On Early Discovery of Mathematically Creative Children using Artificial Neural Networks Modeling (with a case study)

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Abstract: Learning creativity is an interesting educational phenomenon usually observed at children classrooms. Early discovery of individual children having mathematical creativity is a challenging interdisciplinary research issue. This piece of research focuses on quantitative analysis and evaluation of mathematical learning creativity on the basis of acquired "Subjective Domains of Experiences" (SDE) inside children's brain. Acquisition of (SDE) assumed to modify a children's stored experience via application of various multimedia Computer Assisted Learning (CAL) packages (modules). Accordingly, fairly assessment of mathematical learning time response has been adopted herein for analysis and evaluation of learning creativity acquired by (SDE). By some details, early discovery of creativity could be performed well in accordance with obtained learning assessment results. That is after solving correctly a suggested mathematical topic (at children classrooms).Furthermore, interactive interference between Reflective and Spontaneous Vorstellungen* during mathematical education has been simulated using supervised and autonomous Artificial Neural Network (ANN) learning paradigms.
***** The German word Vorstellungen is used in replacement of the vague English expression "internal representation"
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Keywords: Learning Creativity Phenomenon ,Artificial Neural Network, Vorstellungen, subjective domain of experiences, Computer Assisted Learning.

1. Introduction

The field of educational sciences is represented by a growing community internationally. Many educational experts now recognize that conventional ways of conceiving knowledge, educational systems and technology-mediated learning are facing increasing challenges [1]. That is due to rapid technological and social changes arise in this time considering modified educational field applications [1-3]. Quantitative evaluation of learning creativity phenomenon is an interesting, challenging, and interdisciplinary research issue associated with educational field applications and activities [4&5]. So, for long time ago and till recently, educationalists as well as psychologists have been cooperatively interesting in systematic searching for quantified analysis, and evaluation of that interdisciplinary issue. Accordingly, for quantifying learning creativity phenomenon, an interdisciplinary research work integrating : cognitive and educational sciences, with educational psychology and neurobiology has been adopted recently [3&4]. More specifically , this piece of research focuses on quantified analysis, and evaluation of mathematically creative children using a novel interdisciplinary approach. That is by adopting application of realistic Artificial Neural Network (ANN) modeling of acquired children's "Subjective Domains of Experiences" (SDE) [6] ,which build up mathematical learning creativity (at children classrooms). Furthermore, presented ANN models simulate realistically two types of internal children's brain representations Reflective and Spontaneous (Vorstellungen). Respectively these two types have been modeled by ANN as supervised and autonomous learning paradigms. Interestingly, both types of "Vorstellungen" together form individual children's (SDE). It is worthy to note that: intuitive "common-sense" and a conscious knowledge of rules and facts are basically considered in order to perform well development of (SDE) [6]. By some details, both presented ANN models are simulating two types of internal children's brain representations (Vorstellungen) Reflective and Spontaneous.

Referring to Meissner [6], it is announced by words that ("Reflective Vorstellungen" may be regarded as an internal mental copy of a net of knowledge, abilities, and skills, a net of facts, relations, properties,….. etc. The development of "reflective Vorstellungen" certainly is in the center of mathematics education. To reflect and to make conscious are the important activities). Moreover, spontaneous Vorstellungen mainly develop unconsciously or intuitively. Consequently, both presented ANN models are inspired mainly by realistic request to statistical analysis of learning response time according to dynamical internal representations of children's brain, (See Appendices

I&II). By more details, that analysis obtained in accordance with response time assessment results, after solving correctly the presented mathematical topic problem "How to solve long division problem?". Its correct solution is performed well following sequential steps: Divide, Multiply, Subtract, Bring Down, and repeat (if necessary) (See appendix III). A special attention has been developed herein towards comparison between two types of children's brain internal representations (Vorstellungen) considering statistical average of learning response time , and learning rate values.

Conclusively, obtained simulation results revealed the superiority of Spontaneous Vorstellungen over Reflective Vorstellungen in improvement of quantifying mathematical learning creativity provided by (SDE). Moreover, two ANNs design parameters: gain factor (of neuronal sigmoid activation function), and learning rate value, proposed for quantified assessment of mathematical learning creativity. Additionally, effective impact on creativity improvement observed by neurons' number increase via dynamical synaptic connectivity (internal brain Plasticity) during interactive learning process.

The rest of this paper is organized as follows. The basic concept of creativity and its close relation with human brain cells (neuronal and Glial) is presented at the second section. At the third section, general model illustrating concepts of Vorstellungen its relation with diverse ANN learning paradigms are presented. The obtained results for brain functions (number of neurons) in addition to the effect of design ANN parameters on learning performance are illustrated at the fourth section. at the fifth section, some interesting conclusive remarks are introduced.

