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Learning and Recognition of Visual Patterns by Human Subjects and Artificial Intelligence Systems

Algis GARLIAUSKAS, Alvydas ŠOLIŪNAS *

Institute of Mathematics and Informatics
Akademijos 4, 2600 Vilnius, Lithuania
e-mail: galgis@ktl.mii.lt

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Abstract. Comparative study of the recognition of nonsemantic geometrical figures by the human subjects and ART neural network was carried out. The results of computer simulation experiments with ART neural network showed well correspondence with the psychophysical data on the recognition of different complexity visual patterns: in both cases the patterns of medium complexity were recognized with the highest accuracy. On the contrary, the recognition of the patterns by their informative fragments demonstrated different recognition strategies employed by natural and artificial neural systems. For biological systems, it is necessary the presence of not only distinctive features in visual patterns but the redundant features as well for successive recognition. ART neural network ignores redundant features and recognizes visual patterns with equal accuracy whether the whole pattern or only the informative fragment of any completeness is present.

Key words: pattern recognition, neural networks, psychophysics, fragmentation.

1. Introduction

The human cognition using artificial neural networks with learning and adaptive capabilities is more fruitful. This is generating a new educational discipline – the visual cognitive systems with a novel generation of computing systems (Andersen, 1983; Gupta, 1992). The virtual cognitive system is strongly supported by the visual system which is based on the vertebrate visual cortex system of the human brain and artificial neural systems.

These studies have included the comparison of visual information processes in natural neural systems – human brain – and artificial neural approach in visual analysis. One direction in the field of artificial intelligence is to simulate information processes of biological neural systems as close as possible. There are many different artificial neural networks that successfully mimic main properties of biological systems (Garliauskas, 1998; Wallis and Rolls, 1996). We have investigated the presumptions how artificial neural networks perform the recognition of geometrical figures with respect to the factors

*Vilnius University, Dept. Biochemistry and Biophysics, M.K. Čiurlionio 21, 2009 Vilnius, Lithuania
e-mail: alvydas.soliunas@gf.vu.lt

of complexity and completeness. For this task, we chose Adaptive Resonance Theory (ART) neural network designed by Grossberg (1976a, 1976b), Carpenter and Grossberg (1987), Carpenter (1997). ART is autoassociative neural network, i.e., the learning of the network occurs without an explicit teacher-so-called "unsupervised learning" (Cichocki and Unbehauen, 1993; Farmer, 1994; Ripley, 1996). ART neural network well suit for the learning and recognition of the special class of visual figures that was created for the psychophysical experiments.

Psychophysical experiments were performed on human subjects with tachistoscopic stimulus presentation technique and backward masking procedure. ART network simulation experiments were carried out with NeuralWorks Professional II program (Klimasauskas *et al.*, 1989) on IBM PC compatible computers.

2. Learning and Recognition of Patterns by Human Subjects

2.1. *The First Psychophysical Experiment*

Test stimuli were three sets of four 2D meaningless geometrical figures consisting of four, six, and eight line-segments (Fig. 1). The stimuli were presented by a programable tachistoscope which consisted of a personal computer connected via the CAMAC interface with the matrix of light diodes. Sequence of stimuli presentation was as follows: sound signal for attention concentration; test stimulus; interstimulus interval (ISI) followed by a masking pattern and short pause during which the subject should draw the pattern. All 12 patterns were memorised by subjects before experiment. 20 subjects took part in 6 to 14 test sessions. Altogether 480 test stimuli were presented in each test session: 12 patterns $\times$ 40 repetitions. Different patterns were presented randomly with equal probability.

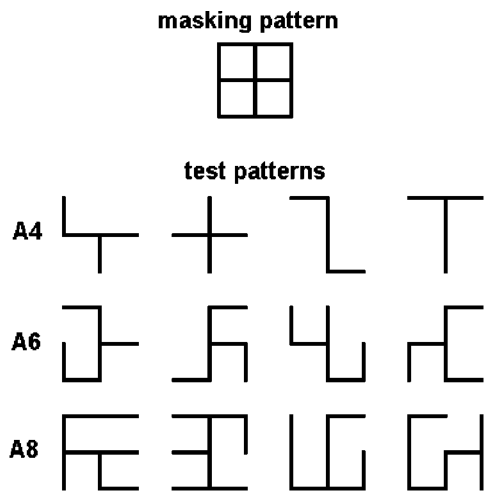

Fig. 1. Test stimuli.

