ON A FIRST ATTEMPT TO MODELLING CREATIVITY LEARNING BY MEANS OF ARTIFICIAL NEURAL NETWORKS

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Abstract

The contribution presents some first results concerning the usability of neural network, obtained from field based study that dealt with children's creativity learning in games. The first question was whether the time series of learning success could be analysed using conventional Kohonen Feature Maps (KFM) in order to find and distinct types of time-dependent learning patterns. The second question was whether the neural network could be used for simulating those learning processes – in order to eventually schedule and optimize those processes individually. The first problem could be solved using Dynamically Controlled Networks (DyCoN: Perl, 2004), which is a KFM-derivate that is able to learn continuously. A number of types of learning patterns could be found which seem to be characteristic for specific learning behaviours. In order to solve the second problem, the concept of DyCoN had to be completed by some properties of "natural" learning: One aspect was to dynamically adapt the capacity of the network to the requirements of the learning process. This could be done by integrating the concept of Growing Neural Gas (GNG: Fritzke, 1995).
Another aspect was to take care of seldom events of high relevance – as creative activities are – which are neglected by all known net approaches. The result is the Dynamically Controlled Neural Gas (DyCoNG: Bischof, 2006; Gerharz, 2006) the concept of which completes the combination of DyCoN and GNG by quality neurons that reflect the quality of information and therefore can measure the creativity of a recorded activity. Initially results from DyCoNG-based simulation show that the network is able to reproduce recorded learning processes and separate main process types.

Methods

(a) Tests design and data recording
The creative learning model used data from a BISp-sponsored project (VF 0407/06/04/2005-2006). 42 children of around seven years of age participated in the field study. The children who were undergoing a non-specific treatment attended the standardized training program by Roth (2004).The task was to recognize gaps in a defence line for passing the ball (cf. Memmert & Roth, 2003). Over a period of 6 month, every two weeks the children's actions were video-recorded, and the player positions were extracted from the video frames. Subsequently, the actions were rated regarding originality and flexibility using the original frames (including context information from the game) as well as using standardized computer-simulated frames (see Figure 3, graphic bottom right).

(b) Net-based modelling of creativity

An action in a specific situation is called creative or of high originality if it is a seldom event in that situation. In terms of networks, the regarding stimulus has a great distance to all stimuli the network has already learned, and therefore – from the information-theoretic point of view – has a high relevance. Conventional KFMs, however, do not care about great or small distances but melt the new stimulus to the best fitting neuron – therefore neglecting the particularity of that specific information. In contrast, DyCoNG embeds every neuron in a sphere that limits its area of attraction. New stimuli outside the spheres of all available neurons are categorized as "strange" and then define new (quality-) neurons of high relevance. This specific quality of information-theoretic relevance can fade out if the same stimulus is fed more frequently to the net, resulting in a slowly opening for different stimuli and therefore eventually merging into different neurons and clusters (see Figure 1). If in turn a neuron is less frequently contacted compared to its neighbourhood it again can become an isolated quality neuron with high relevance.

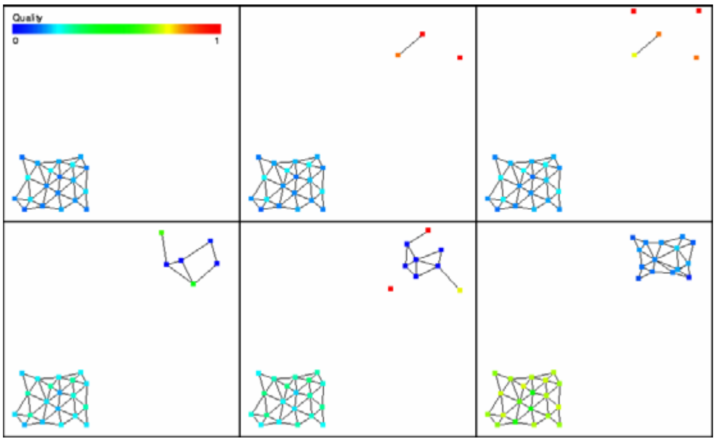

Figure 1: An existing network (top left) is completed by some quality neurons that represent relevant information (top middle and right). After some steps of activation, the new neurons loose their quality: they drift and merge into a new cluster (bottom left and middle) until finally the new cluster has less relevance than the old one (bottom right; the colour of the old cluster has changed from blue to light green, indicating an increase of relevance compared to the meanwhile blue new one).

(c) Net-based analysis and simulation

Two kinds of net-based analysis were carried out:

The first approach was to analyse the time-depending learning profiles (see Figure 2) under the aspect of similarity. This was done using a conventional KFM, where the profiles were fed into as patterns, which then were recognized as members of clusters respectively types of learning behaviour (see Figure 4).