Finally, by the end of this paper, four attached illustrative Appendices are given as follows. At APPENDIX I, a simplified macro level flowchart describing algorithmic steps for simulation learning programs is presented. Two lists of simulation programs for both Vorstellungen types (Reflective and Spontaneous) are shown at APPENDIX II (A&B). At APPENDIX III, a simplified flowchart for Computer Assisted Learning (CAL) packages for suggested mathematical topic problem "How to solve long division problem?" is presented. Furthermore, three print screens samples representing obtained results after running of designed time response assessment program, are shown at APPENDIX IV.

2. Creativity and Brain Function

This section is dedicated to introduce a general clarification about what is meant by creativity and its close relation with human brain. According to recently published article by Dr.Linda Karges-Bone,[7], it is announced that "creativity is the spark that never burns out". Functionally, true creativity is defined to have a goal , a purpose, and an outcome [8]. Both declared evidences are well supported by more recent research results suggests that fresh neurons arise in the adult brain every day and that the cells ultimately help with learning complex tasks—and the more they are challenged, the more they flourish [9]. By more details, thousands of new cells are generated in the adult brain every day, particularly in the hippocampus, a structure involved in learning and memory. Moreover, during a period of two weeks, most of those newborn neurons will die, unless the animal is challenged to learn something new that is a learning task. In other words, by more neural interconnections learning creativity emerges. That is resulting in more extended brain capacity for neural plasticity over time [10]. . Recently, some research papers are published describing quantifying of main brain functional phenomena (learning and memory)[11-16]. Moreover, researchers need essentially to know how neurons synapses inside the brain are interconnected together and communication between brain regions,[17].

In some details, at any instant brain state (synaptic weight pattern) in neural systems leads to some expected spontaneous behavioral response to any of external stimuli. So, dynamically changes of weight synaptic pattern (vector) measures the learning convergence process in consequence with internal / stored level of intelligence. Consequently, the initial brain state of synaptic connectivity pattern considered as pre-intelligent creativity parameter.

In addition to above clarifications about neurons at hippocampus brain area, interesting analysis for the effect of brain Glial cells on learning performance (convergence time factor) is shown at Fig.1, in below. It illustrates mutual inter-communication among Glial cells and typical neuronal brain cells. Noticeably, increasing of synaptic connectivity value is measured as ratio between number of Glial cells versus number of typical neuronal cells. This ratio leads to improvement of learning performance time factor [4][15][16] that considered as number of training cycles. For more details, it is referred to[4],and other references therein is recommended.

3. Effect of Gain factor values on Learning Performance

3.1 Effect of Gain factor values on Learning Convergence time

The obtained results for various gain factor values are comprehensively shown (in a statistical graphical form) at Figure 2.

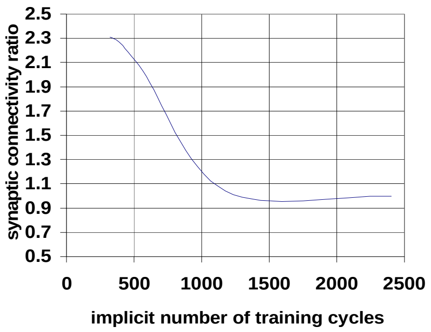

Fig.1: Illustrates the relation between number of training cycles during learning process and the synaptic connectivity (weights) values (adapted from [4]).

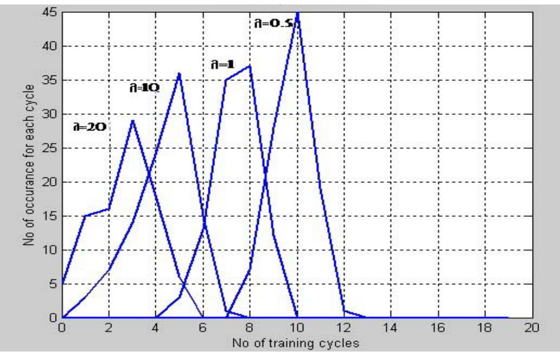

Fig.2. Illustrates improvement of average response time (no. of training cycles) by increase of the gain factor values (adapted from[13])

The above results illustrate gain factor effect on improving the value of time response measured after learning process convergence [13]. These four graphs depicted at Fig.2 are concerned with the improvement of the learning parameter response time (number of training cycles). That improvement observed by increasing of gain factor values (0.5, 1, 10,and 20) that corresponds to decreasing respectively number of training cycles by values (10 ,7.7 ,5 , and 3) cycles, (on approximate averages). Conclusively, Learning creativity is virtually improved by such increase of gain factor values.

3.2 Effect of Gain factor values on Learning Achievement (Scores)

At Fig,3, the effect of increasing number of neurons contributing to learning process_(Inside a child's brain) on learning achievement (scores) is illustrated. That is considering Spontaneous Vorstellungen for different gain factor values (0.5, 1, 2).

