Hemianopic field loss and failures of awareness in simulated driving

Garrett Swan[1], Jing Xu[1,2], Vilte Baliutaviciute[1], Alex Bowers[1]
[1]Schepens Eye Research Institute of Massachusetts Eye and Ear, Department of Ophthalmology, Harvard Medical School, Boston, MA
[2] Envision Research Institute, Wichita, KS

Vision Sciences Society 2021

Hemianopic field loss and failures of awareness in simulated driving

Background

"Looked but failed to see" (LBFTS) incidents are motor vehicle collisions where the driver reports looking, but fails to see the collision object (Treat et al., 1980)

Multiple mechanisms have been proposed to account for such incidents, including change blindness, which is the failure to detect a salient change when that change occurs during a brief disruption (Jensen et al., 2011)

One population of individuals who may be more susceptible to change blindness are those with homonymous visual field loss (HVFL)
- a loss of vision in the same parts of the visual field in both eyes caused by stroke or traumatic brain injury

Individuals with HVFL can compensate for their visual field loss by scanning towards their blind visual field (Gassel & Williams, 1963), but need to scan at least as far as the object of interest in order to see it

Analysis of gaze tracking data suggested that some blind side detection failures of individuals with HVFL may have resulted from a failure of visual awareness (Bowers et al., 2015)

People with HVFL may be more prone to failures of visual awareness than people with normal vision (NV) because there are additional demands placed on memory to represent information in the blind portion of the visual field and they may experience more profound disruptions in vision while scanning than those with NV

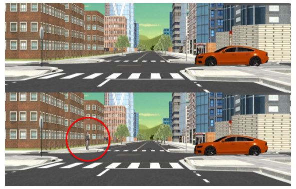
We tested this hypothesis in a driving simulator study with gaze-triggered changes

Participants

	HVFL, n = 11	NV, n = 10	p-value
Current driver, n (%)	3 (27%)	7 (88%)	0.09
Male, n (%)	9 (82%)	5 (50%)	0.18
Age, y, median (IQR)	50.0 (35.0)	55.0 (35.0)	0.32
Race, n (%) reported White	11 (100%)	5 (50%)	0.01
Visual Acuity (LogMAR), mean (SD)	-0.06 (0.1)	-0.03 (0.07)	0.36
Snellen equivalent	20/17	20/19	
Left HVFL, n (%)	8 (73%)	NA	NA
MoCA score, mean (SD)	26.7 (2.3)	NA	NA
Hemianopia caused by stroke, n (%)	5 (45%)	NA	NA
Years since onset, median (IQR)	9.6 (11.2)	NA	NA

LogMAR – Logarithm of the Minimum Angle of Resolution
MoCA – Montreal Cognitive Assessment (Nasreddine et al., 2005)

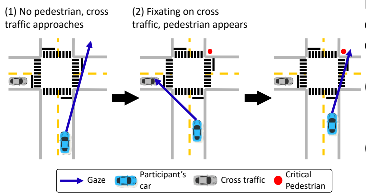
Driving Simulator

Participants used a custom driving simulator with a Tobii eye tracker tracking gaze to drive through a city of intersections with buildings, cross traffic, and pedestrians

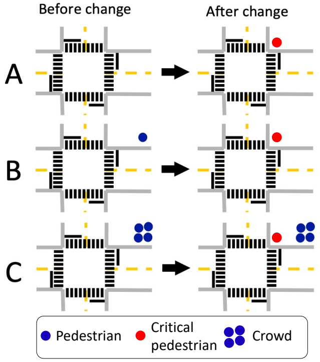
Participants detected pedestrians that suddenly appeared or changed location
- On the right, participants should only make a horn press if they first notice no pedestrian (top right) and then notice the pedestrian appearance (bottom right)

Scenarios



Pedestrians were triggered to change based on the following criteria:

(1) At certain intersections, a car approached from the opposite side of intersection
(2) Once gaze fell within 1 degree of the car for 100ms, then the pedestrian was triggered



We utilized 3 change conditions:

(A) No pedestrian at the intersection, then pedestrian appears near the crosswalk
(B) Pedestrian far from the crosswalk, then pedestrian appears near the crosswalk
(C) Crowd far from the crosswalk, then pedestrian appears near the crosswalk.