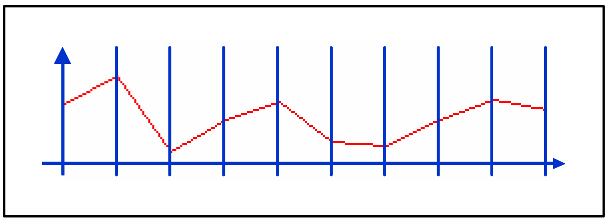

Figure 2: Example of a learning profile, i.e. a time series of creativity values

The second approach was to simulate the learning process itself using a DyCoNG, with the original data as input and learning profiles as output (see Figures 3 and 6). The idea was that the originality or creativity of an action can be described by the quality of the representing neuron: high creativity goes with low frequency and high neuron quality values and vice versa. Figure 3 shows a red neuron of high quality, representing an action of high originality.

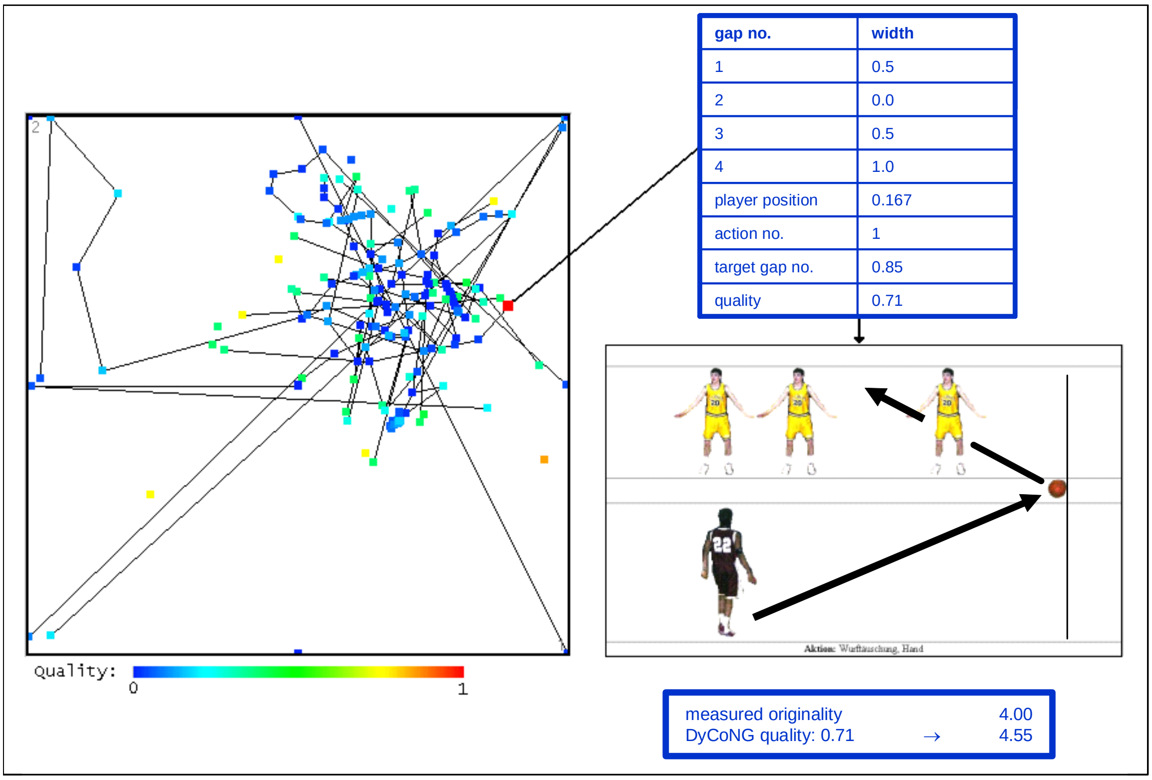

Figure 3: 2-dimensional projection of a trained DyCoNG together with the reconstruction of the action-data represented by the red neuron.

The learning profiles resulting from DyCoNG-training were compared to the regarding rater-evaluations as well as to the learning types obtained from the children's profile analysis.

Results

(a) KFM-based test analysis

The obtained 42 learning profiles (see Figure 2) were tested on the trained net. The resulting entries show clusters of activated neurons, which build a collection of 9 types representing the individual profiles, 7 of which are significant for type definition (see Figure 4).