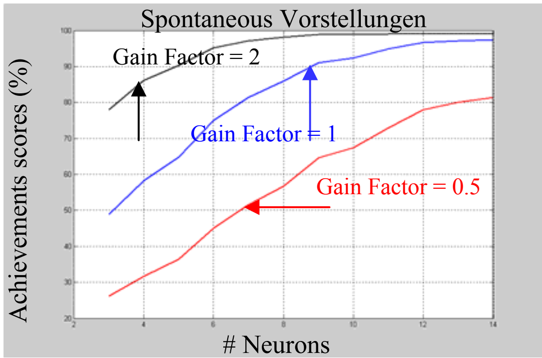

Fig.3 Illustrate learning performance accuracy versus different gain factor values. Shown results obtained at #cycles = 300 and Learning rate = 0.3 (adapted from Hassan & Ayoub [18]).

4. Modeling of Vorstellungen

4.1 General Interactive Block Diagram

Generally, practical performing of interference between Reflective and Spontaneous Vorstellungen utilizes two basic and essential brain cognitive functions[18-21]. Firstly, pattern classification /recognition function based on visual /audible interactive signals stimulated by CAL packages. Secondly, associative memory function is used which originally based on Pavlovian classical conditioning motivated by Hebbian learning rule[19] . Referring to Fig.4, it illustrates a generally modeled block diagram that well qualified to perform simulation of internal brain cognitive functions. At this figure, inputs to Vorstellungen learning model are provided by spontaneous environmental stimuli (autonomous learning).The correction signal, in case of learning under supervision is given by responsive output reflective action of the model. It would be provided to ANN model by either spontaneous (autonomous) learning signal (environmental conditions)or by teacher's reflective (supervision) signal. Interestingly, tutor plays a role in improving the input data (stimulating learning pattern), by reducing noise and redundancy of model pattern input. According to obtained realistic simulation results; tutor's experience concerned with either conventional (classical) learning or CAL provide educationalists with relevant analysis of acquired children's (SDE). Acquiring of experience seems to be tightly related to the increasing number of neurons (inside a child's brain), contributing to learning process as illustrated by simulation results given at the fifth section.

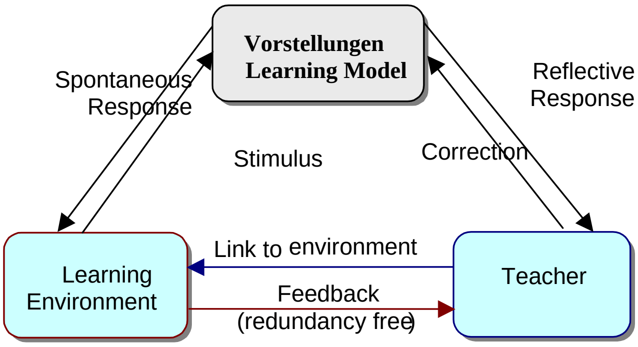

Fig.4: A generally modeled block diagram for interactive interference between Reflective and Spontaneous Vorstellungen in mathematical education.

4.2 Basic ANN Model

Searching for an optimal Reflective and Spontaneous Vorstellungen is inspired by realistic cognitive simulation of classical mathematical teaching as well as computer assisted learning (CAL) performance. By using relevant Artificial Neural Network (ANN) learning model, fairly learning assessment for adopted mathematical topic problem topic has been performed. Consequently, optimal evaluation of mathematical creativity via analysis of fairly obtained simulation results.

At Fig.5, a general block diagram for an ANN learning/teaching model is depicted. It presents realistic simulation of two diverse learning paradigms. Both concerned with interactive tutoring / learning process as well as self-organized learning. The first paradigm is concerned with classical (supervised by tutor) learning observed at our classrooms (face to face tutoring). Accordingly, this paradigm proceeds interactively via bidirectional communication process between a tutor and his learner(s) [18]. The second paradigm performs self-organized (unsupervised) tutoring process [19]

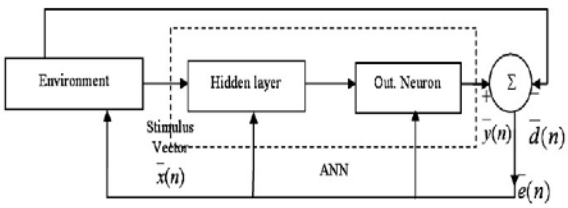

Fig.5: Generalized ANN block diagram, adapted from Hassan [5].

Referring to Fig.5, the error vector at any time instant (n) observed during learning processes is given by:

$$\bar{e}(n) = \bar{y}(n) - \bar{d}(n) \tag{1}$$

Where $\bar{e}(n)$ is the error correcting signal controlling adaptively the learning process, $\bar{x}(n)$ is the input stimulus, $\bar{y}(n)$ is the output response vectors, and $\bar{d}(n)$ is the desired numeric value(s).

