# *CHAPTER XI*

# Early face recognition: What can we learn from a myopic baby neural network?

***Dominique Valentin***
*Université de Bourgogne à Dijon*

and

***Hervé Abdi***
*The University of Texas at Dallas* [1]

Why do we see faces in clouds? How do we recognize familiar faces from very different points of view? Why can't we recognize inverted faces? Why some persons cannot recognize faces but can recognize other objects? Are faces special?

One of the main issues in the current literature on face processing is:

whether there is an innate neural mechanism specialized and

[1](2003). In Pascalis, O., Slater A. (Eds). *The development of face processing in infancy and early childhood*. New York: Nova Science Publications. pp 143-153.
Send correspondence to Dominique Valentin CENSG, Université de Dijon, 2100 Dijon. France; Valentin@u-bourgogne.fr, or to Hervé Abdi, The University of Texas at Dallas. Program in cognition, MS: GR.4.1, herve@utdallas.edu, www.utdallas.edu$~herve

> devoted uniquely to human faces or whether such neural specialization is a result of acquired visual expertise (de Haan, Pascalis, & Johnson, 2002, p. 207).

A striking argument in favor of an innate neural mechanism comes from early infant face processing. Several studies using visual tracking tasks showed that newborn babies prefer to look at face-like visual configurations rather than at other equally complex stimuli (Goren, Sarty, & Wu, 1975; Johnson, Dziurawiec, Ellis, & Morton, 1991; Valenza, Simion, Cassia, & Umilta, 1996). Other studies showed that, despite their low visual abilities, human newborns are able to discriminate the face of their mother from the face of a stranger. For example, Busnell (1982), using a habituation task, showed that five-week-old infants discriminate between the photographies of the face of their mothers and strangers. Using the same paradigm, Field, Cohen, Garcia, and Greeberg, (1984) and Busnell, Sai, and Mullin (1989) also reported that infants younger than 50 hour old discriminate between mothers and strangers. More recently, Walton, Bower, and Bower (1992) showed that newborns would suck more strongly to see a videotaped image of their mother's face rather than the image of a stranger. Pascalis, de Schonen, Morton, Deruelle, and Fabre-Grenet (1995) later confirmed this early discrimination of mother and stranger, but only when newborns were presented with the external features of their mother. It seems that it is only around 6–7 weeks of age that babies start to be able to process facial internal features (Pascalis, de Haan, Nelson, & de Schonen, 1998) and can recognize mother from strangers wearing headscarves (Bartrip, Morton, & de Schonen, 2001). A recent study on facial attractiveness, however, suggests that babies might be able to process internal facial information as early as two days after birth (Slater, 2000).

## XI.1 INNATE NEURAL MECHANISM VERSUS ACQUIRED VISUAL EXPERTISE?

The face recognition abilities of infants are obviously outstanding. As these abilities are functional very early, they need little experience to be functional, and so it is tempting to theorize that they are innate. But, do we really need to assume that face recognition represents an innate ability to explain how newborns can discriminate mother from stranger? Indeed this ability seems paradoxical if we consider that faces are highly similar, that newborns possess poor visual acuity and contrast sensitivity, and therefore cannot resolve high spatial frequencies which are used by adults to recognize faces (Dobson & Teller, 1978; Teller, Mc Donald, Preston, Sebris, & Dobson, 1986). As an illustration of the difficulty of the task performed by infant recognizing faces, Figure 1 shows a series of faces as they are perceived by newborns.

Figure XI.1: The faces such as a normal sighted adult (top line) and a newborn (bottom line) perceive them. The newborn limited acuity removes the details (high frequencies) of the images but very different faces remain distinguishable.

How can babies discriminate faces using so little information? Well, this apparent paradox might result from our evaluation of the complexity of the task performed by newborns through our adult experience. A less biased way of evaluating the complexity of a perceptual task is to simulate it via computational models such as neural networks (cf. Abdi, Valentin, & Edelman, 1999). Artificial neural networks are networks of simple interconnected processing units that operate in parallel. These processing units function like (very) simplified neurons: Each unit receives information from all the other units, integrate this information and send it to other units. Learning results from the modification of the weights of the connections between units. In the past 20 years, several artificial neural networks have been successively applied to face recognition. The performance of such models depends both on the learning algorithm implemented and on the number and perceptual characteristics of the stimuli on which the learning algorithm is applied. By manipulating these two factors (i.e., learning material and structure of the stimuli), Valentin, Abdi, Edelman, and Nijdam (1996) showed that the ability of newborns to recognize the faces of their caretakers is less paradoxical than it first seemed.

