical parameter. There is a value $\tau_{opt}(H)$ for the parameter $\tau(H)$ for each input entropy $H(X)$ to which

$$t_r\left(\tau_{opt}\left(H\right)\right)=t_s+\frac{1}{MSIP}\cdot I_p\left(\tau_{opt}\left(H\right)\right), \tag{2.9}$$

where

$$MSIP=\max\left[R\left(\tau\right)\right]=R\left(\tau_{opt}\left(H\right)\right). \tag{2.10}$$

These aspects can be summarised in the following simple phenomenological model. The $\boldsymbol{P}(X|Y)$ conditional probability matrix, characterising statistically the relation of the X input signals and Y responses, could comprise two components: the $\boldsymbol{E}$ (diagonal) identity matrix corresponding to deterministic decisions and the $\boldsymbol{U}$ homogenous matrix involving full randomness:

$$P(Y/X)=\left[1\text{-}f\left(\tau\right)\right]\cdot E+f\left(\tau\right)\cdot\frac{U}{n}, \tag{2.11}$$

where

- $\boldsymbol{E}$ the identity matrix consisting of n x n elements,
- $\boldsymbol{U}$ the homogenous matrix consisting of n x n elements (each element is identical),
- n the number of elements in the signal set (and also that of the responses),
- $f(\tau)$ the *heuristic* tactical function having the following constraints:
  - (a) $f(\tau = 0) = 1$,
  - (b) $f(\tau)$ is strictly monotone decreasing,
  - (c) $\lim f(\tau) = 0$, if τ tends to infinity,
  - (d) it has a T parameter with the dimension of time/information.

(The matrix construction in (2.11) is based on the theorem of full probability). For a tactical function satisfying the requirements (a) – (d), we can choose the easily applicable

$$f\left(\tau\right)=e^{-\frac{\tau^2}{T^2}} \tag{2.12}$$

Gauss-function, where T is the tactical constant. The finite probability distribution of an X signal set having n stimulus signals is:

$$\left\{P\left(X\right)\right\}=\left\{1\text{-}p,\ \frac{p}{n\text{-}1},\ \frac{p}{n\text{-}1},\ \ldots,\ \frac{p}{n\text{-}1}\right\}. \tag{2.13}$$

If p = (n-1)/n, by changing the p value, the probability distribution of the signal series (thus, its entropy, too) can be continuously varied. The entropy of the signal set under (2.13) is:

$$H(p) = -\left[(1\text{-}p)\cdot\log_2(1-p) + p\cdot\log_2\frac{p}{n\text{-}1}\right]. \tag{2.14}$$

Based on (2.11) and (2.13) the *P(X, Y)* probability matrix of the simultaneous events is:

$$\begin{bmatrix} (1-p)\cdot\left[1-\frac{n-1}{n}\cdot f(\tau)\right] & (1-p)\cdot\frac{f(\tau)}{n} & \cdots & (1-p)\cdot\frac{f(\tau)}{n} \\ \frac{p}{n-1}\cdot\frac{f(\tau)}{n} & \frac{p}{n-1}\cdot\left[1-\frac{n-1}{n}\cdot f(\tau)\right] & \cdots & \frac{p}{n-1}\cdot\frac{f(\tau)}{n} \\ \cdots & \cdots & \cdots & \cdots \\ \frac{p}{n-1}\cdot\frac{f(\tau)}{n} & \frac{p}{n-1}\cdot\frac{f(\tau)}{n} & \cdots & \frac{p}{n-1}\cdot\left[1-\frac{n-1}{n}\cdot f(\tau)\right] \end{bmatrix} \tag{2.15}$$

The probability distribution of responses is as follows:

$$\{P(Y)\} = \left\{q,\ \frac{1\text{-}q}{n\text{-}1},\ \frac{1\text{-}q}{n\text{-}1},\ \ldots\ \frac{1\text{-}q}{n\text{-}1}\right\}, \tag{2.16}$$

where

$$q = q(\tau) = (1-p)\cdot\left[1-f(\tau)\right] + \frac{f(\tau)}{n}. \tag{2.17}$$