The following equations are easily deduced:

$$V_k(n) = X_j(n) W_{kj}^T(n) \tag{2}$$

$$Y_k(n) = \varphi(V_k(n)) = (1 - e^{-\lambda V_k(n)}) / (1 + e^{-\lambda V_k(n)}) \tag{3}$$

$$e_k(n) = |d_k(n) - y_k(n)| \tag{4}$$

$$W_{kj}(n+1) = W_{kj}(n) + \Delta W_{kj}(n) \tag{5}$$

Where X is input vector, W is the weight vector, φ is an activation (odd sigmoid) function characterized by λ as gain factor and Y as its output. e_k is the error value, and d_k is the desired output. Noting that $\Delta W_{kj}(n)$ is the dynamical change of weight vector value connecting the $k^{\underline{th}}$ and $i^{\underline{th}}$ neurons . Eqs. (2-5) are commonly applied for both the supervised (interactive learning with a tutor), and the unsupervised (learning though students' self-study) paradigms. The dynamical changes of weight vector value for supervised phase are given as following:

$$\Delta W_{kj}(n) = \eta e_k(n) X_j(n) \tag{6}$$

where, η is the learning rate value during learning process. However, for unsupervised paradigm, the dynamical change of weight vector value is given by:

$$\Delta W_{kj}(n) = \eta Y_k(n) X_j(n) \tag{7}$$

Noting that $e_k(n)$ in (6) is substituted by $y_k(n)$ at any arbitrary time instant (n) during learning process. At next section, some previously published simulation results are given, after running of two MATLAB programs. Their general common flowcharts are shown at APPENDIX I. Furthermore, the two program listings are given at APPENDIX II (A&B).

5. Results

Referring to previously published work [20] that deals with analysis and evaluation of learning convergence time using ANN modeling. Therein, it is declared that application of technologically improved educational methodologies implies increasing of learning rate values. More recently, an interactive realistic educational model is presented for assessment of children's response time as learning convergence time parameter[21].

That results in better learning performance quality by minimizing of learning convergence (response) time. Therefore, application of presented three teaching methodologies (classical , CAL multimedia modules with visual and with simultaneous auditory and visual tutorial materials).That could be considered as three deferent educational technology levels (representing three teaching methodologies). Consequently, those three methodologies may be mapped (virtually) into three analogous learning rate values. More specifically, the three values(η) =0.05, 0.1, and 0.3 present virtually analogues mapping of the three levels of children's acquiring (SDE): Reflective (classical) , Partially Reflective/ Spontaneous (CAL with visual) ,and Spontaneous (CAL with simultaneous auditory and visual materials) . At Fig.6&7, graphical illustration of obtained simulation results for learning performance considering two case of Vorstellungen (Reflective and Spontaneous). The simplified flowchart of computer simulation program for assessment of time response values (at three different learning rates (η) =0.05, 0.1, and 0.3) is given at APPENDIX I . The comparison between Reflective & Spontaneous Vorstellungen for learning time response is presented at Fig.8. Moreover, tabulated comparative results are given at Table.1. Furthermore, at Table. 2., comparison between considering Output Achievements and Responsive Learning Rate .Finally, Relative improvement of Responsive Learning Rate ratio fulfilled by Spontaneous versus Reflective Vorstellungen is given at Table 3.

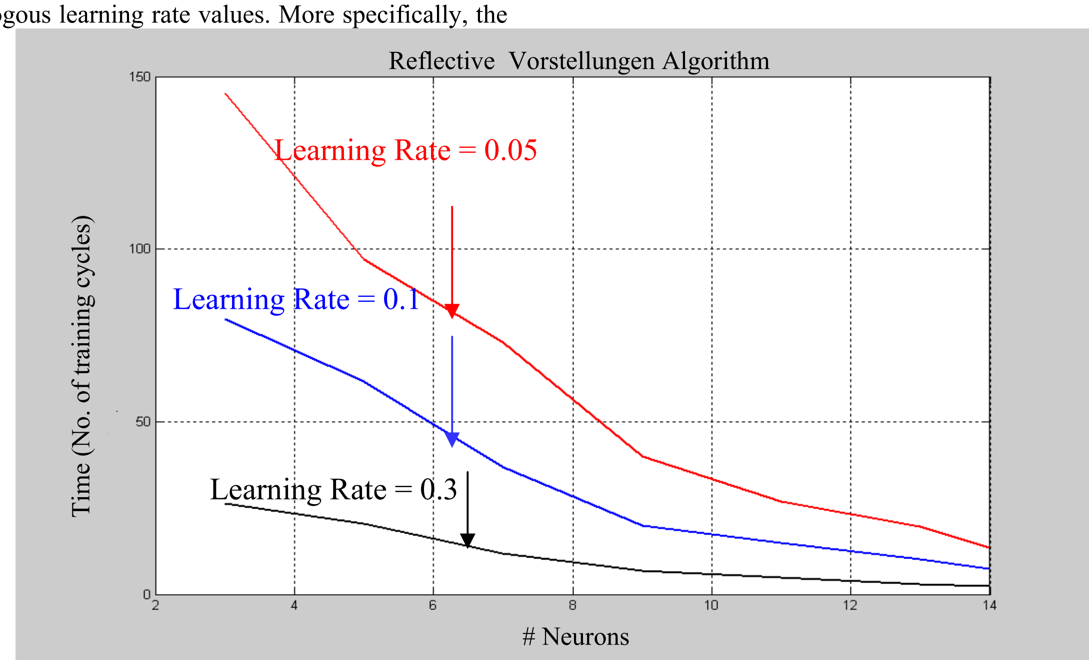

Fig.6: Illustrates Reflective Vorstellungen performance & time factor with considering three different learning rates: 0.05,0.1, and 0.3 for gain factor = 0.5.