## XI.2 PRIMITIVE HEBB VERSUS SOPHISTICATED WIDROW-HOFF

Valentin *et al.,* (1996) theorized that newborns' mode of learning is likely to involve a simpler but faster mechanism than adults. So they decided to evaluate the efficiency of two learning rules applied to different face recognition tasks. Specifically, in a series of simulations, they compared the ability of an autoassociative memory[2] trained with two different learn-

[2]An autoassociative memory is a special case of a neural network model in which the association between an input pattern and itself is learned. The goal of an associative memory is to find a set of connections between input units, so that when a portion of an input is presented as a memory key, the memory retrieves the complete pattern, filling in the missing components. The quality of the memory response can be evaluated by computing the squared

ing algorithms: Hebbian *vs.* Widrow-Hoff. The neural network task was to recognize an increasing number of faces presented in various perceptual conditions. The Hebbian and Widrow-Hoff learning algorithms vary in their level of complexity and in their ability to process subtle information. *Hebbian learning* is a simple learning algorithm based essentially on the processing of low spatial frequency information. It is generally described as unsupervised because it does not need to be given a target value for its output. On the other hand, *Widrow-Hoff* learning is supervised, and the small adjustments occurring during learning permit the processing of high spatial frequency information. So Hebbian learning represents a fast learning system, which does not process details, and Widrow-Hoff represents a more sophisticated learning system, slower but more sensitive to details. Valentin *et al.,* wanted to compare the efficacy of these two learning algorithms as a function of the number of faces that a neural network learned. Their general strategy was to teach a neural network to learn a set of faces and to evaluate its performance when presented with an old face or a new face. They used seven learning conditions.corresponding to the number of learned faces (2, 5, 10, 20, 30, 50, and 100), these faces constituted the *learning* set. The other faces of the database (which comprised a total of 159 faces) were used to evaluate the performance of the neural network on new faces, these faces constituted the *testing* set. For each size condition, 100 samples of learning and testing sets were generated. The performance of the memory was evaluated by comparing the square correlation between a face and its reconstitution by the memory, the larger the correlation, the better the memory. (i.e., the more ”familiar” the face). Figure 2 shows that the performance of the Hebbian and Widrow-hoff trained memories vary in opposite ways when the number of encountered faces increases. For Hebbian learning, the performance of the memory for learned faces decreases whereas the performance of the memory for new faces increases. However, as long as the number of faces learned is less or equal to twenty, learned faces are better reconstructed than new faces. This means that the memory is able to "recognize" old faces. After this point, learned and new faces are equally well reconstructed. This means that the memory cannot distinguish between old and new faces: The memory is now suffering from interference. On the other hand, the larger the number of faces the more details are captured by the Widrow-Hoff algorithm and the better the memory performance. The main difference between Hebbian and Widrow-Hoff learning is that Hebbian learning tends to capture what is common to all the faces whereas Widrow-Hoff learning captures the detailed information that is specific to individual faces. In order to test the robustness of the learning algorithms, Valentin *et al.,* (1996) also manipulated the spatial frequency content at learning and at test. They had their neural networks learning low pass, high pass, and normal (all frequen-

correlation between the input and output patterns. The larger this coefficient the better the memory.

cies) version of the faces. They also use the same spatially filtered version of these faces at test. When looking at the pattern of transfer of learning, they found that Hebbian learning could easily learn a low pass version of faces and generalize its learning to the normal version of the faces. They also explored the effect of adding noise to the faces presented at test. They found that Hebbian learning could cope with a very large amount of noise, but that the performance of Widrow-Hoff learning was clearly impaired by the addition of noise. This set of simulations shows that whereas a Hebbian trained memory is able to recognize only a small number of faces, it is more resistant to noise and spatial frequency filtering than Widrow-Hoff learning.

