

Project Part 3

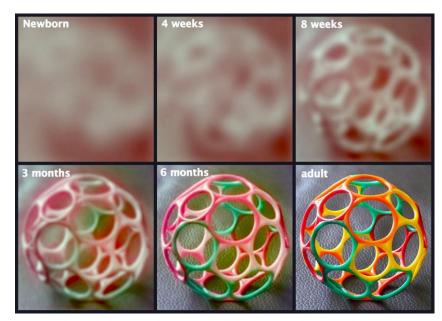
Computational Visual Perception (CompVP)

Bernhard Egger, Andreas Kist, Patrick Krauß, Tim Weyrich

Overall project goal



- What can we learn from infant vision?
- Which properties of infant vision are relevant for adult vision?



https://www.spectacleoptometry.com/blog/what-can-babies-see

How to study infant vision computationally?

Paper 1





Potential downside of high initial visual acuity

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Children who are treated for congenital cataracts later exhibit impairments in configural face analysis. This has been explained in terms of a critical period for the acquisition of normal face processing. Here, we consider a more parsimonious account according to which deficits in configural analysis result from the abnormally high initial retinal acuity that children treated for cataracts experience, relative to typical newborns. According to this proposal, the initial period of low retinal acuity characteristic of normal visual development induces extended spatial processing in the cortex that is important for configural face judgments. As a computational test of this hypothesis, we examined the effects of training with high-resolution or blurred images, and staged combinations, on the receptive fields and performance of a convolutional neural network. The results show that commencing training with blurred images creates receptive fields that integrate information across larger image areas and leads to improved performance and better generalization across a range of resolutions. These findings offer an explanation for the observed face recognition impairments after late treatment of congenital blindness, suggest an adaptive function for the acuity trajectory in normal development, and provide a scheme for improving the performance of computational face recognition systems.

visual development | visual acuity | deep neural networks | spatial integration | sight restoration

This work was initiated by a serendipitous referral to our laboratory of a young boy, RK, with an unusual visual history. perceptual and cortical specialization necessary for faceidentification abilities (1, 6-8). Children like RK, who pass this period without normal exposure to faces, are expected to exhibit compromised face recognition skills later in life. Recent evidence from nonhuman primates who have undergone controlled deprivation is consistent with these results (8). Monkeys reared without exposure to faces lacked face preference in their looking behavior, and did not exhibit face-specialized cortical domains, in contrast to nondeprived controls. These observations suggest that skills which appear early in the developmental timeline, such as face discrimination, may be particularly vulnerable to visual deprivation. It is worth pointing out, however, that the consequences of delayed treatment of congenital blindness are complex and do not all conform to a unitary template. Several highlevel visual skills appear capable of being acquired even after prolonged periods of initial deprivation (9-12). Additional evidence of resilience is provided by studies of low-level vision. Here, findings suggest that the earliest appearing proficiencies of normal development, such as the ability to perceive visual flicker, are also the ones least susceptible to deprivation, a biological analog of the common corporate practice of "first-hired lastfired" (13, 14). Taken together, these studies point to a varied landscape of visual proficiencies following late treatment of congenital blindness, with some skills more susceptible to compromise by visual deprivation during early "sensitive" periods in development. Specifically, impairments of face processing follouing corbugional description may plausibly admit a consitius

SYCHOLOGICAL ANI

COMPUTER SCIENCE



Curriculum Learning with Infant Egocentric Videos

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Structure of project



- Project Part 1: Implement Infant Vision (close to Paper 1)
- Project Part 2: Train a network based on two conditions (close to paper 2)
- Project Part 3: Evaluate the trained networks (close to paper 1 and 2)

How to pass



- Submission via Studon course: "Computational Visual Perception"
- Submission has to be in the exact format

- Three strict project deadlines
 - November 21st,
 - January 2nd (feel free to submit early),
 - February 6th

How to pass



- Pass/Fail for each of the 3 parts,
- You need to pass 2 out of 3 parts
- The best solutions for each part will be released ~ 1
 week after the deadline, to enable others to continue
 with the best solution of another team