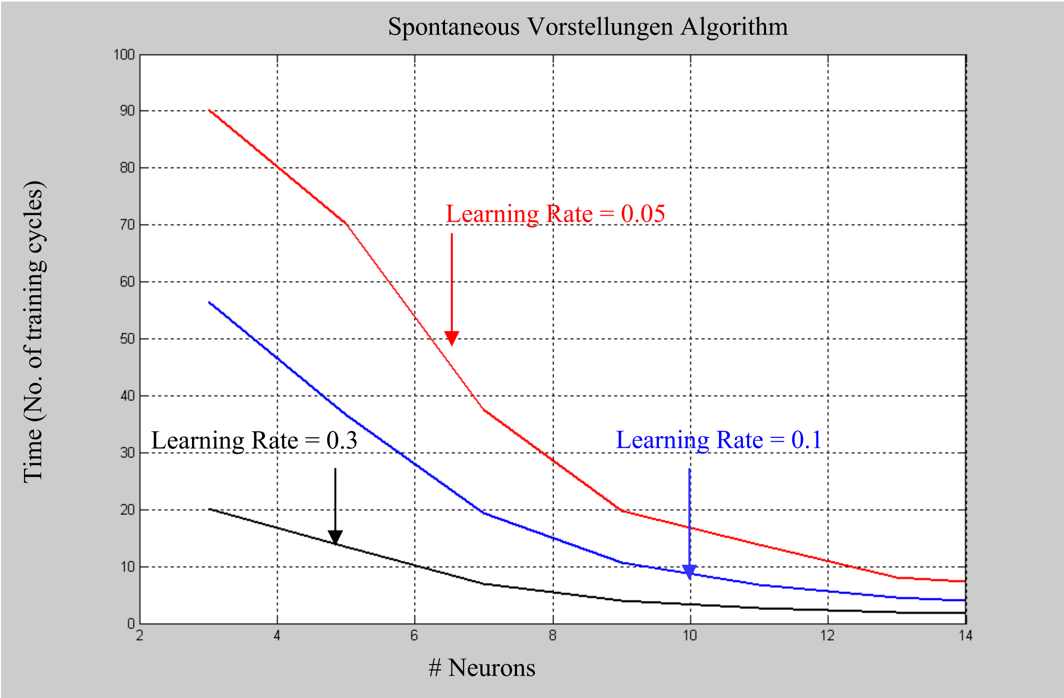

Fig.7: Illustrates Spontaneous Vorstellungen performance & time factor with considering three different learning rates: 0.05,0.1,and 0.3 for gain factor = 0.5.

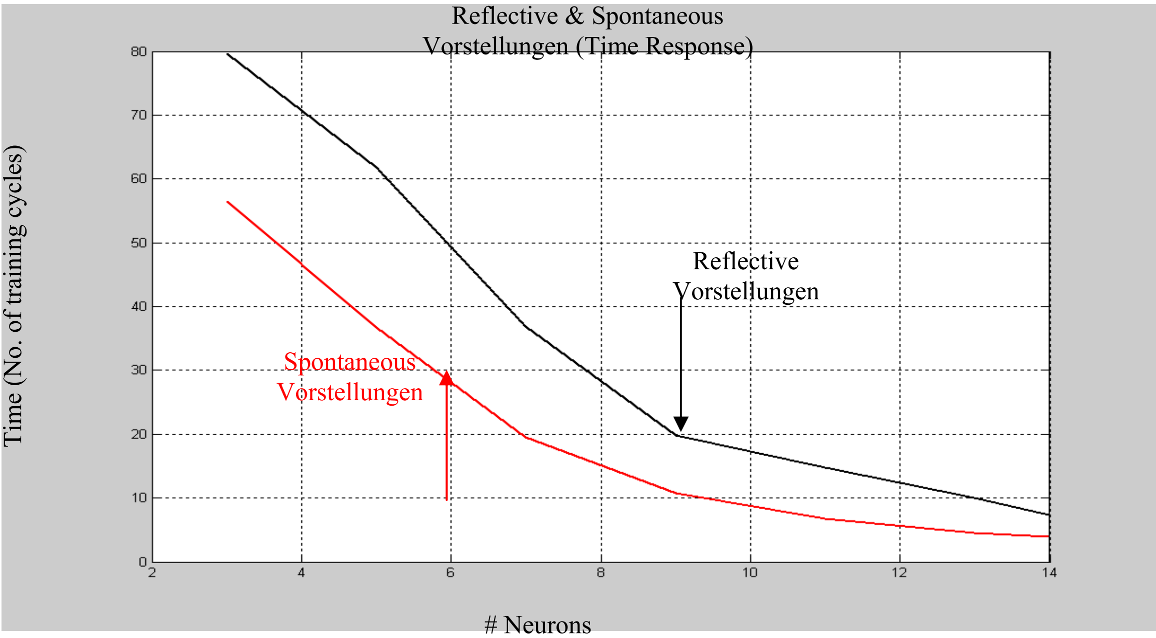

Fig.8: Illustrates comparison between Spontaneous and Reflective Vorstellungen performance associated with learning response time.

