Apparent motion in V1 - Probabilistic approaches

Motion-based prediction is sufficient to solve the aperture problem

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March 23rd, 2012

Second BrainScaleS plenary Meeting - WP5 (Demo 1)

This work is supported by the European Union project Number FP7-269921, ``BrainScaleS''.
Supplementary material can be accessed on the corresponding author's website at `http://invibe.net/LaurentPerrinet/Presentations/12-03-23_Juelich`.

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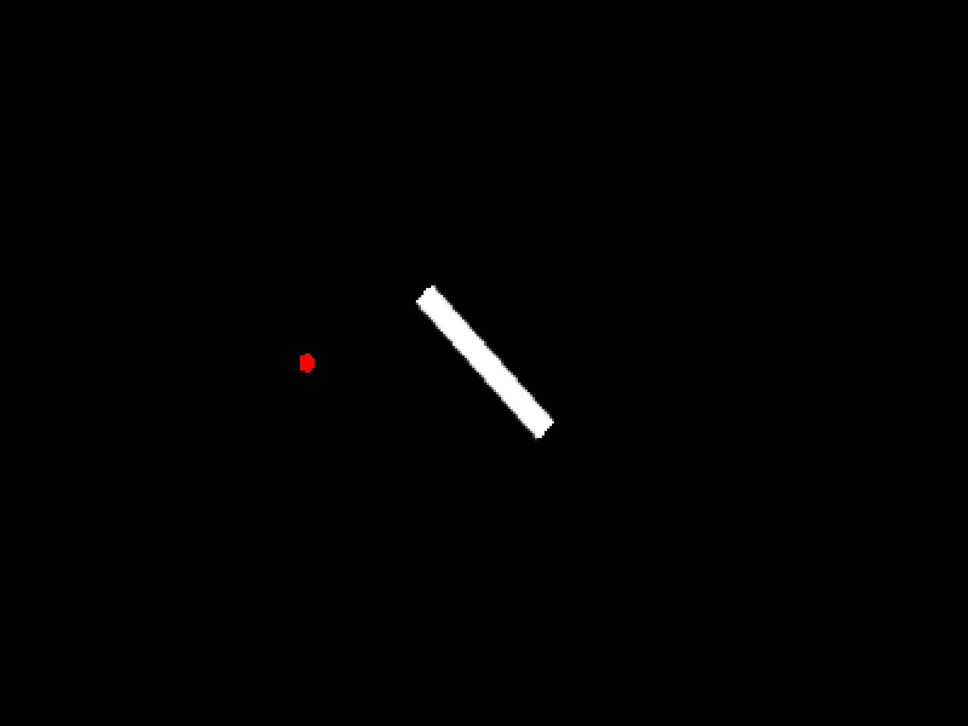
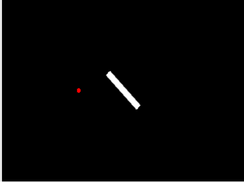
(hello) Hi, I am Laurent U. Perrinet and I work at the team "inference in Vision & Behavior" supervised by Guillaume Masson in Marseille.

(objective) in this talk, as part as the goal set in WP5T4 & 5, my goal is to show that

- (proba) It i possible to construct a functional probabilistic approach adapted to apparent motion
- (AP) I will illustrate by showing that motion-based prediction is sufficient to solve the aperture problem

(dissemination) this may help guide models in demo 1 and also experiments (WP1) to validate our predictions

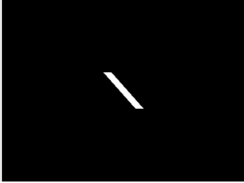




A typical conundrum in neuroscience to illustrate the ambiguity of sensory motion information is the aperture problem:

(definition) imagine that we know a priori that there is a line moving on the visual field but that it is occluded by a small aperture such as shown here. due to the translational symmetry of the line along its axis, the motion component parallel to the line may correspond to any possible solution: the measurement of motion is ambiguous.