## XI.3 BACK TO HUMAN NEWBORNS

These simulations demonstrate that the complexity of a face recognition task and the nature of the information needed to perform this task depend on the number of faces involved. Discriminating among a small number of faces does not require a sophisticated learning mechanism nor does it require the existence of innate abilities. In fact, a very primitive mechanism, able to extract only low frequency information, is able to discriminate a face after a single exposure. The complexity of the task, however, increases with the number of encountered faces. After twenty faces, a more sophisticated mechanism is needed which tune itself with increasing exposure to faces. This dual mechanism hypothesis agrees with Nelson's (Chapter 7, 2003) claims that "the mechanisms controlling face recognition may be different in the newborns than in older infants" and that "experience drives development." Additionally, the difference of sensitivity to noise of Hebbian and Widrow-Hoff trained memories suggests that the flexibility of these two learning mechanisms might be different. Whereas Widrow-Hoff is sensitive to high frequency random noise and high spatial frequency filtering, theses two types of manipulations have no effect on Hebbian learning (Valentin *et al.*,, 1996). This last result can be put in perspective with recent results reported by Pascalis, de Haan and Nelson (2002). These authors showed that whereas 9 month-old infants and adults are able to discriminate only faces from their own species, younger infants could discriminate among both human and monkey faces.

## XI.4 LEARNING MECHANISMS FLEXIBILITY: GENERALIZATION ACROSS EXPRESSIONS

To evaluate the idea that an unsophisticated learning algorithm based on a coarse coding of facial information is by nature more flexible than a more

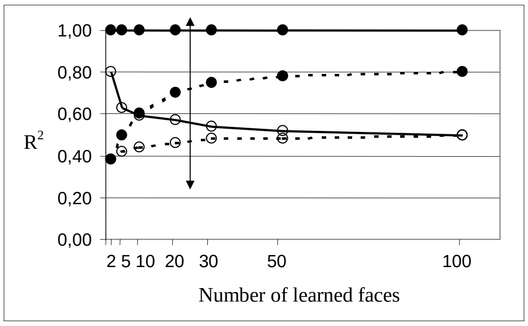


Figure XI.2: Average squared correlations as a function of the number of faces in the learning sets. *Hebbian learning* is represented by empty circles and *Widrow-Hoff learning* by filled circles. The solid lines represent the performance for the *learned faces*. When less than 20 faces have been learned, a Hebbian memory can "recognize" the faces on which it has been trained. After this cutting point, the memory is not able to distinguish learned faces from new faces. This suggests that discriminating between a small number of faces is not as difficult a task as one might think. (From Valentin, Abdi, Edelman, & Nijdam, 1996).

sophisticated learning, we performed a new series of simulations. In these simulations, we evaluated the ability of a Hebbian and a Widrow-hoff trained memory to generalize across expressions. The general procedure was similar to that used by Valentin *et al.,* (1996). Sixty-eight female faces were used as stimuli. Each face was represented by six images: 2 images bearing a neutral expression and the 4 other images bearing one out of four expressions (smile, surprise, disgust, sad). The face images were digitized with a resolution of 230 by 240 pixels with 256 gray levels per pixels (see Figure 3 for some examples). Six learning conditions were used. Each condition corresponded to a different number of learned faces (2, 5, 10, 20, 30, and 50). For each condition, 100 samples of faces were used as learning sets. The other faces were used as testing sets. Training was done using faces with a neutral expression. Testing was done with 1) the learned images, 2) a new neutral image of the learned faces, 3) a new image with an expression of the learned faces, 4) a neutral image of new faces, and 5) an image with an expression of the new faces. The performance of the memories was evaluated by computing the square correlation coefficients between input and output images. Results are summarized in Figure 4. The main point to note on this figure is that, for all learning conditions, the squared correlations obtained for learned faces decrease less after a change in image or expression when the memory was trained with Hebbian learning than when it was trained with Widrow-Hoff learning. In other words,

Figure XI.3: The top row illustrates the different expressions used for each face. From left to right: neutral, neutral, smile, surprise, disgust, sad. The bottom row shows the same expressions after filtering with a Gaussian filter (i.e., such as we thing a newborn, or a Hebbian trained memory, would see them). Clearly, the difference between the expressions decreases with filtering. A learning mechanism based on a coarse coding of the faces should thus be less sensitive to changes in expressions than a learning system based on highly detailed information.