Table 1. Illustrates time response comparison between Spontaneous and Reflective Vorstellungen for different number of neurons contributing in learning process.

Number of Neurons contributing in learning	3	5	7	9	11	14
Reflective Vorstellungen	79.7	61.8	36.9	19.8	14.8	7.3
Spontaneous Vorstellungen	56.5	36.7	19.5	10.7	6.7	3.9
Relative Response Time Gain factor	1.41	1.68	1.89	1.85	2.21	1.9

Table 2. Illustrates comparison between Spontaneous and Reflective Vorstellungen considering Output Achievements and Responsive Learning Rate provided that: Gain Factor = 1.5,Learning Rate=0.05, #Learning Cycles=500.

# Neurons	**Output Achievements (Scores)**		**Responsive Learning Rate**	
	Spontaneous Vorstellungen	Reflective Vorstellungen	Spontaneous Vorstellungen	Reflective Vorstellungen
2	50.31	49.3	0.87	0.62
3	63.39	62.76	1.21	0.82
4	74.47	71.5	1.55	1.02
5	79.9	78.53	2.28	1.38
6	87.04	86.74	3	1.73
7	92.07	90.92	4.65	2.48
8	94.52	93.28	6.3	3.22
9	96.61	95.9	8.57	4.3
10	97.43	96.83	10.83	5.38
11	98.34	97.83	15.23	6.78
12	98.81	98.49	19.62	8.21
13	98.84	98.69	22.18	10.28
14	98.93	98.79	24.73	12.35

Table 3. Illustrates Relative improvement of Responsive Learning Rate ratio fulfilled by Spontaneous versus Reflective Vorstellungen for different number of neurons contributing in learning process.

# Neurons	2	3	4	5	6	7	8	9	10	11	12	13	14
Spontaneous Vorstellungen	0.87	1.21	1.55	2.28	3	4.65	6.3	8.57	10.83	15.23	19.62	22.18	24.73
Reflective Vorstellungen	0.62	0.82	1.02	1.38	1.73	2.48	3.22	4.3	5.38	6.78	8.21	10.28	12.35
Relative improvement of Responsive Learning Rate (Ratio)	1.4	1.48	1.52	1.65	1.71	1.88	1.96	1.99	2.01	2.25	2.39	2.16	2

6. Conclusion

This interdisciplinary research work motivated mainly by two recently published research results: firstly, about internal brain representation (Vorstellungen)[6] and secondly, about the study Einstein's brain based on other half of the brain Glial cells effect in providing creative performance[14]. Moreover, the analysis and evaluation virtual improvement of learning creativity obtained of performance quality for any CAL module is frequently measured after investigational analysis of obtained educational field results [13].

Above presented assessment approach provides educationalists with unbiased fair judgment tool for quantitative measurement of learning creativity based on comparison between Spontaneous versus Reflective Vorstellungen. The obtained results seem to be promising for future extension research work to get more elaborate investigational analysis and evaluation of issues related to learning creativity phenomenon. Furthermore, it is worthy to adopt using realistic implementation of ANNs modeling, as a relevant simulation tool for evaluating other observed educational field phenomena issues.

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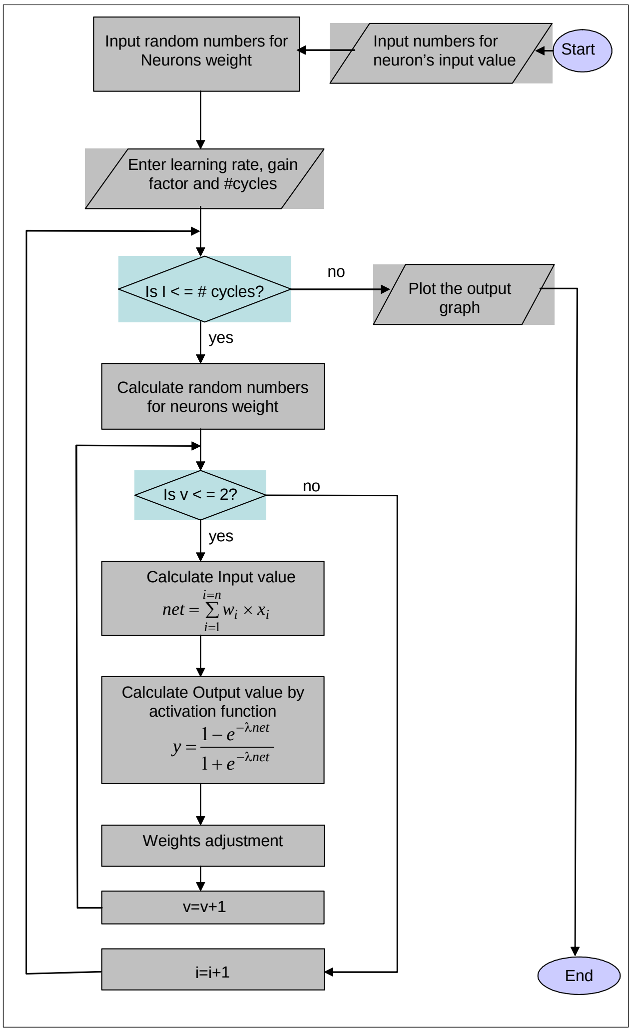
APPENDIX I

