

Optimal cue combination and landmark-stability learning in the head direction system

Kate J. Jeffery¹, Hector J.I. Page^{1,2} and Simon M. Stringer²

1 - Institute of Behavioural Neuroscience, Department of Experimental Psychology, University College London, 26 Bedford Way, London WC1H 0AP

2 - Oxford Centre for Theoretical Neuroscience and Artificial Intelligence, Department of Experimental Psychology, University of Oxford, South Parks Road, Oxford OX1 3UD

Abstract

Maintaining a sense of direction requires combining information from static environmental landmarks together with dynamic information about self-motion. This is accomplished by the head direction system, whose neurons – head direction cells – encode specific head directions. When the brain integrates information in sensory domains, this process is almost always “optimal” – that is, inputs are weighted according to their reliability. Evidence suggests cue combination by head direction cells may also be optimal. The simplicity of the head direction signal, together with the detailed knowledge we have about the anatomy and physiology of the underlying circuit, therefore makes this system a tractable model with which to discover how optimal cue combination occurs at a neural level.

In the head direction system, cue interactions are thought to occur on an attractor network of interacting head direction neurons, but attractor dynamics predict a winner-take-all decision between cues, rather than optimal combination. However, optimal cue combination in an attractor could be achieved via plasticity in the feedforward connections from external sensory cues (i.e., the landmarks) onto the ring attractor. Short-term plasticity would allow rapid re-weighting that adjusts the final state of the network in accordance with cue reliability (reflected in the connection strengths), while longer term plasticity would allow long-term learning about this reliability. Although these principles were derived to model the head direction system, they could potentially serve to explain optimal cue combination in other sensory systems more generally.

Abbreviations

MEC: medial entorhinal cortex

PoS: postsubiculum

RSC: retrosplenial cortex

Introduction

Self-localisation and navigation benefit from maintenance of a stable sense of direction so that a navigator knows which way they are facing, and therefore how to interpret the field of view and plan movements through the surrounding space. In the mammalian brain, this sense is constructed and maintained by a network of structures known collectively as the head direction system (Taube *et al.*, 1990; Taube, 2007). Cells in these areas, called head direction cells, fire when an animal's head faces in a particular direction; they do this by combining external, environment-based information together with internally generated, dynamic information about self-motion (Blair & Sharp, 1996).

When an animal enters a new environment the head direction system first has to learn about the local landmarks, which it uses to establish a frame of reference relative to which head directions can thereafter be specified (Taube & Burton, 1995). To do this, the animal has to identify those environmental features that are directionally useful; namely, features that are stable, and are thus part of the static background (or *allocentric*) frame of reference. *Instability* can take two forms – it can occur because the objects themselves move, or it can occur because small and nearby fixed objects, which can be walked around, also change their apparent direction relative to the background and so are less useful as directional landmarks. Deciding which objects are distant and stable vs nearby and/or unstable poses something of a chicken-and-egg problem because the purpose of stable landmark identification is to establish the directional reference frame, but the reference frame itself is used to decide whether a given landmark is stable or not. Landmark-learning thus involves a process of continual cue conflict resolution as the system constantly judges, on balance of probabilities, whether its own signal has accrued an error or whether a given landmark is uninformative.

The question addressed by this article, then, is how – at a neural level – the head direction system resolves conflicts between sets of incoming signals. Cue integration and conflict resolution is an area that has had extensive theoretical treatment in other domains, but the neural basis of this process remains unknown. Understanding cue combination by head direction cells, which form a relatively simple sensory system, may shed light not just on navigation computations but also on more general principles of optimal cue combination.

Optimal sensory integration

Sensory integration in the nervous system is often optimized (Ernst & Banks, 2002), such that better or more reliable information is given a stronger role in the final sensory decision. Several experiments have shown that subjects are able to combine sensory information in a way that gives more weight to the more reliable cue: for example, Ernst and Banks found that subjects judging the texture of a surface using both vision and touch benefitted from use of both senses, and tended to weight the lower-variance visual stimulus more strongly. Similar findings have arisen from studies investigating the combination of stereo cues and texture cues to estimate surface slant (Knill & Saunders, 2003), and combination of vision and sound to estimate speaking direction (the so-called "ventriloquist effect": Alais & Burr, 2004) or temporal order (Shams *et al.*, 2005).