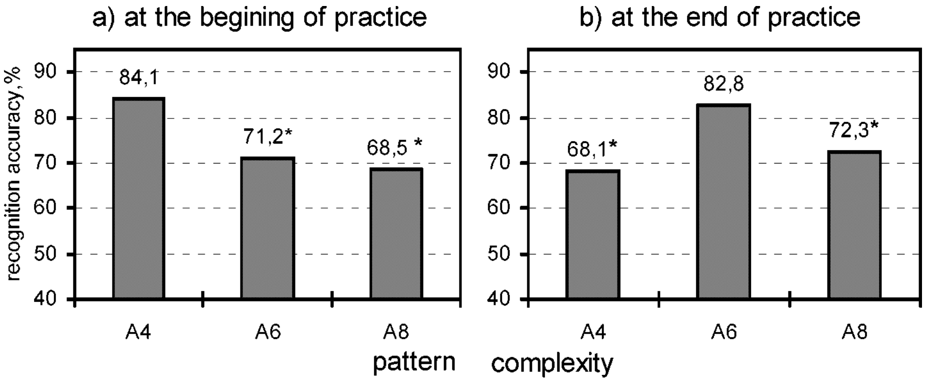

Fig. 2. Recognition of visual patterns as a function of complexity and practice level. A4, A6, and A8 – four-, six-, and eight-line patterns, * – significant difference at $p < 0.05$ with respect to highest accuracy.

Exposition time of test stimulus – 10 ms, masking pattern – 500 ms. ISI was established individually for each subject as a shortest time interval permitting recognition accuracy of 50% – 80%. Recognition accuracy for three sets of different pattern complexity was measured.

The dependence of recognition accuracy on the complexity (number of line-segments) was influenced by the practice level. For unexperienced subjects (the first few test sessions) the recognition accuracy had reverse dependence on the number of elements (Fig. 2). For experienced subjects (the last few test sessions, after results stabilisation) the six-line patterns were recognised with the highest accuracy.

2.2. *The Second Psychophysical Experiment*

The same kind of test stimuli, $2D$ meaningless geometrical figures consisting of vertical and horizontal line-segments, were used in this experiment. Test stimuli were three sets of eight geometrical figures consisting of six, seven, and eight line-segments and named as B6, B7, and B8, respectively. All conditions of this experiment were the same as in the 1st experiment except the presentation order of different sets of complexity. Three sets were presented separately varying the presentation order in each test session. 480 test stimuli were presented in each test session. Four subjects took part in 4 to 5 test sessions.

Recognition accuracy had reverse dependence on the number of line-segments: the more complex the pattern, the less the recognition accuracy was (Fig. 3). This dependence did not change during the practice.

3. Simulation Experiment with ART Network

3.1. *Characteristics of ART Neural Network*

We used ART 1 type of network architecture that is designed for classifying binary input patterns (for details see Grossberg (1976a, 1976b); Carpenter and Grossberg (1987)).

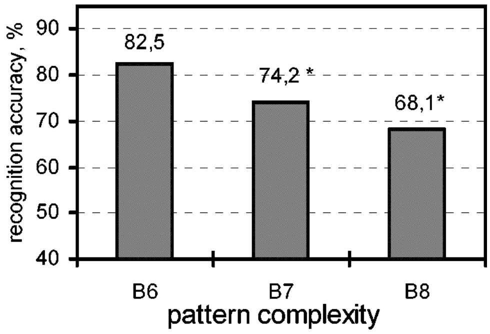

Fig. 3. Recognition of visual patterns as a function of complexity. B6, B7, and B8 – six-, seven-, and eight-line patterns.

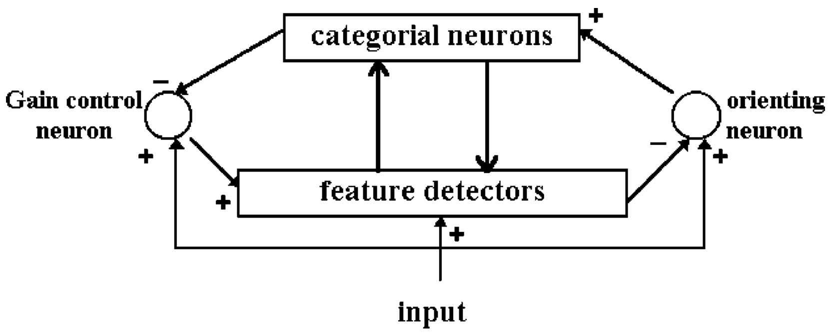

Fig. 4. Basic structure of ART network.