The shown simplified macro-level flowchart in below briefly describes algorithmic steps for realistic simulation learning program using Artificial Neural Networks. The results are shown in three figures (6, 7, and 8) after running the program.



APPENDIX II

Listing of two simulation programs written using MATLAB-VER.5. These programs designed to measure learning response time for both Vorstellungen types (Reflective and Spontaneous) are shown at (A&B) respectively.

A- Reflective Vorstellungen

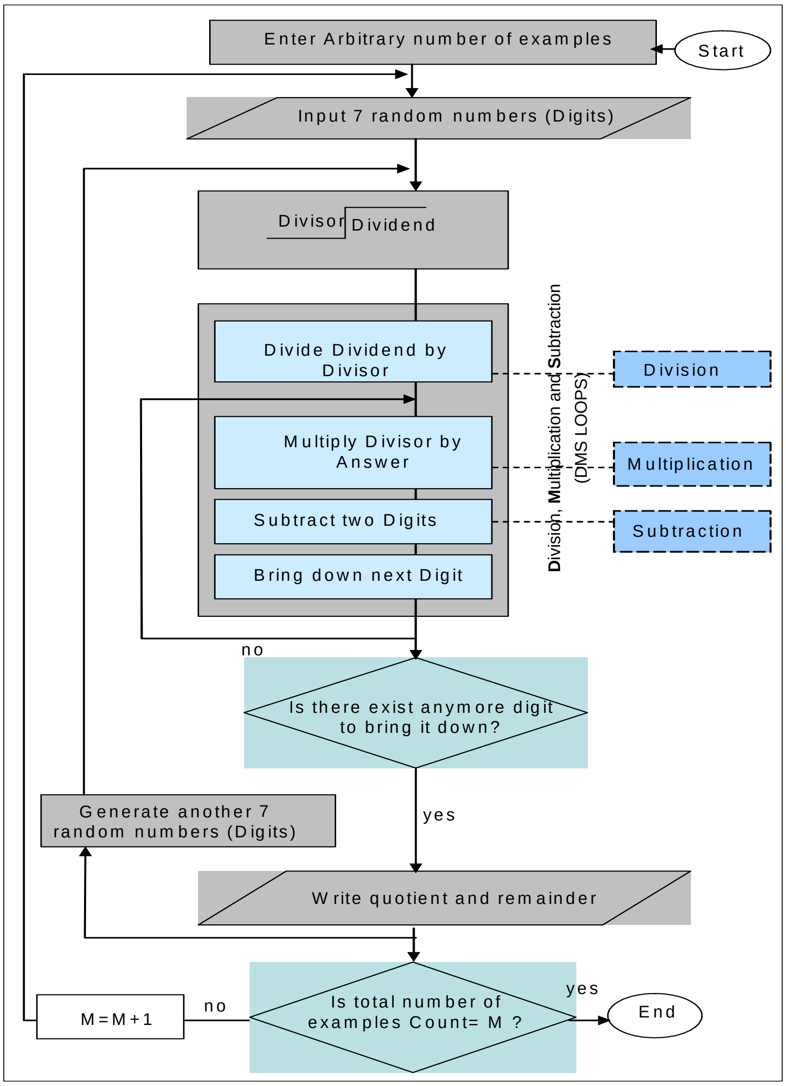
```
w = rand(3,1000);
x1 = 0.8; x2 = 0.7; x3 = 0.6;
L = 0.5; eata = 0.3;
h = 0; s = 0; f = 0; m=0;

for i=1:100
 w1=w(1,i); w2=w(2,i); w3=w(3,i);
 net=w1*x1+w2*x2+w3*x3;
 y=(1-exp(-L*net))/(1+exp(-L*net));
 e=0.8-y;
 no(i)=0;
 while e>0.05
 no(i)=no(i)+1;

 w1=w1+eata*e*x1;
 w2=w2+eata*e*x2;
 w3=w3+eata*e*x3;

 net=w1*x1+w2*x2+w3*x3;
 y=(1-exp(-L*net))/(1+exp(-L*net));
 e=0.8-y;
 end
end
for i = 1:100
 nog(i) = 0;
 for x = 1:100
 if no(x) == i
  nog(i) = nog(i) + 1;
 end
 end
end
for i = 1:99
 h = i * nog(i);
 s = s + h;
 F = f + nog(i);
end
m = s / f;
i = 0:99;
plot(i,nog(i+1),'linewidth',1.5,'color','blue')
plot((i+1)/100,nog(i+1),'linewidth',1.5,'color','black')
xlabel('Time (No. of training cycles')
ylabel('No of occurrences for each Time)
title(Reflective Vorstellungen algorithm')
grid on
hold on
```