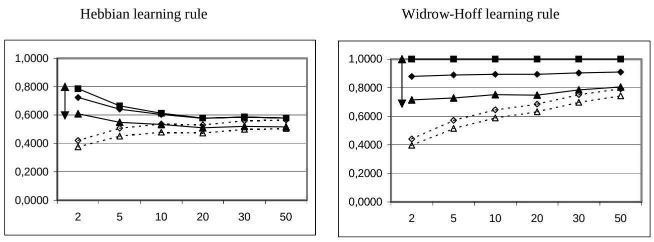


Figure XI.4: Average $R^2$ represented as a function of the number of faces in the learning sets. The solid lines represent the performance for the learned faces (square: same image, diamond: new image, neutral expression, triangle: new image, new expression) and the dashed lines the performance for the new faces (diamond: neutral expression, triangle: other expressions). For all training conditions, the Hebbian trained memory is less disrupted by a change in the images or in the expressions than the Widrow-Hoff trained memory.

a Widrow-Hoff trained memory is less flexible than a Hebbian memory. If we take this metaphor further, this would suggest that for an equivalent amount of learning (i.e., a few encounters) newborns might be less sensitive to changes in expressions that adults.

### XI.4.1 ARE ALL EXPRESSIONS EQUALLY WELL RECONSTRUCTED?

Figure 5 shows the square correlations obtained for the learned faces with different types of expression. We can note on this figure that for both learning algorithms, the smile expression is systematically better reconstructed. This means that the memories are better able to transfer their knowledge from a neutral expression to a smiling expression than to another expression. This result, albeit surprising, is reminiscent of some results by Bau-

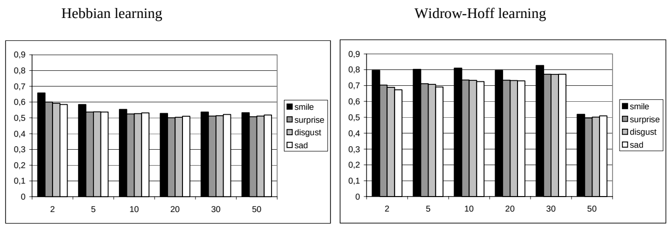


Figure XI.5: Average squared correlation as a function of the number of trained faces and the expression of the test faces (the test was done only with learned faces). Curiously, in all learning conditions and for both learning algorithms, the smiling faces are better reconstructed than the other expressions. This suggests that the smile advantage—sometimes described in the literature—might be due, in part, to the statistical properties of face images.

douin, Gilibert, Sanson, and Tiberghien (2000). These authors found that smiling faces are judged more familiar than neutral faces, regardless of the actual familiarity of the faces. Other authors also reported that familiar smiling faces are better recognized than non-smiling faces (Endo, Endo, Kirita, & Maruyama, 1992; Kottoor, 1989; Sansone & Tiberghien, 1994). According to Baudouin *et al.*, (2000) this "smiling bias" would results from both the social importance, and the frequency of occurrence of smile in everyday life. Our face processing module would be tuned to smiling faces and so "when we perceive a smiling person who looks at us, our first feeling may be to believe that we know this person" (p. 291). As we obtained such a "smiling bias" without encoding social and frequency knowledge, this suggests that another explanation can be cast in terms of the properties of the stimuli themselves. These properties, in addition, should be in part captured by low frequency information since the smile superiority was observed, although to a smaller extent, with Hebbian learning as well as Widrow-Hoff learning. Again this result is somewhat puzzling because essentially expression is represented in the face internal features which are somewhat blurred in low frequency facial representations (cf. Figure 3).

## XI.5 PRIMITIVE HEBB AND INTERNAL FEATURES

To verify that a Hebbian-trained memory was able to attend to the internal features of faces we carried out a last series of simulations. The general principle was the same as in the previous simulations. Six learning conditions corresponding to a different number of learned faces (2, 5, 10, 20, 30, and 50) were used. Training was done using whole face images. Testing was done with using only the internal features of learned and new faces (cf Figure 6). The performance of the memories was evaluated by computing the square correlation coefficients between the whole images and

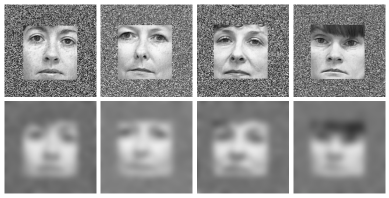

Figure XI.6: The top row shows the internal features of four faces. The bottom row shows the same faces after filtering with a gaussian filter (i.e., such as we thing a newborn, or a Hebbian trained memory, would see them). Clearly, the difference between the faces decreases with filtering. A learning mechanism based on a coarse coding of the faces should have difficulties recognizing learned faces from their internal features only.