The probability of errors and the accuracy:

$$r(\tau) = \sum_{i=1}^{n}\sum_{j=1}^{n} p(x_i, y_j) = \frac{n\text{-}1}{n}\cdot f(\tau), \quad i \neq j.$$
$$\mathrm{a}(\tau) = 1 - r(\tau) = 1 - \frac{n\text{-}1}{n}\cdot f(\tau) \tag{2.18}$$

Finally, the processed information is [Reza, 61]:

$$I_p = \sum_{i=1}^{n}\sum_{j=1}^{n} p(x_i, y_j)\cdot\log_2\frac{p(x_i, y_j)}{p(x_i)\cdot p(y_j)} \tag{2.19}$$

3 Results and important features of our model

The numerical evaluation of the mathematical model above was performed by MAPLE V for Windows. The processed information can be calculated on the basis (2.19) and (2.15):

$$I_p(\tau)=(1-p)\cdot(1-r)\cdot\log_2\frac{1-r}{q}+p\cdot(1-r)\cdot\log_2\frac{(n-1)\cdot(1-r)}{1-q}+ \\ +(n\text{-}1)\cdot(1-p)\cdot\frac{f(\tau)}{n}\cdot\log_2\frac{(n-1)\cdot f(\tau)}{n\cdot(1-q)}+p\cdot\frac{f(\tau)}{n}\cdot\log_2\frac{f(\tau)}{n\cdot q}+ \\ +(n\text{-}2)\cdot p\cdot\frac{f(\tau)}{n}\cdot\log_2\frac{(n-1)\cdot f(\tau)}{n\cdot(1-q)}. \tag{3.1}$$

The transmission speed $R(\tau)$, can be calculated with equations (2.5), (2.3) and (3.1), and we get a function (see Figure 1).

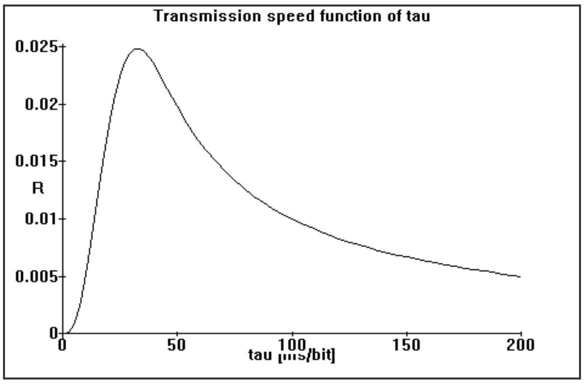

Figure 1: The transmission speed function of tactical parameter (τ) in our model.

The optimal work-point τ_{opt} can be determined by $\left.\frac{dR}{d\tau}\right|_{\tau_{opt}}=0$, following a numerical analysis, the $MSIP = R(\tau_{opt})$ maximum transmission speed (channel capacity) was plotted as a function of input entropy (Figure 2.).

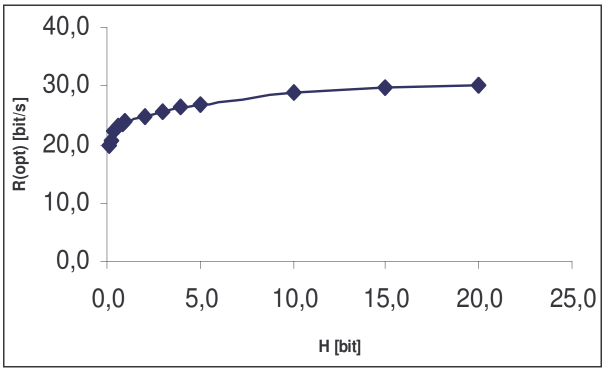

Figure 2: The optimal transmission speed (MSIP) function of input entropy.