B- Spontaneous Vorstellungen

```
w = rand(14,1000);
x1 = 0.8; x2 = 0.7; x3 = 0.6;
h = 0; s = 0; f = 0;
cycles = 200;
L = 1;
eata = 0.3;
for g = 1:100
 nog(g) = 0;
end

for i = 1:cycles
 w1 = w(1,i); w2 = w(2,i); w3 = w(3,i);
 for v = 1:2
 net = w1*x1 + w2*x2 + w3*x3;
 y = (1-exp(-L*net))/(1+exp(-L*net));
 e = 0.9-y;

        w1=w1+eata*y*x1;
        w2=w2+eata*y*x2;
        w3=w3+eata*y*x3;

 end
 P = uint8((y/0.9)*90);
 nog(p) = nog(p)+1;
end

for i = 1:99
 h = i * nog(i);
 s = s + h;
 f = f + nog(i);
end
m = s / f;

i = 0:99;
plot((i+1)/100,nog(i+1),'linewidth',1.5,'color','black')
xlabel('Accuracy')
ylabel('No of occurrences for each Accuracy value')
title(' Spontaneous Vorstellungen algorithm')
grid on
hold on
```

APPENDIX III

The figure shown below illustrates a simplified macro level flowchart which describes briefly basic algorithmic steps considered by suggested Computer Assisted Learning package. It is designed to perform fairly unbiased assessment process of learning a mathematical topic. After the running of the program, children time response (scores) are obtained, (samples of print screens is shown at APPENDIX II). These samples are obtained in accordance with steps of long division process: Divide, Multiply, Subtract, Bring Down, and repeat (if necessary) as given in reference [].



APPENDIX IV

Three Print Screen samples are shown in Figures (A, B, and C) to illustrate three different output phases of mathematical creativity assessment package

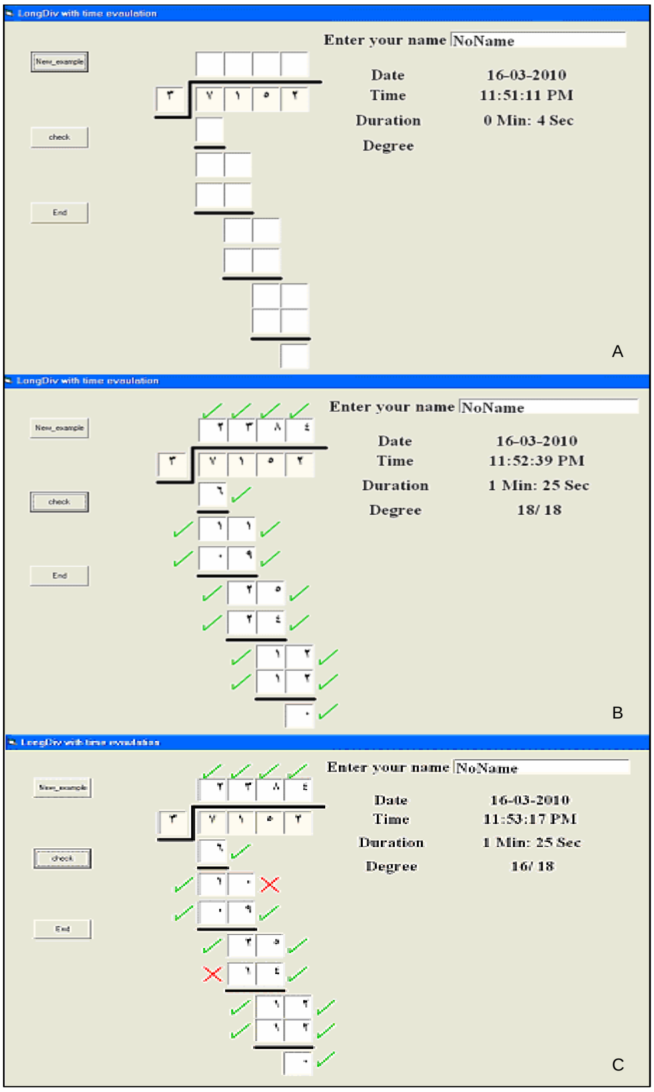


Figure 2: A) Basic print screen sample for initial mathematical Long Division process. B) For fairly solving of Long Division problem (detecting no mistake). C) A print screen for fairly assessment processes results with two mistakes.

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