Cue combination has been well described by maximum likelihood estimation (Ernst & Banks, 2002), in which each parameter (e.g., a visual stimulus and a tactile stimulus) is modelled by a Gaussian curve, which depicts the probability of the stimulus location in parameter space (for example, the probability that surface has a given texture, given its visual appearance). The height of these Gaussian curves is proportional, and width inversely proportional, to the reliability of the estimate (Figure 1), so that a tall narrow curve reflects a more accurate estimate, and a lower broader one a more diffuse or uncertain estimate. The process has been formulated in Bayesian terms (Knill & Pouget, 2004), in which the height and width of the Gaussian probability density estimates reflects the prior information present in the system about each cue. For example, if a subject has learned that tactile cues are less reliable (let's say they are wearing gloves, and have learned from experience that gloves reduce tactile accuracy), then the shape of the tactile Gaussian probability distribution will change to reflect the lower informativeness, and so tactile cues should have less impact on the final decision. Given two such distributions, corresponding to two sets of cues, cue combination in theory simply involves multiplication of these probabilities. It is a property of Gaussians that the product of two curves is itself a Gaussian curve, located between the originals and closer to the taller narrower one, producing optimal cue combination exactly as required.

Insert Figure 1 near here

Cue combination and prior-informed sensory processing are highly relevant to spatial processing (Cheng *et al.*, 2007), including directional estimation. Cue combination could occur when head direction cells are faced with more than one indicator of direction and have to decide how best to exploit these. Examples of multiple directional cues include self-motion cues from the vestibular and motor systems vs static landmarks in the environment, both of which can vary in reliability: animals can become internally disoriented, or landmarks can be unstable. Studies in which landmark stability and/or internal cues have been manipulated have found a re-weighting of the relative influence of these cues, both in behavioural and physiological observations. Behaviourally, one of the first experiments, by Biegler and Morris, found that rats would only use landmarks as a guide to food location if the landmarks were spatially stable (Biegler & Morris, 1993). Physiologically, Knierim *et al.* found that place and head direction cells would not use landmarks to reset their firing directions if the landmarks were not consistently aligned with the rats' sense of direction (Knierim *et al.*, 1997). Similarly, hippocampal place cells would not use landmarks to orient their firing if the landmarks had been experienced by the rats as spatially unstable (Jeffery & O'Keefe, 1999)(Figure 2A). This latter experiment also found that weighting could shift progressively from one cue to another: if rats were deprived of vision for only short periods of time, so that the internal sense of direction had had less time to drift and lose accuracy, cells followed the internal cues more and the cue card less: with longer periods of visual deprivation the balance reversed, and cells were more likely to be "reset" by the landmark (Figure 2B). Thus, it seems that the weighting of cues can be adjusted by experience of their relative reliability.

Insert Figure 2 near here

If optimal cue combination involves reliability-weighted integration, then how might this occur at a neural level? As yet, there currently exists no generally accepted neural-level model of how these Gaussian likelihood estimations might be accomplished by real neurons, although some investigators have started to tackle this issue (Ma *et al.*, 2006; Fetsch *et al.*,

2012). The head direction system may offer some new insights: it may be that the same mechanism that head direction cells use for optimal landmark use might be employed for optimal cue combination in other sensory systems too.

The head direction ring attractor

To begin with we will examine the basic principles of landmark processing by the head direction system, before turning to the question of how the network might achieve cue combination. The basis of the head direction signal, generated in the brainstem (Clark & Taube, 2012), is thought to comprise a *ring attractor* (Skaggs *et al.*, 1995; Zhang, 1996), in which excitatory interconnections between neurons of similar preferred directions (e.g., two “north” neurons both firing when the animal faces north) cooperate with inhibitory interconnections between neurons with dissimilar preferences (“north” vs “south”, etc) to restrict activity to just one part of the imaginary ring of neurons (Figure 3A). Activity can be moved from one part of the ring to another, either by the animal’s own movements or by detection of familiar landmarks which adjust the signal to correct errors (Figure 3B). Note that in mammals, these neurons are not arranged in an actual physical ring (Figure 3C), although recent evidence suggests that in insects they might be (Seelig & Jayaraman, 2015). While the generative and updating parts of this process are intrinsic and may even operate in the absence of visual landmark information (in the dark, or – in infant rats – pre eye-opening (Bjerknes *et al.*, 2015; Tan *et al.*, 2015), the landmark-based setting and resetting depend on learned information about the environment and about which elements of it are stable and thus useful as directional indicators. Since excitatory interconnections have not been observed in the known head direction areas, variants of the basic attractor model have been proposed that use inhibitory interconnections to achieve the same result (Song & Wang, 2005). The lack of excitatory interconnections may be due to the deleterious effect these are predicted to have on the speed of updating during movement (Page *et al.*, 2015).