We can find few important facts from study of accuracy of information processing. The accuracy of information processing at optimum working point is independent of *T* individual characteristic parameter and shows an interesting dependence of *H*(*X*) input entropy: the accuracy approaches to 100%, when *H*(*X*) approaches to 0 bit and approaches under 70% when the input entropy is increasing (*H*(*X*) >> 1 bit).

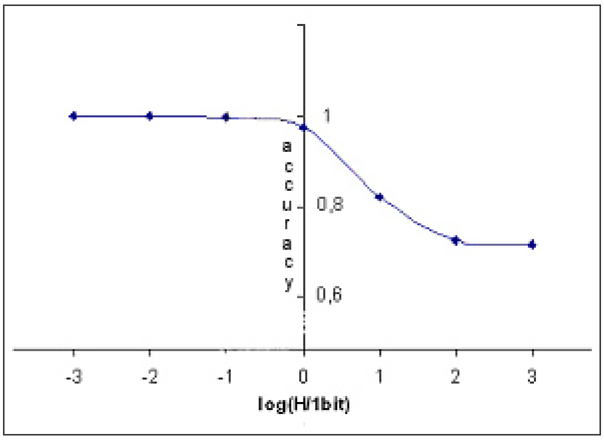

Figure 3: The optimal transmission speed (MSIP) function of input entropy.

Moreover, information theory distinguishes between the concepts of *a priori* and *a posteriori* information [Reza, 61]. The *a priori entropy* is determined by the generation of the signal sequence (so it is independent of the subject's consciousness). The *a posteriori entropy* is a quantity generated during the perception of the signal sequence in the subject's consciousness and the tactic (τ) is fitting to *a posteriori entropy*, so the subject changes its tactic below *H*(*X*)=1 bit.

Through the reduction of *H*(*X*) input entropy the I_p /*H*(*X*) processing ratio and the accuracy are increasing and its value approaches 1, while at non-zero entropy these values are less than 1 essentially. Therefore a phase-change-like transition occurs below *H*(*X*) = 1 bit – like as the physical phase-changes. Consequently we cannot involve the zero bit measurement into the determination of *IPA*, while the traditional measurements are performed only at two distinct values of entropy: at 0 bit and at a not too high *H*(*X*) value (e.g. 2 bits/symbol). Similarly through the increasing of *H*(*X*) input entropy (*H*(*X*)>>1 bit) the I_p /*H*(*X*) processing ratio and the accuracy approaches to an individual characteristic value, the subject changes the working method of information processing. We found that the most essential behaviour of our model is widely independent of the concrete choice of f(τ) heuristic tactical function and other parameters on the analogy of the universality features of the critical-phenomenon in statistical physics.

Depending on the quantity of the input information the signal processing in human brain has at least three different levels or working-phase, e.g.:

- Level of simple reactions (reflex): The input entropy (information) is 0 bit and there is no processing of signals in the cortex. This level is characterised by the time of simple reaction (*SRT*).
- Level of quantitative information processing: It means a quasi-exact identification of signals having small entropy. There is signal processing and classification in the cortex.
- Level of associative information processing: It is not possible to process the signals exactly since they have large amount of entropy and/or they are disturbed by noise. The simplest way of classification needs a different form: the pattern recognition approach for the identification of signals.

On the basis of the phenomenological model above the PSYCHOKONDI measuring methodology was developed and patented ([Remes, 91], [Bagány, 91] and [Bagány, 95]).

4 The measurement of human associative information processing

In accordance with our model the third level of human information processing is the associative level. Clearly, the obvious goal in designing the measurement protocol for this level is to preserve the basic methodology described above in this paper. Moreover, it is necessary to generate signals of high entropy from signals of the basic measurement process. Our solution for these tasks is summarized below.

The main question to be answered is a fundamental one: what is the suitable „etalon" for comparison of the measured data in investigating the human associative information processing? To recent knowledge of the authors, there is no such „etalon", that is, we have no exact (mathematical) and subject-independent cognitive psycho-physiological model suitable for the comparison in question.