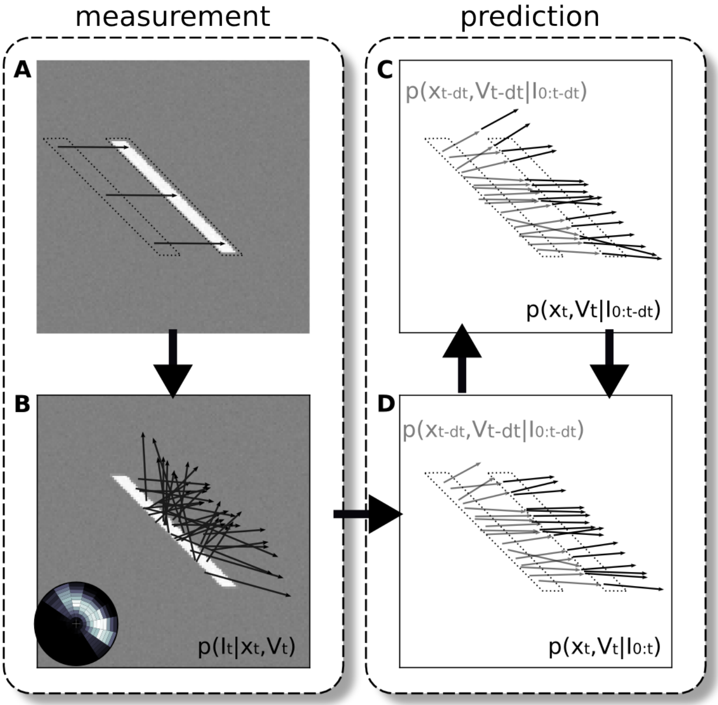
(neural) this is an important problem since it sketches a situation faced by neurons in low-level sensory areas: due to the limited size of their dendritic arborisation, each neuron is only directly sensitive to a bounded part of the visual field -its classical receptive field . it is as if each neuron is looking through a small window or aperture. This is what I roughly sketch here: if you fixate on the red dot on the left, the aperture will approximately correspond to the extent of the classical receptive field of a neuron from the cortical area typically associated to the extraction of motion (area MT).

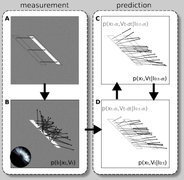


... but if we now enlarge this static aperture, it is enough to introduce a bias which rotates the perceived direction of motion: here along the longer axis of the aperture. if we now think back in terms of the neurones in the previous example, the raw input is still the same in the classical receptive field, still the global response is influenced by the contextual information that lies outside the classical receptive field to give the horizontal motion... Note that there is not one solution (here are still other objects leading to the same stimulus), but I will speak about the horizontal motion as the right "solution" following the classical terminology.

(inference) In this perspective, we will follow the seminal contributions to theories of vision from German physicist Hermann von Helmholtz and study perception as a detection process for which we may use statistical inference. In that context, the goal of low-level sensory processes is to recover the most likely objects in the world based on the ambiguous visual evidence.

(ill-posed) Detection of motion, as a one-to-many mapping of sensible space (retina) to motion space, is thus an ill-posed problem. Note that the same problems faced by perception are found in other mathematical problems such as optical flow estimation in computer vision. that's certainly the reason why there is such great convergence between both fields.


measurement
prediction
A
B
p(It|xt,Vt)
C
p(xt-dt,Vt-dt|I0:t-dt)
p(xt,Vt|I0:t-dt)
D
p(xt-dt,Vt-dt|I0:t-dt)
p(xt,Vt|I0:t)