Insert Figure 3 near here

The attractor model in its simplest form predicts that sensory cue integration should be not Bayesian but rather “winner take all”, with the strongest cue dominating over all the others,

because the sensory cue with the strongest inputs to the attractor would continue to preferentially drive activity in that part of the ring until the activity moves there (Touretzky, 2005). Thus, when there are conflicting information sources onto head direction cells (Figure 3D), one source should always win out. However, numerous experiments over many years show that when there is a conflict between a landmark and the current state of the network (“current state” being the animal’s current estimate of its directional heading) then the landmark’s correction of the error is incomplete (see (Knight *et al.*, 2014) for a compilation of these studies). This incomplete correction is manifested as an under-rotation of the head direction cell’s firing direction relative to the cue rotation, and indicates that the strongest cues – the landmarks – do not always capture the network completely. The degree to which the system “compromises” between the two cue sets – the cues that supported the initial firing direction, and the now-rotated landmarks that drive the new one – can be a function of experience (Knight *et al.*, 2014) suggesting that head direction cells can also perform weighted cue integration.

How could a ring attractor perform weighted cue integration, in light of the capture dynamics discussed above? Given the two basic premises: (i) that weighted cue integration requires the resulting final activation on the ring attractor to be located between the two initial external (cue-driven) inputs, but closer to the stronger one, and (ii) that activation of a ring attractor will always settle to a stable state centred at the location of the strongest drive onto the ring attractor, then logically, there is only one solution, which is to dynamically rewire the connections so that the incoming afferents shift their drive onto the ring to the desired intermediate location. In other words, for cue integration, inputs should be adjusted so that the strongest drive onto the attractor *is* the location corresponding to the integrated decision. For this shift to occur, there needs to be plasticity that alters the pattern of incoming synaptic weights. This plasticity would have to occur rapidly and dynamically as the attractor is processing the cues, so that the strongest cue comes to drive activation at a new location predicted by a weighted combination of the two original contributing cues.

In a recent modelling study we have found that Hebbian long term potentiation (LTP) based on co-activation of pre- and post-synaptic neurons, combined with long term depression (LTD) due to synaptic weight vector renormalisation, can in principle accomplish this re-

weighting, in the direction and by the amount required (Page *et al.*, 2013). To see how this could occur, this re-weighting process is shown using a linearized attractor in Figure 4. The pattern of drive from the two cue sets, one broad/weak (corresponding to the activation of the network from self-motion – “idiothetic” – cues, and corresponding to current head direction estimate) and one narrow/strong (corresponding to a landmark), is shown by the two Gaussian curves, whose “reach” far exceeds the zone of actual cell spiking (shown as red cells in the Figure). Because of an additive co-activation effect in the overlap zone between the weak and strong cues, plasticity occurs in the connections onto those cells within reach of both of the activations. This has the effect of selectively strengthening those connections only, such that the distribution of synaptic weights now becomes shifted in the direction of the weaker cue, although still remaining close to the strong one. As this process iterates, activation eventually comes to settle in in the intermediate portion of the ring, between the two cues but closer to the stronger one, exactly as required.