Our proposition for solution of this problem is the application of an artificial neural network (ANN) for the same classification task working in parallel with the human operator investigated, and to quantify the classification process with a suitable and computable parameter of the ANN. Such a manner the data computed by the ANN can be considered as a basis for comparison of the information processing abilities of the subjects in case of high entropy stimulus signals (which needs – to our basic assumptions – human associative information processing).

4.1 The application of the Hamming-network for the IPA measurement

After investigating several artificial neural network architectures in this respect, we have concluded that the binary Hamming-MAXNET network (HMN) [Lippmann, 87] is the most suitable for our purposes because of its easy (analytical) training, large storing capacity [Hassoun, 96] [Meilijson, 95] and because of its optimality in Bayes-sense when performing the classification task during recall [Lippmann, 87] [Hassoun, 96]. Also, it is easy to acquire the stored pattern after the final decision. A single-iteration version of the original network has been developed [Meilijson, 95] and the practical application of the Hamming-network is a recent topic [Ikeda, 01].

The basic goal of the HMN is to perform a 1-NN classification using the Hamming distance between the stored binary patterns and the input pattern (or the so called key pattern). That is, the minimum value of Hamming distances is necessary for decision.

However, in our case, the computations have to be performed by artificial neurons, that is, the basic operations are dot-product between the actual neuron's synaptic weight-vector and the input vector, the subtraction of the synaptic threshold value and the application of the output function in order to compute the output „activity" value. Moreover, there is a special ANN (the MAXNET) for determining the maximum (instead of minimum) of components of the nonnegative input vector, so it is necessary to rearrange the basic 1-NN computations above. In order to achieve this goal, first we have to notice, that in case of finite binary vectors there is an upper bound of d_{max} for the maximum of the Hamming-distance (namely the dimension N of the vector), so the determination of the minimum is equivalent to the determination of the maximum of the difference between the dimension of N and the actual Hamming distance. Moreover, by changing over to {-1, +1}-type binary representation instead of {0, 1}, finally we get:

$$s_j = d_{\max} - d(x, p_j) = \sum_{i=0}^{N-1} \frac{p_{j,i}}{2} \cdot x_i - \left(-\frac{N}{2}\right), \tag{4.1}$$

where s_j denotes the output value of the j-th neuron, d_{max} is the value of the dimension $d(x, p_j)$ denotes the actual Hamming distance between the key and the j-th stored pattern $p_{i,j}$ denotes the i-th component of the j-th neuron in the Hamming layer in {-1, +1} representation and x_i denotes the i-th component of the key in {-1, +1} representation. So that, according the conventional ANN-terminology we get that the synaptic weight vector of the j-th neuron is $w_j = p_j/2$, and the value of the synaptic threshold is -N/2. The learning in this case means simply storing the ideal prototype vectors after halving them and setting up the universal synaptic threshold of -N/2.

The Hamming-layer sets up the initial values for the MAXNET-iteration, while the MAXNET performs the final computations necessary for recall. That is, the third layer is the co called MAXNET, which is a full-connected lateral-inhibition-type network. The number of the neurons is the same as in the Hamming-layer (that is, the number of M of the stored patterns), the value of the weight of self-feedback is 1, and for the values of other weights $0 < \varepsilon < 1/M$ holds for every neurons of the MAXNET. The value of synaptic thresholds is 0. The output function is the so-called threshold-logic-type. The operation of the MAXNET layer is given by the equations below:

a) initial values from the Hamming-layer:

$$y_j(0) = f(s_j) \tag{4.2}$$

b) T iteration steps:

$$y_j(t+1) = f\left(y_j(t) - \varepsilon \sum_{k \neq j} y_k(t) \right) 0 \leq t < T \quad 0 \leq j, k < M \tag{4.3}$$

c) output function of the MAXNET neurons:

$$f(x) = \begin{cases} 0 & x < 0 \\ x & 0 \leq x < N \\ N & N \leq x \end{cases} \tag{4.4}$$

After convergence the output of only one neuron remains positive, and based on its index the recall is completed. The classification (or in other words the association) process can be characterized by the number of iterations necessary for convergence.