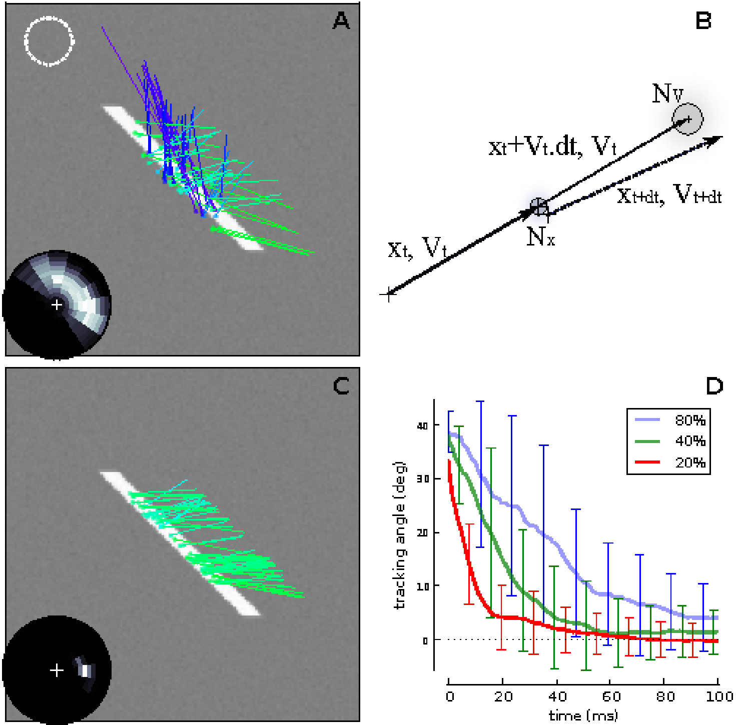
Our hypothesis is that predictive coding is sufficient to solve the AP. To validate that, we use a classical HMM model. This model is constituted by a classical measurement stage and of a predictive coding layer. The measurement stage consists of inferring from

(A) two consecutive frames of the input flow,

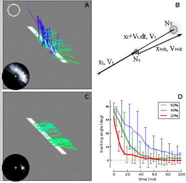
(B) : a best estimate of motion. This layer interacts with the predictive layer which consists of

(C) : a prediction stage that infers from the current estimate and the transition prior the upcoming state estimate and

(D) an estimation stage that merges the current prediction of motion with the likelihood measured at the same instant in the previous layer (B).



A
B
Nv
xt+Vt.dt, Vt
xt+dt, Vt+dt
xt, Vt
Nx
C
D
80%
40%
20%
tracking angle (deg)
time (ms)
0
10
20
30
40
60
80
100



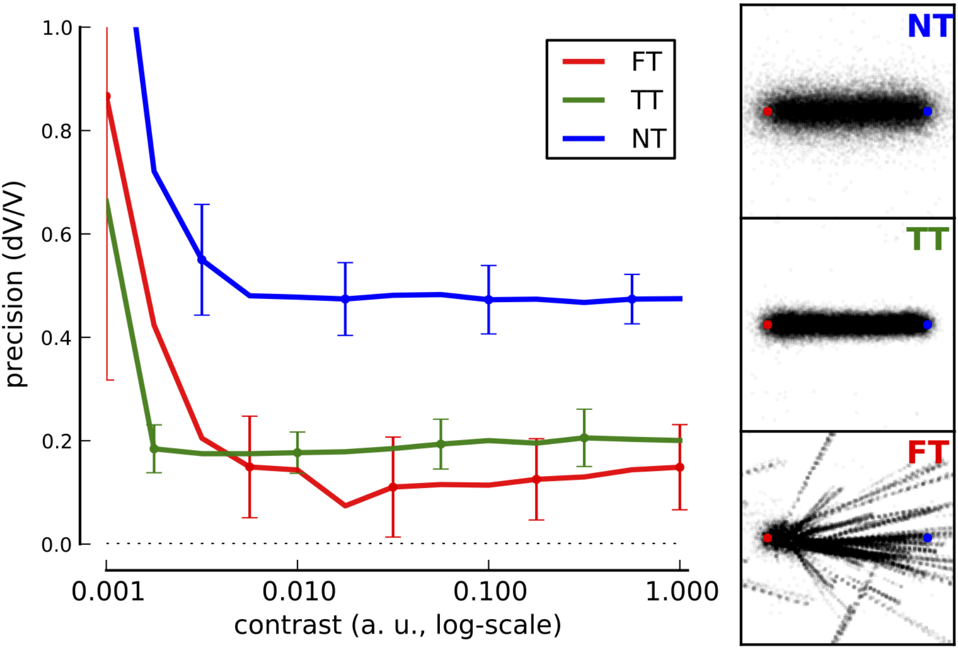
Let's see the results on the slanted line

