Analytical Calculation of Weights in Temporal Sequence Learning

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Most artificial learning systems converge after a certain number of interations but the final weight distribution cannot be predicted or calculated from the initatial conditions. In several cases general boundary conditions can be devised to guarantee convergence (e.g. Hopfield networks). In this study we use the Isotropic Sequence Order (ISO) learning rule to show that the final weights of an agent which learns in complex environment can be calculated analytically. The ISO learning rule is a differential Hebbian learning rule for temporal sequence learning. Weight change is defined as the correlation between the band-pass filtered input u_i and the derivative of the output v: $d\rho_i/dt = \mu\, u_i\, v'$ where μ is the learning rate. Ultimately the temporal difference between two input signals T drives the learning (Fig. 1a). In our experiments we use a simulated robot with vision and collision sensors to this end. The robot has a built-in retraction reflex as soon as it touches an obstacle. Its goal is to avoid this by using the signals from its vision sensors for steering. Consequentially their weights are initially zero and will develop through ISO-learning. Temporal intervals T are determined as the differences between the earlier vision signal and the later following collision signal. In an older study (Porr and Wörgötter, 2003) we have shown that it is possible to calculate each individual weight change by integrating the learning rule (see Fig. 1b) to obtain the learning window $\rho(T)$. Since ISO-learning is strictly linear (for $\mu \rightarrow 0$) it seems evident that the complete set of all weights in the learning robots should be determined by the distribution of all values of T encountered during learning. The equation for the final weights ρ_f integrates essentially over the complete distribution p(T) of all values of T and simply reads:

$$\rho_f = \int_{-\infty}^{+\infty} \rho(T)\, p(T)\, dT$$

The goal of the current study is to demonstrate that this equation indeed gives the final weight in different scenarios. Complications arise from the finite, non-zero learning rate μ, which leads to a violation of linearity and from the fact that in real learning scenarios “wrong” values of T can occur as a consequence of collisions preceding a vision signal, which indeed would correspond only to the next following collision. In spite of this we show that the above equation captures the weight development with high accuracy. Hence, if it is possible to arrive at a guided guess of the T-distribution prior to learning, then one can calulate the final weights without actually having to preform the learning process.

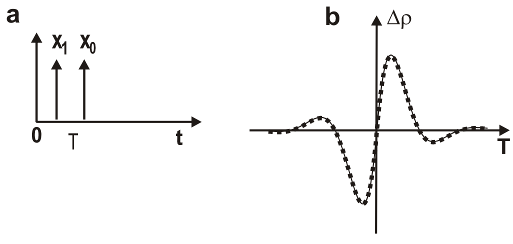

Fig. 1. Weight change function $\rho(T)$ calculated analytically.

References
Porr, B., and Wörgötter, F. (2003). Isotropic Sequence Order Learning. Neural Comp. 15, 831-864.