Insert Figure 4 near here

Landmark-learning and dynamic re-weighting

Dynamic re-weighting can in principle explain within-trial cue integration; it can account for the online adjustment of the head direction signal when there is a transient mismatch. However, a second important function of cue conflict resolution is to produce long-term learning about relevant and irrelevant landmarks. If a landmark is unstable, for example, then it may fail to acquire the ability to influence, or “reset”, the head direction network (Knierim *et al.*, 1997; Jeffery, 1998). Even if a landmark is spatially stable, its proximal location relative to an exploring animal may mean that it is located at many different directions relative to the animal and hence is not useful as a directional cue (Zugaro *et al.*, 2001). In such cases, it is necessary to disconnect the irrelevant (i.e., unstable) landmarks from the network so that they can no longer drive head direction cell activity (Figure 5A), and also necessary to strengthen the relevant ones so that they can reorient the head direction network in future. How does this occur?

Insert Figure 5 near here

For this, we need to recruit longer-term plasticity; that lasting days or more. Using a Hebb-Stent rule in which connections become stronger with repeated agreement, while with repeated conflicts then the connections become weaker (Figure 5B), the system could become strongly attached to stable landmarks (those that constantly agree with the attractor state) while disconnecting from unstable ones. In this way the system is able to assimilate long-term learning about landmark reliability, and in so doing establish a stable reference frame which can be used in short-term correction of a drifted ring attractor network.

Future directions

How could cue combination in the head direction system be investigated further? The first task is to identify where, in the head direction network, such plasticity (both short- and long-term) between landmarks and the ring attractor might occur. Likely candidate areas are the cortical head direction areas, including retrosplenial cortex (RSC), postsubiculum (PoS) and medial entorhinal cortex (MEC; Yoder *et al.*, 2011), because of their proximity to the incoming sensory signals pertaining to landmarks. RSC and PoS cortices both have direct connections with primary visual areas (Vogt & Miller, 1983), and it seems likely that these two areas perform different functions that may be related to visual landmark processing, although what these might be remains a mystery. Interestingly, evidence from human neuroimaging suggests a function for RSC in learning about landmark stability, both in processing familiar landmarks (Auger *et al.*, 2012) and in learning about novel ones (Auger *et al.*, 2015). Humans also show RSC activation guided by local environmental cues rather than by global directional ones (Marchette *et al.*, 2014). In further support of a role for RSC in landmark processing, we have recently found neurons in dysgranular RSC that respond to environmental directional cues in preference to the main head direction signal (Jacob *et al.*, 2014), suggesting that this region might indeed be the interface between landmarks and the head direction ring attractor. The cortical head direction areas also show plasticity (Garden *et al.*, 2009; Dumont *et al.*, 2012; Shires *et al.*, 2013). Little is yet known about the interactions between these three cortical structures, nor of how such interactions may

adapt with experience, but it seems likely that this would be the place to start looking for such cue combination processes.

Having identified the locus of plasticity, the next step is to determine what happens when a cue is moved. The first prediction of our model is that blocking synaptic plasticity should abolish the undershoot of head direction cells in response to a shifted landmark. Although the mechanisms of synaptic plasticity in this system have not yet been identified, a good place to start would be the NMDA receptor, since these receptors have been widely implicated in plasticity in a wide range of brain systems (Sweatt, 2016). Ultimately, however, imaging of dendritic networks will be necessary to determine how the pattern of incoming landmark projections alters with learning.

The third task is to find out where in the system the putative attractor dynamics occur. The hypothesis, well established though it is, still lacks strong experimental support (Knierim & Zhang, 2012) but it remains a compelling idea, and one that has applicability to other brain systems (Hopfield, 1982; Lansner, 2009). If so, then perhaps the ideas about cue combination presented here have general utility: in any attractor system we can apply the notion of short-term dynamic plasticity acting to “drag” the network state as it tries to move towards one cue and away from another, together with long-term plasticity acting to re-weight the cues, and in doing so yield a potential mechanism for cue combination in these other domains too.

Conclusion

This review has examined optimal cue combination, a widely studied form of perceptual decision-making and learning, in the context of landmark learning by the head direction network. Understanding this network is important in understanding spatial cognition, but more than that, it is a simple perceptual/cognitive system that provides a useful model system with which to study the neural basis of sensory processing. We have reviewed the proposal that the head direction system might undertake optimal cue combination by re-weighting the incoming inputs from landmarks, as a function of experience of their stability. This re-weighting achieves, in practical terms, the same reliability-weighted cue combination that has been seen experimentally in a variety of settings, and modelled

mathematically by maximum likelihood estimation. We suggest that such synaptic plasticity might subserve cue combination in other sensory domains too.