The HMN is suitable for our purposes because the original (ideal, non-distorted) stimulus patterns can easily be stored in the Hamming-layer's neuron's weights, and when the key is a distorted version of one's stored pattern, the recall process not only simulates the „time" (that is, the number of iterations) necessary for final decision, but it gives back the result of the decision in form of the stored ideal pattern as well. Therefore, the conditional probability matrix could also be set up and all the calculations necessary for computing the *IPA* could be completed.

4.2 Simulation of the Hamming–MAXNET network for the *IPA* measurement

In order to simulate the behaviour of the HMN in the *IPA* measurement task, it is necessary to set up the network according to the basic PHYCHOKONDI protocol. The number of ideal patterns are 8, a particular pattern has been created by hand as a 7×5 matrix of values from {-1, +1}, the value of the lateral inhibition has been set up as $\varepsilon = 10^{-3}$, the stopping condition of the iteration is based on the value of the threshold of $\delta = 10^{-4}$. The iteration has been stopped, when all the outputs of the MAXNET's neurons except only one are lower than this threshold. Obviously, it is possible to run into an infinite iteration process – this is exactly the case, when two or more neurons in the Hamming-layer have equal output values. This problem was investigated thoroughly, and it was concluded that this event occurs rarely [Floréen, 92], therefore we solved this problem by stopping the iteration after MAXITER = 1000 steps in our simulations, and by excluding these iteration values from calculation of the iteration average.

After setting up the network, the next step is to generate the stimulus patterns (signals), which are distorted versions of the ideal, stored patterns. After selecting an ideal pattern according to the basic measurement protocol, the components of the pattern vector are inverted at random using uniformly distributed, independent pseudo-random numbers. Given a fixed value of p, several key vectors (i.e. the distorted version of the selected stimulus pattern) have been generated (10 keys with $0 < p \leq 0.196$ and 100 keys with $0 < p \leq 0.401$ respectively in experiments A and experiments B). The sequence of p values have been chosen so that the Shannon-entropies of the generated keys form an arithmetic series, so the sequence in question was the following: 0.003, 0.007, 0.011, 0.015, 0.02, 0.026, 0.031, 0.037, 0.043, 0.05, 0.057, 0.064, 0.071, 0.079, 0.088, 0.096, 0.105, 0.115, 0.125, 0.135, 0.146, 0.158, 0.17, 0.183, 0.196, 0.211, 0.226, 0.243, 0.261, 0.281, 0.304, 0.329, 0.36, 0.401. At a given value of p not only the average iteration number has been computed as described above, but the relative frequency of correct classifications has also been determined as well. The results of our numerical experiments can be seen on Figure 4.