Network consists of two basic interconnected layers of neurones which comprise the attentional system. The first layer (input) is the feature detector neurones, the second one (output) is represented by the categorial neurones. The activity of categorial neurones is characterised by the principle of winner-take-all, i.e., the neurones compete with each other, so that at any instant, only the most active neurone generates output signal. Number of neurones in the output layer must be no less than the number of different categories the network should learn and recognise. The number of input neurones equals to $n \times m$, where n is the height and m is the width of the $2D$ input matrix. During the learning, the strength of interconnections are set and they do not change during the recall. In addition, the network has so-called attentional gain control neurone that permits the input layer to distinguish between top-down and bottom-up (input) signals. There is also orienting subsystem represented by one neurone that determines how much different inputs can vary and still be put in the same category. Orienting subsystem has a single parameter, vigilance parameter v, that determines how large a mismatch between two stimuli is tolerated recognising them as belonging to the same category. This parameter was a basic independent variance in our simulation experiments.

Some important characteristics of ART network were determined prior to simulation experiments by testing ART network with various values of network parameters and various input stimuli:

1) constant proportion of signal/noise elements in the input patterns for correct recognition of learned patterns, i.e., the more elements of learned pattern were presented in the input pattern during the recognition session, the more noise elements the network tolerated. This signal/noise level differed for different sets of learned categories.
2) recognition stability depends only slightly on the duration (number of cycles) of learning. Only at the low values of vigilance parameter the categorisation was unstable if the number of learning cycles was small (1–100 cycles).
3) probability to correctly classify input patterns depends only on the value of vigilance parameter during the recognition. Variation of v value did not influence the recognition results.

In simulation experiment, as an input pattern we used 15×15 matrix each element in which has either 0 or 1 value. The number of output units varied from 4 to 8 depending on experiment. Learning consisted typically of 200 random presentations of examples. Each category was represented by a single example, i.e., if there were four categories, four different examples were presented 50 times in random order during the learning stage.

3.2. *Experiment Based upon ART Neural Network*

Two networks were created which differed only by the number of output units: the fist network had four output neurones and the second one had eight output neurones. Both networks had 225 input neurones. Learning amount was 200 cycles.

Six input pattern files were created: A4, A6, A8, B6, B7, and B8 corresponding to the six pattern sets used in psychophysical experiments, e.g. file A6 consisted of four input patterns each of which represented one geometrical figure on a 15×15 input matrix (Fig. 5).

The sequence of events in the experiment was as follows: initialisation of network (randomisation of incoming weights to each layer); training with one of six pattern sets; setting of vigilance parameter; successive recognition of all learned patterns.

The independent variable was vigilance parameter v and the dependent variable was the number of distinguished categories. Vigilance parameter is close related to interstimulus interval in the psychophysical experiments. The shorter the ISI, the smaller amount of pattern features reaches the recognition system and the smaller amount of information is available for decision making. The same is relevant for v parameter: the less the v, the less match of presented input stimulus with learned category is needed for attaching this stimulus to the learned category.

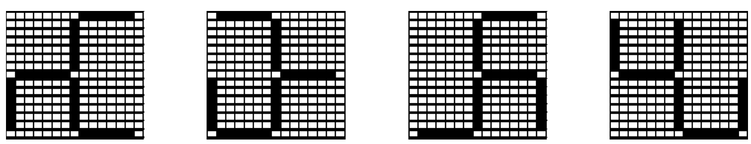

Fig. 5. Input pattern file A6 in a graphical mode. Filled squares in a matrix correspond to the value +1 in the input layer of the ART network; open squares – input value 0.