Additional information

Competing Interests: The authors declare no competing interests.

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Figure legends

Abstract figure – Optimal cue combination using a ring attractor. (A) Hypothetical head direction cells ring attractor being activated by two cues, one highly reliable (cue 1, red) and one less reliable (cue 2, pink). According to classic attractor winner-take-all dynamics, cue 1 should capture activity in the ring. According to optimal cue combination theory, the resultant activation should be between the two activations, and closer to the stronger one. (B) The two scenarios could be reconciled if Gaussian inputs onto a ring attractor experience Hebbian plasticity in the overlap region, causing re-weighting of the inputs, and a shift towards the other cue. (C) The final outcome of this re-weighting process is that the strong cue captures activity in a winner-take-all fashion, but does so at a part of the ring attractor that is close to the other cue, as predicted by optimal cue combination theory.

Figure 1 – Cue conflict by combination of Gaussian activations. The x-axis refers to some quantifiable parameter distributed across a sensory network such as size, optical slant, spatial location, heading direction etc, and the y-axis reflects intensity of the sensory drive. The Gaussian curves depict the distribution of drive across the parameter space: the red curve denotes a strong (tall) and reliable (narrow) cue, and the pink curve a weaker and less reliable one. The blue curve reflects the outcome of a decision process that has taken both cues into account and derived a weighted average, in which the more reliable cue has exerted a stronger positioning effect.

Figure 2 – Re-weighting of internal vs. external directional cue use by hippocampal place cells (adapted from Jeffery and O'Keefe, 1999). Place field rotation was assessed in rats exposed to a combination of landmark cue-card rotation and self-rotation: rats either saw the cue card move, or did not. (A) For those that saw the cue card move, cells stopped rotating with (“following”) it (left) and started rotating with the rat’s internal direction sense (right). (B) The longer the rats were deprived of visual cues, less likely they were to rotate with the rat and the more likely they were to rotate with the cue card. This suggests that the propensity to follow one or other cue type was a function of its reliability (longer visual deprivation = less reliability of internal direction sense).

Figure 3 – Hypothetical ring attractor structure for neurons in the rodent head direction system. The diagram shows neurons arranged according to their preferred firing direction. (A) When the animal faces a landmark, neurons corresponding to that facing direction become activated (shown in red). (B) When the animal turns to face a new landmark, the combination of internally generated self-motion information together with the sight of the new landmark now drives activity in the part of the network corresponding to the animal's new facing direction. (C) The physical arrangement of the neurons is thought to be random in mammals. (D) When two cues simultaneously try to drive activity in different parts of the network (for example, due to conflict between the rat's current directional estimate and one of the landmarks), theory makes one of two predictions. In a winner-take-all scenario, the strongest cue dominates, and activity moves to the appropriate part of the network. In cue combination, both cues influence the final outcome to a degree proportional to their intensity and/or reliability, with the final result being a compromise.

Figure 4 – Shift of activation in a ring attractor network from a strong cue towards a weaker one. The attractor is shown linearized for convenience; the Gaussian curves depict the external drive (from sensory cues; idiothetic for the weak cue and landmark-based for the strong one) onto the network. Because of the overlap of this drive, an asymmetry of activation occurs, with greater activation in the zone between the two cues. For the stronger cue, which is able to drive neurons to their activation threshold, this asymmetry results in asymmetric synaptic strengthening (dotted line), which will result in a shift of the activation peak in the direction of overlap, with the final result as shown in Figure 1.

Figure 5 – Disconnection (“re-weighting”) of spatially unstable sensory cues from the head direction cell attractor network. (A) Top: Landmarks become associated with activation of the HD ring attractor by Hebbian re-weighting, forming strong connections (red arrows). Bottom: When a landmark moves, the existing connection with the ring attractor weakens (dotted arrow). (B) How unstable landmarks could become disconnected by Hebbian re-weighting. When a given set of sensory neurons has activity reliably associated with the same set of head direction neurons (left-hand panels), connections become stronger by Hebbian associativity. If the cues are spatially unstable and are associated with different parts of the attractor network on different trials, the connections will weaken by an anti-Hebbian mechanism (Hebb-Stent rule) and connections will lose strength.