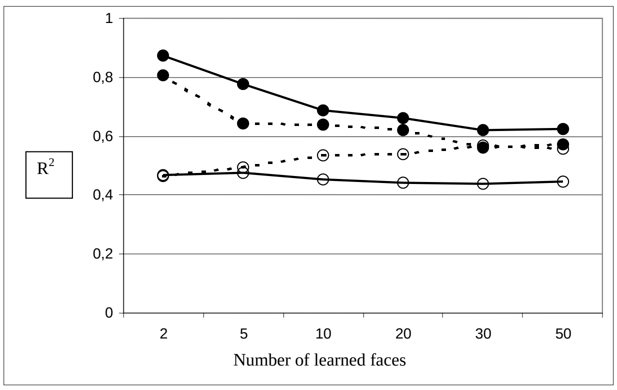


Figure XI.7: Average squared correlations as a function of the number of faces in the learning sets. Hebbian learning is represented by dashed lines and Widrow-Hoff learning by solid lines. Filed circles represent the performance for the learned faces and the empty circles the performance for the new faces. The difference between learned faces and new faces is much larger for the Widrow-Hoff trained memory than for the Hebbian trained memory: Thus Widrow-Hoff learning allows for a better recognition from internal features than Hebbian learning. However, when less than 20 faces have been learned the Hebbian memory can make the difference between learned and new faces. This suggests that there is enough information in a low frequency representation of internal facial features to distinguish known from unknown faces.

responses of the memories to the internal features.

Results are summarized in Figure 7. Clearly, the Widrow-Hoff trained memory distinguishes known and unknown faces from their internal features better than the Hebbian trained memory does. However, when less

Figure XI.8: Responses of an autoassociative memory trained to reconstruct five faces (top row) with Hebbian learning (middle row) or Widrow-Hoff learning (bottom row) to the learned faces. The responses of the Widrow-Hoff trained memory resemble more the original faces than the responses of the Hebbian trained memory which provides the same response to all faces. Thus, if the Hebbian memory is able to distinguish a known face from an unknown face, it is not able to discriminate between two known faces.

than 20 faces were learned, the Hebbian memory was able to recognize known faces since learned faces are better reconstructed than new faces. Figure 8 shows the faces reconstructed by a Hebbian and by a Widrow-Hoff memory trained with five faces. The learned faces are displayed in the first row. The response of the memories to the internal features of these five faces are displayed in the second (Hebbian) and third (Widrow-Hoff) rows. Interestingly, this figure shows that although the Hebbian memory is able to discriminate learned from new faces, the response it gives for learned faces is identical for all faces. This suggests that there is enough information in a low frequency representation of internal facial features to distinguish known from unknown faces but not to distinguish between known faces. It would be interesting to know if this phenomenon hold true also for newborns. Is a newborn able to distinguish between two caretakers encountered equally often before testing? With the same number of faces, a learning mechanism based on detailed information is able to provide different responses to different faces and thus can distinguish between known faces.

## XI.6 CONCLUDING REMARKS

What can we learn from a myopic baby neural network? Clearly, the neural network approach will not help us deciding between the “innate neural mechanism” and the “acquired visual expertise” hypotheses (de Haan *et al.*,, 2002) nor can it provide responses for all unanswered questions on early face processing (cf. Nelson, 2003—this volume, Chapter 7). However, this approach might provide a tool for exploring some of the issues raised by these questions. In particular, it is very useful to understand the constraints inherent to a given task in a particular context. For example, by manipulating the *number of faces* learned by a network, we showed that the complexity of a face processing task depends on the number of faces to be processed. This observation makes less paradoxical the ability of human newborns to recognize the face of their caretakers. By manipulating the *nature of the faces* learned by a network we can also gain insight on the "kinds of experiences" necessary to perform different face processing tasks. Using this strategy, O'Toole, Abdi, Deffenbacher, and Bartlett (1991) demonstrated that an autoassociative memory trained with a majority of faces from a given race exhibits an "other race" effect similar to that displayed by human adults. Examination of the memory inner workings showed that, during learning, the network extracts a set of features that becomes more and more optimal for the set of faces from which they are extracted but less and less appropriate to discriminate between other faces. Finally, the neural network approach can also raise new issues or lead to new hypotheses: Is a newborn able to distinguish between two familiar caretakers? Is a newborn less sensitive to change in expressions than an adult?

## REFERENCES

Abdi, H., Valentin, D. & Edelman, B. (1999). *Neural Networks*. Thousand Oaks: Sage Publications.