Table 1

Number of categories distinguished by ART network as a function of pattern complexity (A4, A6, A8) and value of vigilance parameter. * – reffer to the value of vigilance parameter at which the network begins to make errors

Input	Vigilance parameter								
patterns	0.9	0.8	0.76	0.75	0.7	0.67	0.66	0.5	0.1
A4	4	4	4	2*	2	2	2	2	1
A6	4	4	4	4	4	4	2*	2	1
A8	4	4	4	3*	3	3	3	2	2

Table 2

Number of categories distinguished by ART network as a function of pattern complexity (B6, B7, B8) and value of vigilance parameter

Input	Vigilance parameter								
patterns	0.9	0.88	0.87	0.86	0.85	0.84	0.83	0.82	0.6
B6	8	8	8	8	8	8	7*	6	4
B7	8	8	8	7*	5	6	6	6	4
B8	8	8	7*	7	6	6	6	6	3

Varying the value of vigilance parameter during the recognition we found that the most stable are the six-line patterns. ART network recognises all four patterns as different categories until v value is diminished to 0.67. Table 1 represents the "failing points"' – the value of vigilance parameter at which the network begins to make errors, i.e., some patterns that were recognised as different categories at the highest v values now are attached to the same category. In the case of eight categories the most stable categorisation was found also for six-line patterns (Table 2).

These results correspond very well to the psychophysical data. One note should be done here: the results of computer simulation best correspond to the results obtained with experienced subjects, after they acquired some skills.

4. Recognition of Pattern Fragments

Are coding and analysis of images based on all features or only on informative ones? Psychophysical data do not permit an unambiguous answer. It depends on the type of stimuli, experimental conditions, the task, and other factors.

At the present work we used special class of visual figures that were made in such a way that it was possible to divide each figure into two three-line fragments: the first, an entirely informative fragment, i.e. belonging to only one figure and having all distinctive

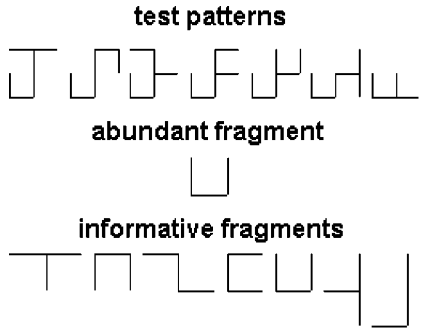

Fig. 6. Test stimuli of the 1st experiment.

line-segments of this figure; the second, an abundant fragment common for all figures and thus not providing any information about the figures (Fig. 6).

4.1. *Psychophysical Experiments*

The procedure of the first experiment was similar to the previously described psychophysical experiments. Prior to experiment subjects memorized seven six-line patterns and, during the test session, the whole patterns and informative fragments were presented in random order. Exposition duration of test stimuli, masking pattern and the duration of ISI were set according to the same rules as in the experiments on complexity investigation.

There were distinguished two groups of subjects. The most of subjects (eight) showed clear advantage of the whole patterns' recognition. The mean accuracy of whole patterns vs informative fragments was 81% vs 69% $(p < 0.0001)$. For other three subjects there was no significant difference between two variants of recognition accuracy (69% vs 73%).

In the second experiment, six patterns were made in such a way that each pattern could have four informative fragments of different completeness – two, three, four, and five line-segment fragments respectively. In this way six whole patterns and 24 informative fragments were presented for subjects that were acquainted only with whole patterns.

Direct dependence of recognition accuracy on the fragment completeness was found $(F(4, 30) = 20.552, p < 0.0001$, Fig. 7).

4.2. *Simulation Experiment with ART Neural Network*

One ART network (225 input units, 7 output units) and four input pattern files (two whole patterns' files and two informative fragments' files, according to the stimuli of the 1st and 2nd psychophysical experiments) were created for this experiment. As the human subjects had been acquired with whole patterns and were presented with whole patterns and informative fragments, the ART network was trained with whole patterns but, during the recognition stage, the whole patterns and informative fragments were presented successively. We measured the value of vigilance parameter at which the network began to make errors.