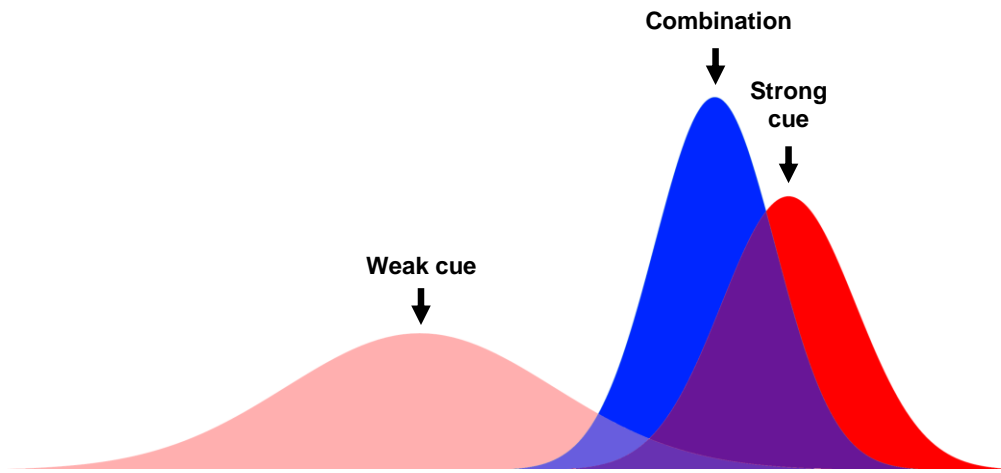


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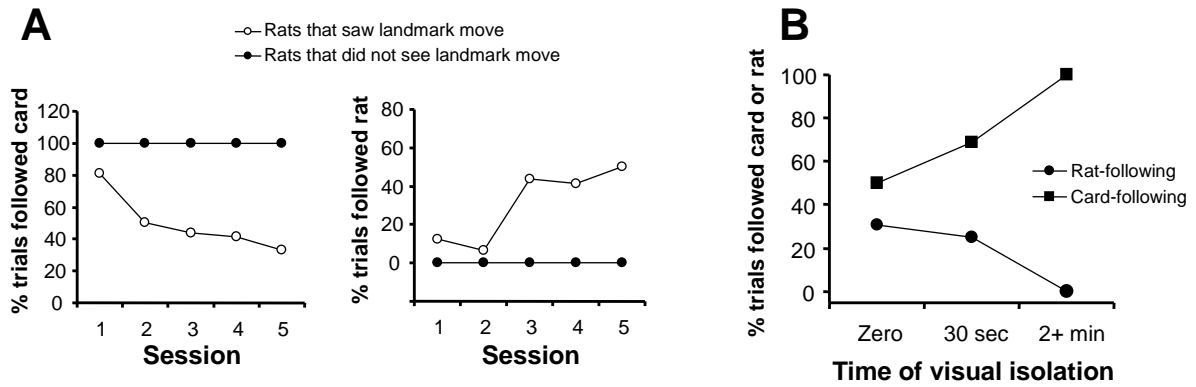


Figure 2 – Re-weighting of internal vs. external directional cue use by hippocampal place cells (adapted from Jeffery and O’Keefe, 1999). Place field rotation was assessed in rats exposed to a combination of landmark cue-card rotation and self-rotation: rats either saw the cue card move, or did not. (A) For those that saw the cue card move, cells stopped rotating with (“following”) it (left) and started rotating with the rat’s internal direction sense (right). (B) The longer the rats were deprived of visual cues, less likely they were to rotate with the rat and the more likely they were to rotate with the cue card. This suggests that the propensity to follow one or other cue type was a function of its reliability (longer visual deprivation = less reliability of internal direction sense).