Bartrip, J. Morton, & J. de Schonen, S. (2001). Responses to mother's face in 3-week to 5- month-old infants. *British Journal of Developmental Psychology, 19*, 219–232.

Baudouin, J.Y., Gilibert, D., Sanson, S., & Tiberghien, G. (2000). When the smile is a cue to familiarity. *Memory, 8*, 285–292.

Bushnell, I. (1982). Discrimination of faces by young infants. *Journal of Experimental Child Psychology, 33*, 298–309.

Bushnell, I., Sai, F. & Mullin, J. (1989). Neonatal recognition of the mother's face. *British Journal of Developmental Psychology, 7*, 3–15.

De Haan, M., Pascalis, O., & Johnson, M.H. (2002). Specialization of neural mechanisms underlying face recognition in human infants. *Journal of Cognitive Neuroscience, 2*, 199–209

Dobson, D., & Teller, V. (1978). Visual acuity in human infants: A review and comparison of behavioral and electrophysiological studies. *Vision Research , 8*, ***–***.

Endo, N., Endo, M., Kirita, T., & Maruyama, K. (1992). The effect of expression on face recognition. *Tohoku Psychologica Folia, 51*, 37–44.

Field, T.M., Cohen, D., Garcia, R., & Greenberg, R. (1984). Mother-stranger face discrimination by the newborn. *Infant Behavior and Development, 7*, 19–25.

Goren, C., Sarty, M. & Wu, P. (1975). Visual following and pattern discrimination of face-like stimuli by newborn infants. *Pediatrics, 56*, 544–549.

Johnson, M.H., Dziurawiec, S. Ellis, H. D., & Morton, J. (1991) Newborns preferential tracking of faces and its subsequential decline. *Cognition, 40*, 1–20

Kottoor, T.M. (1989). Recognition of faces by adults. *Psychological studies, 34*, 102–105.

Nelson, C. A. (2003). The development of face recognition reflects an experience-expectant and activity-dependent process. In O. Pascalis and A. Slater (Eds.) *The development of face processing in infancy and early childhood*. New-York: Nova science publications. pp. 77–98.

O'Toole A.J., Abdi, H., Deffenbacher, K., & Bartlett, J. (1991). Simulating the "other-race effect" as a problem in perceptual learning. *Connection Science Journal of Neural Computing, Artifical Intelligence, and Cognition Research, 3*, 163–178.

Pascalis, O., & de Schonen, S. (1994). Recognition memory in 3- to 4-days-old human neonates. *NeuroReports, 5*, 1721–1724.

Pascalis, O., de Schonen, S., Morton, J., deRurelle, C., & Fabre-Grenet, M. (1995). Mother's face recognition by neonates: A replication and an extension, *Infant Behavior and Development, 8*, 79–85.

Pascalis, O., de Haan, M., Nelson, C.A., & de Schonen, S. (1998). Long-term recognition memory for faces assessed by visual paired comparison in 3- and 6-month-old infants. *Journal of Experimental Psychology : Learning, Memory, and Cognition, 24*, 249–260.

Pascalis, O., de Haan, M., & Nelson, C.A. (2002). Is face processing species-specific during the first year of life? *Science, 296*, 1321–1323.

Sanson, S., & Tiberghien, G. (1994). Facial expression coding and face recognition : Independent or interactive processes. *Psychologie Française, 39*, 327–343.

Simion, F., Valenza, E., Umiltà, C., & Della Barba, B. (1998) Preferential orienting to faces in newborns: A temporal-nasal asymetry. *Journal of Experimental Psychology: Human Perception and Performance, 24*, 1399–1405.

Slater, A., Bremner, G., Johnson, S., Sherwood, P., & Hayes, R. (2000). Newborn infants' preference for attractive faces: The role of internal and external facial features. *Infancy , 1*, 265–274.

Teller, D., McDonald, M., Preston, K., Sebris, S., & Dobson, V. (1986). Assesment of visual acuity in infants and children: The acuity card procedure, *Develomental Medecine and Child Neurology, 28*, 779–789.

Valentin, D., Abdi, H., Edelman, B., & Nijdam, A. (1996). Connexionist "face-off": Different algorithms for different tasks. *Psychologica Belgica, 36*, 65–92.

Walton, G., Bower, N. and Bower, T. (1992). Recognition of familiar faces by newborns, *Infant Behavior and Development, 15*, 265–269.