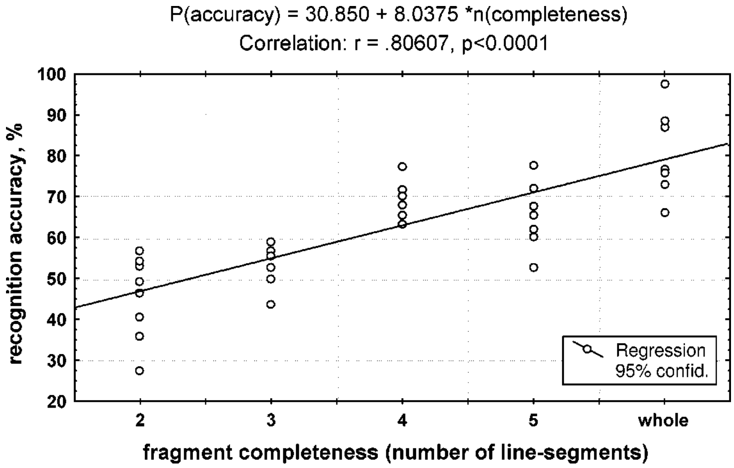

Fig. 7. Recognition accuracy of test stimuli as a function of fragment completeness.

Table 3

Number of categories distinguished by ART network as a function of test stimulus completeness and value of vigilance parameter

Input patterns	Vigilance parameter 0.9	0.84	0.83	0.82	0.8
whole pattern	7	7	4*	3	3
fragment	7	7	4*	3	3

The characteristics of ART network predetermined the results: no difference between recognition of whole patterns and their informative fragments was found (Table 3). Even the less complete two-line fragments were recognized with the same success as the whole patterns in all range of v values. As the identical simulation results on ART network were obtained with test stimuli of the first and the second psychophysical experiments, in the sense, that there was no difference between recognition of whole patterns and informative fragments, Table 3 represents simulation results only with test stimuli of the first psychophysical experiment.

5. Conclusions

The effect of complexity and completeness of memorized visual figures on the recognition accuracy was investigated in psychophysical experiments on human subjects and in simulation experiments on ATR neural network. Experimental data revealed different effect of complexity and ART network.

ART network repeated very well the performance of human subjects in the recognition of visual figures of different complexity. Based on these results, we can conclude that the algorithms of learning and recall of ART network correspond to the functioning of biological neural systems in the recognition of memorised patterns. On the contrary, the figure completeness had the different effect on recognition accuracy for human subjects and ART neural network. Direct dependence of recognition accuracy on fragment completeness was obtained for absolute majority of human subjects. ART network showed no difference in recognition of whole figures or informative fragments of various completeness. We can conclude that for human beings, and probably for other biological organisms, the redundant features of visual patterns are necessary for successful pattern recognition. This is one of the basic difference between natural and artificial neural systems. Artificial intelligence systems very often ignore redundant information and they behave more "logically", more "rational". It may be suggested that artificial neural systems has advantage in the situation of deterministic image description whereas natural neural systems demonstrate more possibilities in unstable dynamic environment due to prolonged perceptual practice.

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A. Garliauskas received his Habil. Dr. degree of technical sciences from the Computer Center, the Department of the USSR Academy of Sciences, Novosibirsk, USSR, in 1977. He is a head of the Laboratory of Neuroinformatics, Institute of Mathematics and Informatics. His research interest includes neuroinformatics methodology, control problems and development of neural networks algorithms, chaos processes.
A. Šoliūnas PhD of natural sciences, received PhD degree at Vilnius University in 1997. At present he is a research fellow at the Department of Biochemistry and Biophysics, Vilnius University. His research interests are dynamic of image recognition in human visual system, memory and consciousness in visual perception.

Žmogaus ir dirbtinio intelekto sistemos regimųjų figūrų apmokyme ir atpažinime

Algis GARLIAUSKAS ir Alvydas ŠOLIŪNAS

Buvo tiriamas dirbtinių neuroninių tinklų sugebėjimas atpažinti regimuosius vaizdus. ART neuroniniam tinklui ir žmogui buvo pateikiamos dvimatės geometrinės figūros, charakterizuojamos elementų skaičiumi ir fragmentų pilnumo laipsniu. ART tinkle gauta atpažinimo priklausomybė nuo elementų skaičiaus visiškai atitinka analogiško eksperimento su žmonėmis priklausomybei. Tuo tarpu figūrų fragmentų atpažinimas atskleidė skirtingas strategijas, naudojamas ART tinkle ir eksperimente su žmonėmis. ART tinklas mokosi remdamasis tik informatyviais figūros elementais, o žmogus – dar atlieka ir perteklinių elementų analizę.