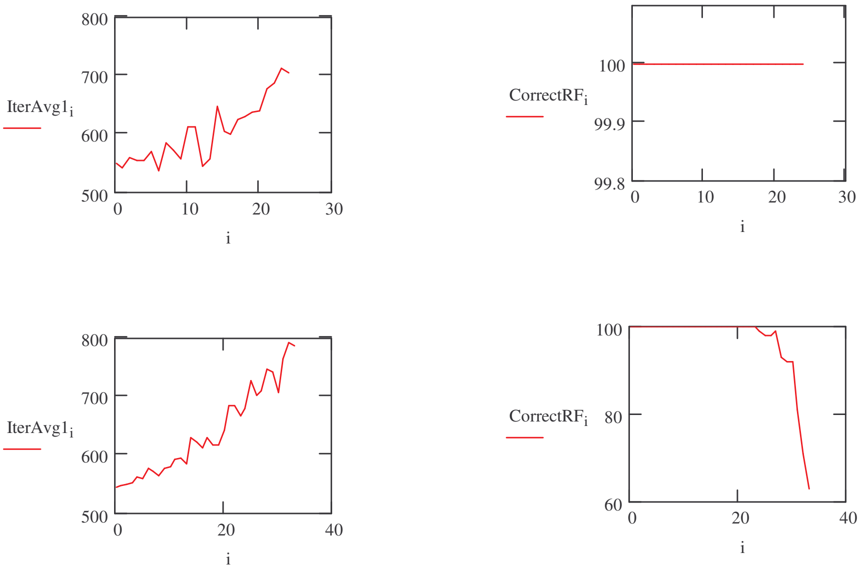

Figure 4: The average iteration numbers (left columns) and the relative frequencies of correct classifications (right columns) in experiment A (upper trace) and experiment B (lower trace) as a function of key's entropy (given by the index in the above sequence of p values for simplicity).

As it can be checked on the Figure 4, the average iteration number has an increasing tendency with increasing key entropies and in an acceptable range of key entropies there are no misclassifications. Therefore the HMN defined in this paper can be considered as an *etalon* when measuring the human associative information processing, so that the original PSYCHOKONDI measurement protocol can be extended for higher-entropy stimulus signals.

5 Outlook

Since the formal description of few neutral network models is identical to some models of statistical physics (for example the Hopfield model to the Ising spin glass), the field of neural network attracted many physicist to study the impact of phase transitions on the stability of neural networks. With this deep analogy we can understand better the activity of brain and information processing. For example [Hoshino, 96] has shown that the transition between the pattern itinerant state and pattern fixed state in neural networks may be induced by the self-organized infinitesimal synaptic changes if the dynamical state of the network is near the transition point. On the other hand, the early stages of mammalian visual processing has been successfully modelled and realised on silicon, using CNN chips [Gál, 04]. The paper has also described the straightforward predictions of models that have relevance to visual neuroscience.

6 Conclusions

The model discussed in this paper gives the following basic features resulted from requirements and experiences.

- The process has a statistically manageable stochastic nature: the t_c cortical (decision) time is determined by the tactical parameter so t_c is a random variable characterised by its mean value and standard deviation.
- It has been proven that the $I_p - t_c$ function comes from theory above corresponds to the experimental results. Moreover the $R = I_p / t_c$ formula of transmission speed provides a qualitatively correct function to determine the optimal work point, i.e. channel capacity.
- This channel capacity, defined as the maximum of transmission speed for a given T parameter, is approximately constant in the $H(X)$ entropy range of few bits. Therefore the individual's *MSIP* information processing ability (independent of entropy) can be determined.
- Through the reduction of $H(X)$ input entropy the $I_p/H(X)$ processing ratio and the accuracy are increasing and its value approaches 1, while at non-zero entropy these values are less than 1 essentially. Therefore, a „phase-change" occurs below $H(X) = 1$ bit point − like as the physical phase-changes. Consequently we cannot involve the zero bit measurement into the determination of *IPA,* while the traditional measurements are performed only at two distinct values of entropy: at 0 bit and at a not too high $H(X)$ value (e.g. 2 bits). Similarly, through the increasing of $H(X)$ input entropy ($H(X) >> 1$ bit) the $I_p/H(X)$ processing ratio and the accuracy approaches to an individual characteristic value, the brain change the working method of information processing.
- Based on the HMN simulations the last conclusion is that a possible method for measuring the human associative information processing ability is based on the Hamming-MAXNET network defined in the fourth section of this paper, the suitable number of iterations is in the order of 100 at each key-entropy value and the suitable interval for the p values is $0 < p \leq 0.196$. In case of human associative information processing, the verification of the HMN-based measurement method is the next task, that is, first it is necessary to conduct a series of measurements on human operators working on the same task in parallel with the HMN in case of stimulus signals of higher entropy.

References

[Amari, 80] Amari, S.: Topographic Organisation of Nerve Fields; Bul. Math. Biol. 42, pp. 339-364, 1980

[Bagány, 91] M. Bagány, P. Nagy, A. Nádas, P. Remes: Method for measuring of human visual information processing, Hungarian patent b. sz. 1451/91.