(A) On a polar representation of possible velocity vectors (the cross in the center corresponds to the null velocity, the outer circle corresponding to twice the amplitude of physical speed), we plot the empirical histogram of detected velocity vectors. This representation gives a quantification of the aperture problem in the velocity domain: At the onset of motion detection, information is concentrated along an elongated constraint line (white=high probability, black=zero probability).

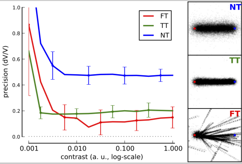
(B) We use the prior knowledge that in natural scenes, motion as defined by its position and velocity is following smooth trajectories. Quantitatively, it means that velocity is approximately conserved and that position is transported according to the known velocity. We show here such a transition on position and velocity (respectively $\vec{x}_t$ and $\vec{V}_t$) from time t to $t + dt$ with the perturbation modeling the smoothness of prediction in position and velocity (respectively $\mathcal{N}_x$ and $\mathcal{N}_V$).

(C) Applying such a prior on a dynamical system detecting motion, we show that the motion converges to the physical motion after approximately one spatial period (the line moved by twice its height). **(C-Inset)** The read-out of the system converged to the physical motion: Motion-based prediction is sufficient to resolve the aperture problem.

(D) As observed at the perceptual level in vision behavior or tomatosensory, size and duration of the tracking angle bias decreased with respect to the height of the line. Height was measured relative to a spatial period (60%, 40% and 20%). Here we show



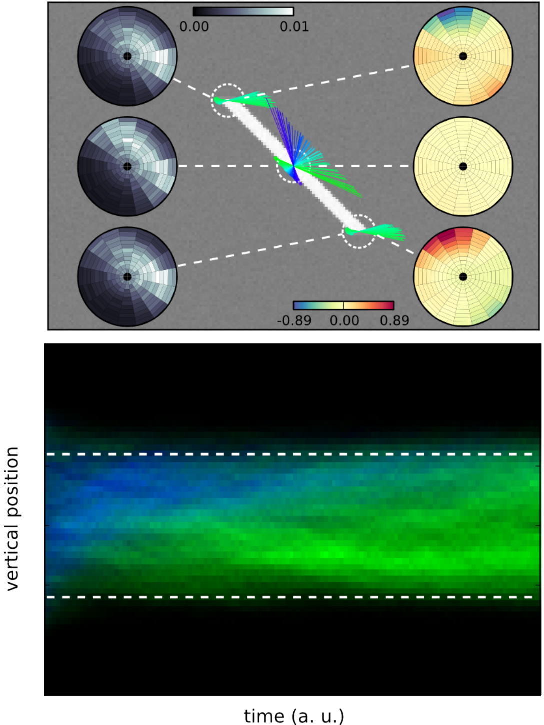
precision (dV/V)
1.0
0.8
0.6
0.4
0.2
0.0
0.001
0.010
0.100
1.000
contrast (a. u., log-scale)
FT
TT
NT
NT
TT
FT



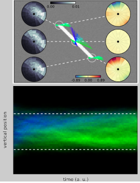
So it works, but why? A first reason why we solve the aperture problem is that the system tracks coherent features such as the line endings. To explore the state-space of the dynamical system, we simulated motion-based prediction for a simple small dot (size 2.5% of a spatial period) moving horizontally from the left to the right of the screen. We tested different levels of sensory noise with respect to different levels of internal noise, that is, to different values of prediction strength.

(**(Right)**) : Results show the emergence of different states for different prediction precisions: a regime when prediction is low showing relatively high tracking error and variability (No Tracking - NT), a phase for intermediate values of prediction strength (as in previous slide) exhibiting a low tracking error and low variability in the tracking phase (True Tracking - TT) and finally a phase corresponding to higher precisions with relatively efficient mean detection but high variability (False Tracking - FT). We give 3 representative examples of the emerging states at one contrast level ($C = 0.1$) with starting (red) and ending (blue) points and respectively NT, TT and FT by showing inferred trajectories for each trial.

