An Active Efficient Coding Model of the Development of Amblyopia

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Amblyopia is a common developmental disorder of the visual system, which leads to decreased visual acuity in the amblyopic eye and impaired stereo vision. A key mechanism in amblyopia is the suppression of signals from the amblyopic eye. How this suppression develops is not fully understood. However, recent years have seen substantial progress in theoretical accounts of the healthy development of binocular vision in the context of the Active Efficient Coding (AEC) framework. AEC is a generalization of classic efficient coding theories to active perception. It describes the simultaneous learning of receptive fields and movements of the sense organs to jointly maximize sensory coding efficiency. Along these lines, computational models for the healthy development of active binocular vision and active motion vision have been proposed (1, 2). Here we investigate whether AEC can also account for the developemt of amblyopia in the case where the two eyes have different refractive powers.

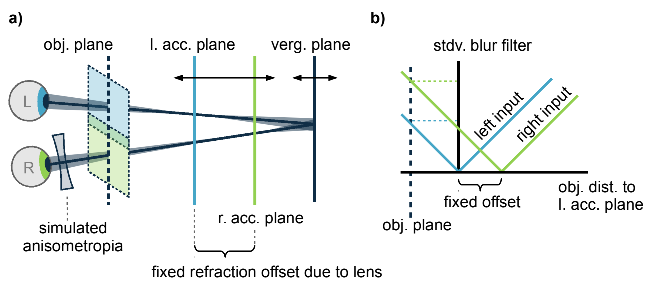

Fig. 1. a) Object position, eye focus, and eye fixation at different distances are represented as different plane positions. Vergence (verg.) errors are modelled by pixel shifts between the left (l.) and the right (r.) eye input image. **b)** Accommodation (acc.) error is a function of the distance between object (obj.) and the left or right accommodation plane, respectively. Defocus blur is realized with a gaussian filter of variable standard deviation (stdv.).

Methods. We extend a previous model for the learning of active binocular vision in two directions. First, in addition to vergence eye movements the model also learns to control accommodation of the lenses to focus on near and far objects. Second, we add a suppression mechanism which allows the attenuation of signals from one eye by neurons whose sensitivity is biased towards the other eye. The model learns to control vergence and accommodation in an environment where planar objects are presented at different depths. The control can be thought of as the shifting of three different planes (Fig. 1a) relative to the plane where an object is presented. The distance between the object plane and the vergence plane determines the disparity between left and right eye. The distance between object plane and the two accommodation planes determines how sharp or blurry the input to the two eyes is (Fig. 1b). The input is whitened and encoded by sparse coding models at two scales (coarse and fine) sensitive to different spatial frequencies. For this we employ the matching pursuit algorithm (3) (Fig.2, right). Vergence and accommodation commands are learned by two natural actor-critic reinforcement learners (4) to maximize the overall coding efficiency (Fig.2, left). We include within-scale interocular suppression by introducing a mechanism where strong responses from monocular neurons suppress input signals from the other eye.

Results. In the healthy condition without anisometropia, the model learns to accommodate correctly and to perform precise vergence eye movements. Most neurons develop binocular receptive fields.

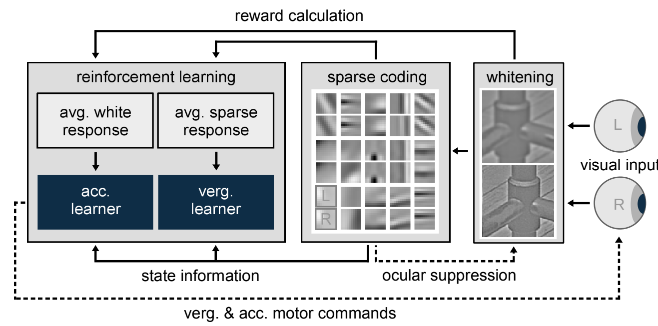

Fig. 2. Model architecture with solid arrows representing the flow of sensory information and dashed arrows representing the flow of control commands. Only the fine scale is shown. Sampled input images with given blur and disparity are whitened **(right)**. Thereafter, they are sparsely encoded by a set of binocular bases in analogy to V1 simple cells **(center)**. The average sparse activity (of both scales) serves as state information for two reinforcement learners **(left)** which control vergence (verg.) and accommodation (acc.) commands, respectively. Accommodation commands are learned to maximize the mean squared response after whitening (avg. white response). The vergence learner reward is the negative reconstruction error of the sparse encoding stage, which can be read out as the average squared sparse response. Together this can be understood as maximizing the mutual information between the whitened and sparse representation. Finally, if mostly left(right)-monocular bases are used to encode the whitened input, the right(left) eye input is suppressed in the next time step. Here, suppression is scale specific, i.e., when the left eye in the fine scale is suppressed, the left eye in the coarse scale may still provide unattenuated input.

In an anisometropic case where the ranges over which the two eyes can focus differ, an amblyopia-like state develops. As one eye more consistently suppresses the other, the receptive fields become increasingly monocular, favoring the suppressing eye. Visual acuity decreases for the suppressed eye. However, by recruiting neurons tuned to lower spatial frequencies that retain binocular receptive fields, the system maintains a certain level of vergence control. Interestingly, for one myopic and one hyperopic eye, the model develops monovision, i.e., it learns to focus on close objects with the myopic eye and on distant ones with the hyperopic eye.

Conclusion. In conclusion, we demonstrate an Active Efficient Coding model that a) describes the development and self-calibration of active binocular vision and accommodation control under healthy conditions and b) explains how anisometropia might lead to amblyopia by recruiting interocular suppression mechanisms. Future work should address if interocular suppression can also be understood as a result of generic learning mechanisms.

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