Learning through Spatially Localized and Temporally Correlated Spontaneous Activations

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The supremacy of mammalian neocortex in terms of learning, robustness, and computational efficiency compared to other contemporary computational systems can be attributed to a number of powerful neocortical properties. Some of these properties have been studied in more detail than others. Here, we study a *not so well* understood aspect of the neocortex i.e. the spatially localized and temporally correlated spontaneous activations and their role in development of neocortical maps and generation of invariant pattern representations.

Experiments show that spontaneous neuronal activations occur throughout the mammalian visual cortex [1, 2]. Given that the structure of the neocortex is relatively uniform [5], it is reasonable to assume that similar spontaneous activations are also present in other neocortical regions. We hypothesize that these spontaneous patterns of activations, which are spatially localized and temporally correlated [1], result in both the automatic development of cortical maps as well as the generation of invariant pattern representations.

Previously, we investigated a cortically inspired learning model which utilized random activations of minicolumns to promote the initial learning of unique features [4]. Similar to the effects of synaptic noise in the neocortex, this system modeled the ability of a minicolum to randomly activate even without strong synaptic correlation with the present inputs. Through uniformly distributed random activations, lateral inhibition between minicolumns, and the concept of object permanence, the minicolumns within a hypercolumn learn to recognize unique patterns stimulating their synaptic inputs. These hypercolumns are then hierarchically organized to perform complex tasks.

In this work we extend our cortical column based model [4] to include the ability to generate spatially localized and temporally correlated spontaneous activations. Rather than having uniformly distributed random activations throughout a hypercolumn, firing minicolumns prime spatially localized (neighboring) minicolums to exhibit random activations during a training interval. Given that input patterns display object permanence, --i.e. input stimuli tend to be present for reasonable time intervals and are temporally correlated-- variations of a single pattern are recognized by spatially localized minicolumns. Thus, over time, spatial maps of various temporally correlated patterns develop automatically without the need of any distance based error evaluation metric. In essence, these self organizing maps are quite robust and informative as they spatially localize the temporally correlated input patterns.

These spatially localization of similar patterns allows us to use an ART-like [3] vigilance parameter to control the spatial resolution of a hypercolumn. Over time a hypercolumn can learn to control the granularity of its resolution i.e. if vigilance is quite high, then an element W_i of the weight vector W is activated only by an element X_i of the input vector X. On the other hand, if the vigilance is low, W_i can become activated by $X_{i-K..i+K}$. Here, K is inversely proportional to the vigilance of the hypercolumn and is modified over time on a need-to-know basis. If two truly different patterns are being recognized as the same, K can be decreased using a supervised feedback signal. This will initiate an unpooling mechanism which will promote learning of the two patterns by distinct minicolumns. On the other hand, if two variations of the same pattern are recognized as different, K can be increased to pool the two variations together. Such a mechanism allows our hierarchical model to learn generalizations rather than specific patterns (i.e. it combats over-fitting of the input data). Thus, using the vigilance parameter, the hierarchical arrangement of hypercolumns can learn to create invariant representations for similar patterns while at the same time differentiating them from other dissimilar patterns.

References

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