(**(Left)**) We define tracking error as the ratio between detected speed and target speed and we plot it with respect to the stimulus contrast as given by the inverse of sensory noise. Error bars give the variability in tracking error as averaged over 20 trials. As prediction strength increases, there is a transition from smooth contrast response function (NT) to more binary responses (TT and FT) and to higher biases in FT.



0.00
0.01
-0.89
0.00
0.89
vertical position
time (a. u.)

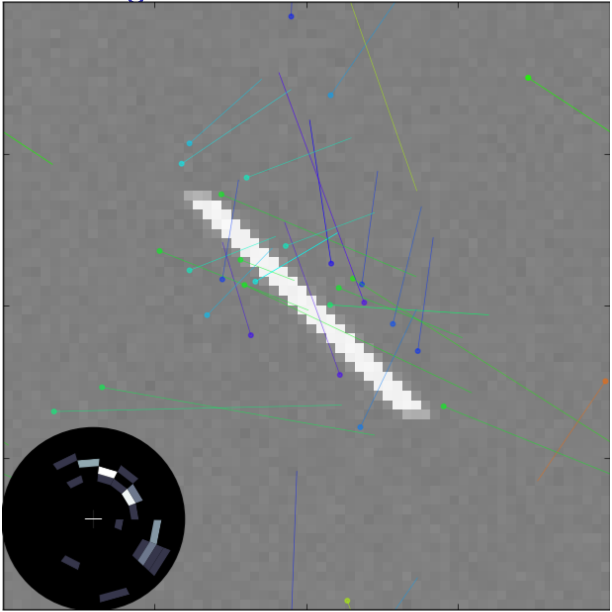


Secondly

(Left) Prediction implements a competition between different trajectories. Here, we focus on one step of the algorithm by testing different trajectories at three key positions of the segment stimulus: the two edges and the center (dashed circles). Compared to the pure sensory velocity likelihood (left insets in grayscale), prediction modulates response as shown by the velocity vectors (direction coded as hue as in the figure 2 slides ago) and by the ratio of velocity probabilities (log ratio in bits, right insets). There is no change for the middle of the segment (yellow tone), but trajectories that are predicted out of the line are ``explained away'' (navy tone) while others may be amplified (orange tone). Notice the asymmetry between both edges, the upper edge carrying a suppressive predictive information while the bottom edge diffuses coherent motion.

(Right) : Finally, the aperture problem is solved due to the repeated application of this spatio-temporal contextual information modulation. To highlight the anisotropic diffusion of information over the rest of the line, we plot as a function of time (horizontal axis) the histogram of the detected motion marginalized over horizontal positions (vertical axis), while detected direction of velocity is given by the distribution of hues. Blueish colors correspond to the direction perpendicular to the diagonal while a green color represents a disambiguated motion to the right (as in the line figure). The plot shows that motion is disambiguated by progressively explaining away incoherent motion. Other trajectories are weighted as improbable as they fall off the line or are not smooth.

Take-home message



L. U. Perrinet, and G. S. Masson

Motion-based prediction is sufficient to solve the aperture problem *Under revision*

Take-home message

L. U. Perrinet, and G. S. Masson
Motion-based prediction is sufficient to solve the aperture problem *Under revision*
http://invibe.net/LaurentPerrinet/Publications/Perrinet12pred

To summarize, during this talk I hope I convinced you that

- we achieved a practical Probabilistic modeling of dynamic sensory integration and the AP is a good framework to test it
- Motion-based prediction is sufficient to solve the aperture problem.
- Our future goal is to translate the probabilistic model to the multi-whisker stimulation protocol (CNRS-UNIC) / implement in neural networks (with KTH and TUG) / close the loop."

Thank you for your attention.

For Further Reading

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Motion-based prediction

Results

Take-home message