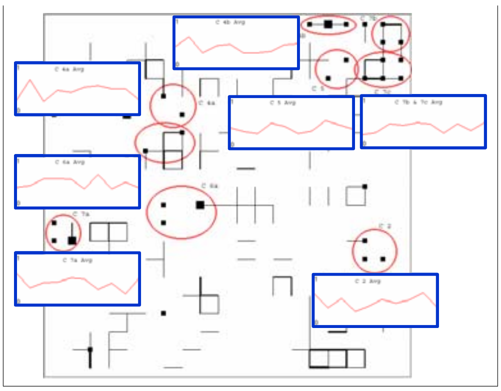

Figure 4: Trained network with marked clusters of neurons representing typical profiles.

Those 7 types show relevant differences and were used for further investigations: Overlaying those profile types smoothing approximations results in a sequence of prototypes that ranges from super-compensation-like behaviour over linear increase to something like inverse super-compensation, where the learning success first was increasing and afterwards decreasing (see Figure 5).

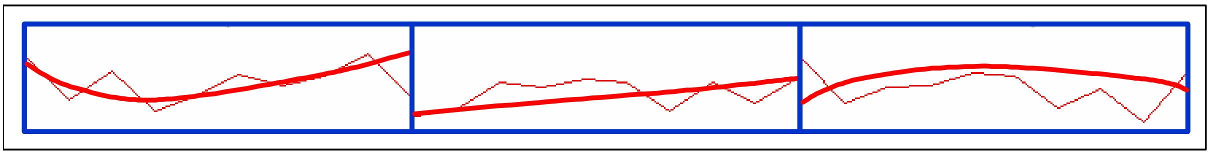

Figure 5: Three characteristic prototypes of learning behaviour, ranging from super-compensation over linear increase to inverse super-compensation.

(b) DyCoNG-based simulation of learning processes

In order to check whether the net-based neuron quality meets the measured action originality the time-specific data sets of the children (i.e. the training stimuli for the net) were classified into three classes: The (red) class of high originality (values 6 and 5), the (green) class of medium originality (values 4 and 3), and the (blue) class of low originality (values 2 and 1). Training the net with stimuli from the respective classes and taking the mean quality values of the corresponding neurons results in specific time series representing the learning behaviour of the net with regard to the particular class. As can be seen from Figure 6 (left graphic), the plotted profiles are not only similar to those from children's learning but also are separated regarding the levels of originality. Moreover, there seems to be a certain qualitative correspondence between the simulated and the original profiles (Figure 6, right graphic) – which however has to be taken with care because of significant differences regarding the quantitative aspects and the need for deeper analyses and interpretation.

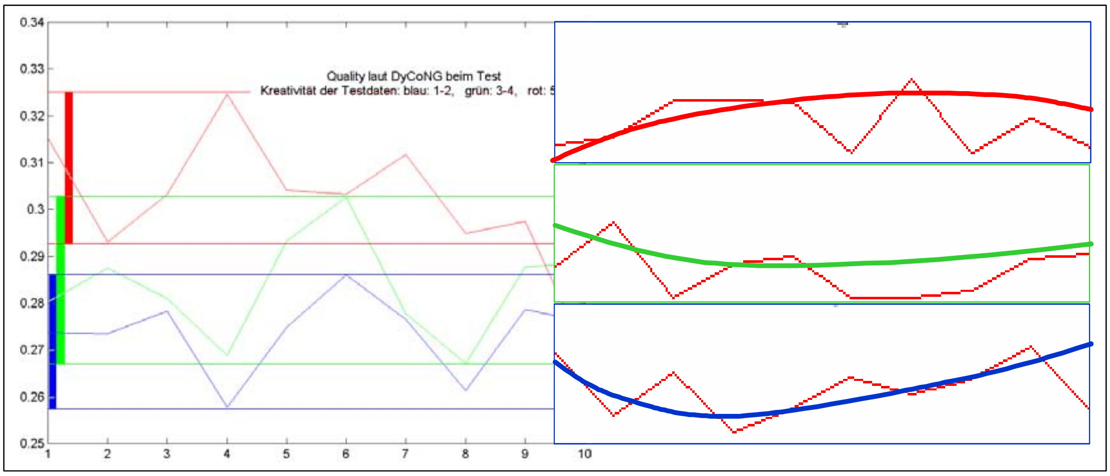

Figure 6: Profiles of mean quality values corresponding to the originality classes high (red), middle (green) und low (blue), compared to corresponding types of original learning profiles.

Conclusion

It could be demonstrated that networks can be helpful for classifying types of creativity learning, which can support a more individual adaptation of training programs to athletes. First preliminary result from learning process analysis could be confirmed (Memmert & Perl, 2005). Additionally, a first step has been done in order to simulate learning behaviour by means of networks, which can be helpful for optimizing individual training processes. More future work is necessary in order to analyse more data and improve the simulation techniques.

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