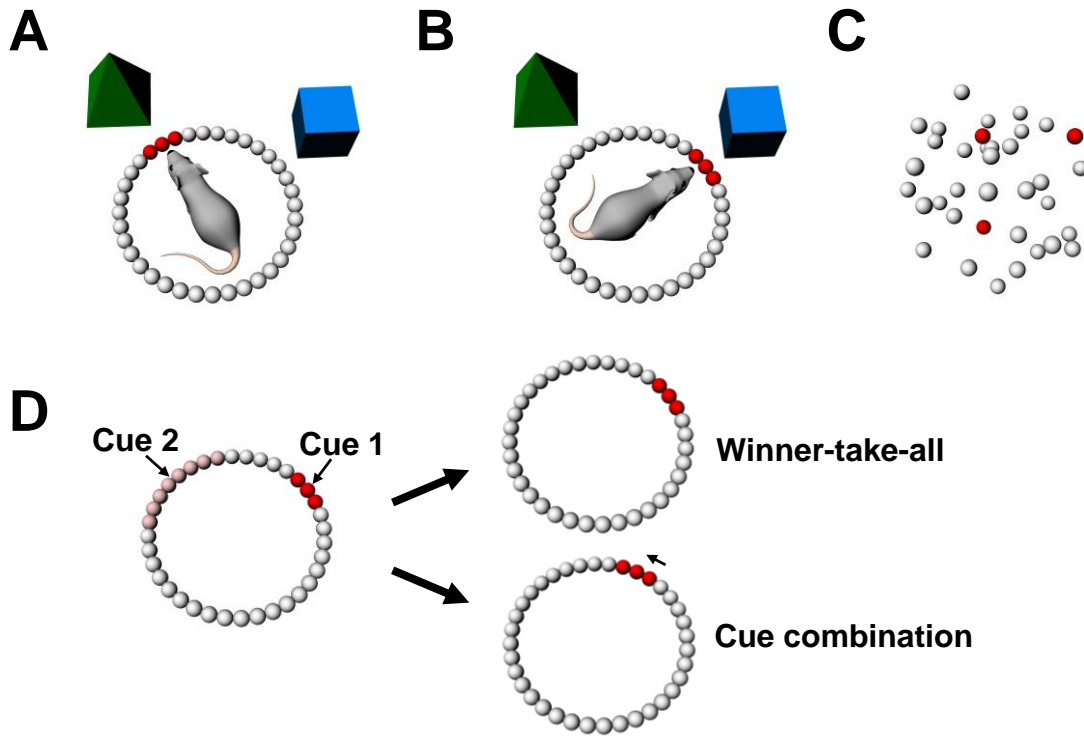


Figure 3 – Hypothetical ring attractor structure for neurons in the rodent head direction system. The diagram shows neurons arranged according to their preferred firing direction. (A) When the animal faces a landmark, neurons corresponding to that facing direction become activated (shown in red). (B) When the animal turns to face a new landmark, the combination of internally generated self-motion information together with the sight of the new landmark now drives activity in the part of the network corresponding to the animal's new facing direction. (C) The physical arrangement of the neurons is thought to be random in mammals. (D) When two cues simultaneously try to drive activity in different parts of the network, theory makes one of two predictions. In a winner-take-all scenario, the strongest cue dominates, and activity moves to the appropriate part of the network. In cue combination, both cues influence the final outcome to a degree proportional to their intensity and/or reliability, with the final result being a compromise.