[Bagány, 95] Bagány, M., Nagy, P., Kalmár, S., Remes, P., Pozsgai, A.: Information processing in brain IEEE Proc. of Workshop on Computational Modelling and Imaging in Biosciences (COMBIO'95), Kecskemét, Hungary, Hungarian Academy of Sciences, pp. B.12-16, 1995.

[Boff, 86] eds. Boff, K. R., Kaufman, L., Thomas, J. P.: Handbook of Perception and Human Performance. Wiley-Interscience Publ., 1986

[Floréen, 92] Computational Complexity Problems in Neural Associative Memories. Doctoral Thesis. University of Helsinki, Department of Computer Science, 1992.

[Gál, 04] Gál, V; Hámori, J; Roska, T; Bálya, D; Borostyánkői, ZS; Brendel, M; Lotz, K; Négyessy, L; Orzó, L; Petrás, I; Rekeczky, CS; Takács, J; Venetiáner, P; Vidnyánszky, Z; Zarándy, Á.: Receptive field atlas and related CNN models, International Journal of Bifurcation and Chaos, 2004.

[Hassoun, 96] Hassoun, M. H., Watta, P. B.: The Hamming Associative Memory and its relation to the Exponential Capacity DAM. ICNN'96 IEEE International Conference on Neural Networks, Vol. I. pp. 583-587., Washington, USA, June, 1996.

[Hideg, 82] Hideg, J., Bognár, L., Remes, P.: Psycho-physiological Performance Examination Onboard the Orbital Complex Salyut–Soyuz. 33rd International Congress of the International Astronautical Federation, Paris, France, 1982.

[Hideg, 85] Hideg, J., Remes, P., Bognár, L., Ágoston, M.: Modern Method and Instrument for Measuring Psychic Performance. Acta Astronautica, vol. 12; pp. 707-712., 1985

[Hoshino, 96] O. Hoshino, Y. Kashimori, T. Kambara: Self-organized phase transitions in neural networks as a neural mechanism of information processing, 1996

[Ikeda, 01] Ikeda, N., Watta, P., Artiklar, M., Hassoun, M. A.: A two-level Hamming network for high performance associative memory. Neural Networks, Vol. 14., 2001. pp. 1189-1200.

[Lippmann, 87] Lippmann, R. P.: An Introduction to Computing with Neural Nets. IEEE ASSP Magazine, April, 1987, pp. 4-22.

[Meilijson, 95] Meilijson, I., Ruppin, E., Sipper M.: A single-iteration threshold Hamming network. IEEE Transactions on Neural Networks. vol. 6. no. 1. pp. 261-266. January, 1995.

[Nechaev, 85] Nechaev, A.P., Ponomareva, I.P., Hideg, J., Bognár, L., Remes, P.: O dopolnitelnykh vozmozhnostiakh metodiki izuchenia psikhicheskoy rabotosposobnosti cheloveka (po rezultatam issledovaniy na orbitalnoy stantsii Salyut–7). 18th Intercosmos Conference, Gagra, S.U., 1985.

[Remes, 83] Remes, P., Hideg, J., Bognár, L., Pozsgai, A., Lehoczky, L., Sidó, Z.: Kiss, Gy., Kalmár, S.: Changes in Information Processing Ability (IPA), EEG, EOG Using Passive Orthostatic and Antiorthostatic Test. Physiologist Supplement, vol. 26., pp. S-70, S-71, 1983.

[Remes, 91] Remes, P., Lehoczky, L., Nagy, P., Bagány, M., Kalmár, S., Pintér, I.: Theory of Measuring of the Information Processing Ability and Results Obtained by Testing Candidates for Space Flight Carried Out with the BALATON Device. USAF, Brooks, 1991

[Reza, 61] Reza, Fazlollah M.: An Introduction to Information Theory. McGraw-Hill, 1961.