How to pass



- Scope of project ~ 150 hours per student
- Teams of 1-3 students
- Steps can be performed in new group
- If you are looking for a group, please stay after the class and talk to people who also stay
- If you are looking for a group and can only join virtually, please use the forum in "Computational Visual Perception" to team up
- Finding a group is your responsibility



Tasks:

- 1. Choose a solution for part 2 to start from (your own or from a recommended group)
- 2. Choose 100 images from a dataset to evaluate
- 3. Calculate at least 9 RDMs based on those 100 images
- 4. Evaluate the networks against the human brain Alternatively come with an own suggestion!
- 5. Draw a conclusion
- 6. Write a 2 page report to sell your solution



- Choose a solution for part 2 to start from
- Only continue with your own solution if it was selected or if your solution at least did not miss any implementation points
- Declare which solution you started from in your report (correct attribution)



- Choose a dataset to test/calculate RDM on
 - Any image dataset is fine.
 - Total of 100 images
 - You might apply transformations to some of them (e.g. 25% no transformation, 25% low acuity, 25% other, 25% both)
 - This will make RDM more interesting



- Calculate at least 9 Representational Dissimilarity Matrices
 - You will learn about RDMs in next weeks lecture
 - Calculate RDMs at least for all the networks learned with transformations against the network without transformation (that gives you 3 RDMs)
 - Calculate all 3 RDMs for 3 different layers in your network (which leads to the total of 9 RDMs)
 - You need to extract layer activity (feel free to use libraries)



- Evaluate/Compare all four trained networks against the human brain
 - E.g. using brainscore benchmark Brain-Score
 - Or publicly available benchmark/data/code
- Alternatively: suggest an own way to evaluate the trained networks (e.g. a transfer learning task as in paper 2).
 - If you come with an own suggestion, write the suggestion to me via email (1-2 sentences is fine)



- What do your results mean?
 - Interpret RDMs
 - Interpret brainscore/evaluation results



- Write a 2 page report
- Should advertise your solution (selected reports will be shared
- Page 1:
 - Declare which solution you started from (own vs. peers)
 - Description of choices and implementation
- Page 2:
 - RDMs
 - Figure/Table with evaluation (e.g. brainscore values)

Part 3 deliverables



- Per project team 1 single zip file
- The zip file contains:
 - readme.pdf a 2 page report, selling your solution to other project teams, there is no template
 - a folder called code
 - That folder contains the *.py files to calculate the RDMs
 - That folder contains potential code you need for task 4
 - a folder called raw
 - That folder contains the raw data behind the RDM (network activities for brain regions
 - a folder called Al
 - Contains protocol or project file of any generative AI tool used

Part 3 Upload



- In Studon course :
 "Computational Visual Perception"
- You will upload up to ~1GB (don't!)
 Plan in internet speed, upload at university

If you run into issues uploading, you send an md5 hash of your zip file **before** the deadline and you provide an alternative download link within 24h

Part 3 grading



- Correct file structure
- readme.pdf contains useful information about the approach taken
- readme.pdf contains interpretation of results
- readme.pdf contains RDMs
- readme.pdf contains Evaluation, i.e. Brainscore
- Code delivered
- Raw data delivered
- Pass: not more than 1 of those points missing/wrong (binary)
- Selected solution: all points fulfilled to full satisfaction
- Plagiarism will have serious consequences
- Use of AI tools is allowed, but has to be declared including how exactly it is used. Protocol of usage or "project file" hast to be handed in in folder AI

Project Consulting



- You can ask questions in the forum "Computational Visual Perception"
- You come with concrete questions
- I'll open a thread in the forum, where you can respond till Tuesday each week if you want to meet
- I'll distribute time slots on Wednesday

Extra offers part 3



- If you still need a pass in part 3, I do offer to look at your solution till Tuesday before de deadline to provide you feedback if it will be a pass
- Since there are no consulting sessions on the 16th and 23rd: contact me via email if you need help and we will find time to discuss
- I might recruit from the best teams

Don't start late



PROCRASTINATION