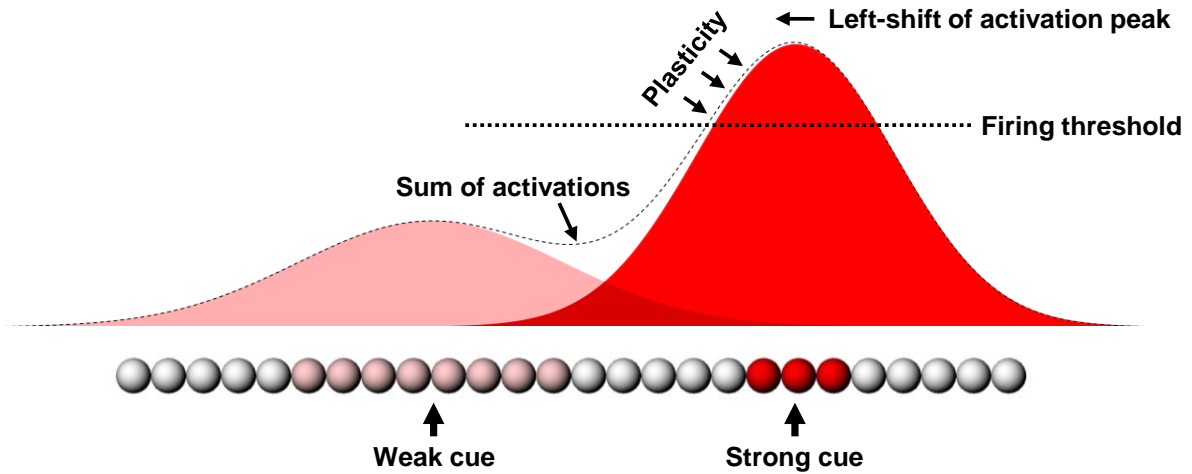


Figure 4 – Shift of activation in a ring attractor network from a strong cue towards a weaker one. The attractor is shown linearized for convenience; the Gaussian curves depict the external drive (from sensory cues; idiothetic for the weak cue and landmark-based for the strong one) onto the network. Because of the overlap of this drive, an asymmetry of activation occurs, with greater activation in the zone between the two cues. For the stronger cue, which is able to drive neurons to their activation threshold, this asymmetry results in asymmetric synaptic strengthening (dotted line), which will result in a shift of the activation peak in the direction of overlap, with the final result as shown in Figure 1.

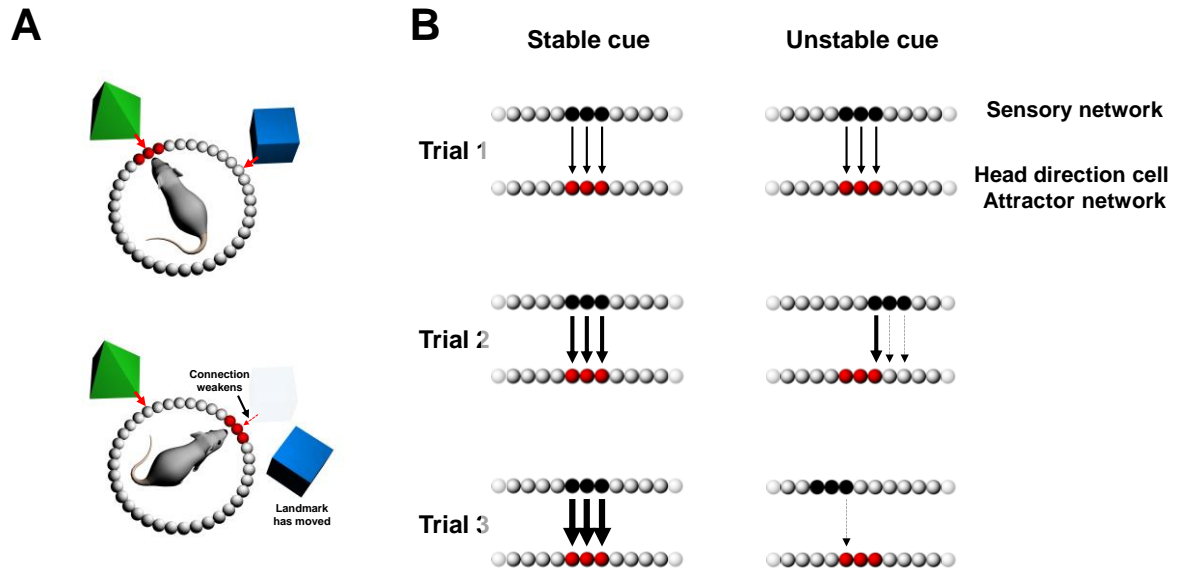


Figure 5 – Disconnection (“re-weighting”) of spatially unstable sensory cues from the head direction cell attractor network. (A) Top: Landmarks become associated with activation of the HD ring attractor by Hebbian re-weighting, forming strong connections (red arrows). Bottom: When a landmark moves, the existing connection with the ring attractor weakens (dotted arrow). (B) How unstable landmarks could become disconnected by Hebbian re-weighting. When a given set of sensory neurons has activity reliably associated with the same set of head direction neurons (left-hand panels), connections become stronger by Hebbian associativity. If the cues are spatially unstable and are associated with different parts of the attractor network on different trials, the connections will weaken by an anti-Hebbian mechanism (Hebb-Stent rule) and connections will lose strength.