Hierarchical Incremental Slow Feature Analysis

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Abstract. Slow feature analysis [1] (SFA) is an unsupervised learning technique that extracts features from an input stream with the objective of maintaining an informative but slowly-changing feature response over time. Due to some promising results so far [1,2], SFA has an intriguing potential for autonomous agents that learn upon raw visual streams, but in order to realize this potential it needs to be both hierarchical and adaptive. An incremental version of Slow Feature Analysis, called IncSFA, was recently introduced [2,3,4]. Here, we focus on its hierarchical extension (H-IncSFA). H-IncSFA networks are composed of multiple layers of overlapping IncSFA units, where each unit has a local receptive field. Figure 1 shows an example H-IncSFA network, based on the one specified by Franzius *et al.* [5].

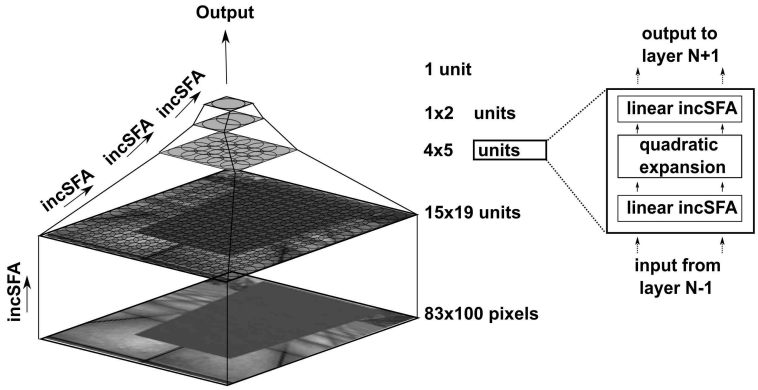

Figure 1: Example H-IncSFA Architecture. Each receptive field feeds data into an IncSFA unit. There are a set of receptive fields on each layer, converging towards a single set of slow features at the top layer.

Deep networks deal with the high nonlinearity and large search spaces inherent in extracting slow features from real-world image streams. Spatial partitioning lets us feasibly expand the search space by nonlinearly expanding the input data within each receptive field. It is not feasible to do a nonlinear expansion on image pixels directly. Deep SFA networks have several other advantages: by breaking up the signal, they reduce computational costs, and they are highly amenable to parallelization.

H-IncSFA was implemented, and two proof of concept results are shown in Fig. 2. First [3], the network in Fig. 1 was applied to a scenario of a stable agent observing a moving interactor, modeled as a rectangular flat board moving back and forth in depth over the range $[1, 3]$ meters in front of the agent (Fig. 2(a)). The input is high-dimensional (83×100) video, and the top-layer slow feature extracted corresponds to the object's position information. This result shows the feasibility of a hierarchical incremental SFA.

A new result(Fig. 2(b)) has a moving agent within a stable 160×160 environment. In this case, the lower layers of the hierarchy, which usually code for low-level primitive

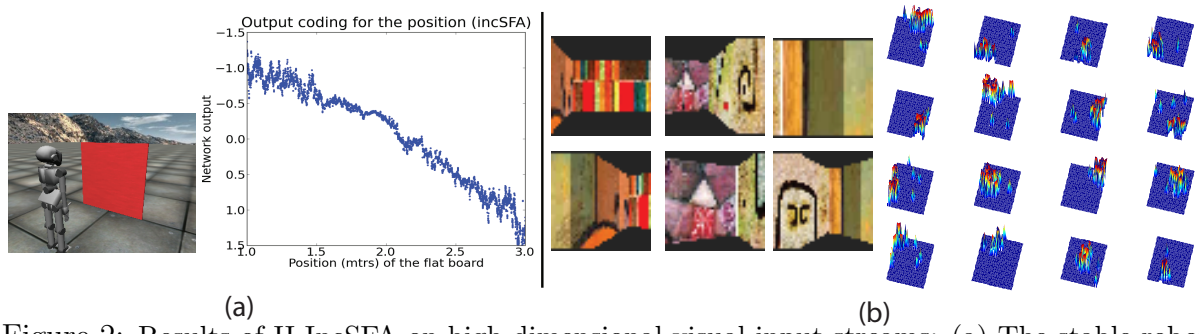

Figure 2: Results of H-IncSFA on high-dimensional visual input streams: (a) The stable robot learns the distance of the moving interactor, (b) A moving agent learns its own relative position from the visual experience of moving within a square enclosure. An additional competitive learning layer learns place cells upon the position-coding slow features.

features, are handled differently: they are trained via hierarchical batch SFA (20,000 images accumulated through randomized exploration) and frozen. Then, top layer IncSFA units learn to code for higher level behavioral properties in the input data stream. As a proof of concept, the agent's movement paradigm [5] was such that the slowest features would correspond to its position, and these features indeed emerged after 20,000 time steps. We trained a linear regressor using 20% of the data and achieved position RMSE 7.58 in the x-direction and 8.77 in the y-direction. A top-level competitive learning layer develops place cells.

We expect the importance of H-IncSFA to be for vision-based autonomous learning agents. Due to vision, a hierachical approach is necessary. Due to the challenges of autonomous learning, an incremental approach is necessary.

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