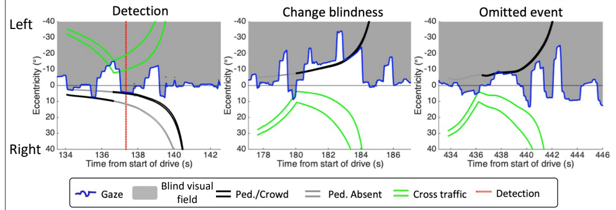
In all three conditions, the critical pedestrian (in red) appeared in the same location

24 gaze-triggered pedestrians, equally left and right

16 pedestrians triggered when driver was within 40m of pedestrian, equally left and right

12 catch-events, e.g., pedestrian standing at intersection, cross traffic but no pedestrian, etc

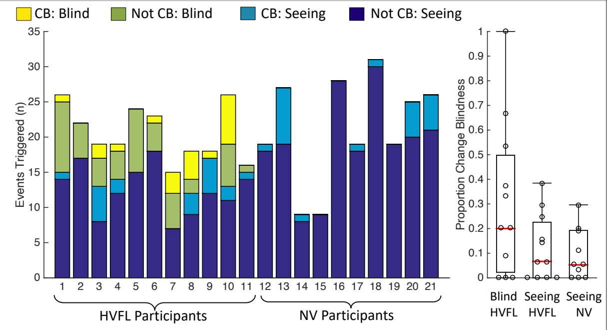
Data processing



Examples of horizontal gaze (blue) and eccentricity of pedestrians (black) and cross traffic (green). These examples correspond to a participant with left HVFL, so the blind visual field (gray) is to the left of gaze

We only analyzed events if the location of the change was visible before and after the change occurred
- Left panel: change was detected (red dotted line)
- Middle panel: change was not detected
- Right panel: the location of the change was never visible before the change occurred, so the event was omitted

Results – change blindness rates



Change blindness rates were significantly greater in individuals with HVFL vs NV
- Average HVFL = 18.0% (SEM = 4.7%) vs. NV = 9.4% (SEM = 3.2%)
b=2.4, se=0.9, t=2.7, p=0.007

Significantly more change blindness for changes on the blind than seeing side
- Average = 31.0% (SEM = 9.6%) vs seeing side average = 12.4% (SEM = 4.1%)
b=1.3, se=0.49, t=2.6, p=0.01

Other results of interest

Reaction time as a function of vision group:
- Not significant (1.1s vs 1.02s), b=-0.04, se=0.06, t=0.74, p=0.46
- Blind side RT was slower than seeing side (1.43s vs 0.98), p = 0.03

Change blindness rate as a function of pedestrian eccentricity:
- Not significant, b=0.02, se=0.02, t=0.9, p=0.37

Change blindness rate as a function of condition:
- Not significant, ps > 0.27

Change blindness rate was not correlated with age (ps > 0.26), visual acuity (ps > 0.22), nor scores on the MoCA (p = 0.85)

General Discussion

We found significantly more change blindness in those with HVFL than those with NV, supporting our hypothesis
- For those with HVFL, there was significantly more change blindness in changes that occurred on the blind than seeing sides

There were wide individual differences in change blindness rates, which is a characteristic of the literature on detection performance in individuals with HVFL

This paradigm produced change blindness for changes in the blind and seeing portions of the visual field, suggesting that this paradigm could be used in measuring change blindness events while driving

Future versions of this paradigm will utilize pedestrians that change from "non-hazardous" to "hazardous" to see if driving relevance influences detection

Potential limitations:
- Low sample size limits interpretation of within-subject comparisons
- Critical pedestrians may have been too distinct from other objects in the virtual environment (given lack of eccentricity and condition effects)

Contact: garrett_swan@meei.Harvard.edu, No conflicts of interest, Funded by: **R01**-*EY025677*

- Treat, J. R. (1980). A study of precrash factors involved in traffic accidents. *HSRI Research Review*. *10*(6), 35.
- Jensen, M. S., Yao, R., Street, W. N., & Simons, D. J. (2011). Change blindness and inattentional blindness. *Wiley Interdisciplinary Reviews: Cognitive Science*, *2*(5), 529-546.
- Gassel, M. M., & Williams, D. (1963). Visual function in patients with homonymous hemianopia: The completion phenomenon; insight and attitude to the defect; and visual functional efficiency. *Brain*, *86*(2), 229-260.
- Bowers, A. R., Alberti, C. F., Hwang, A. D., Goldstein, R., & Peli, E. (2015). Pilot study of gaze scanning and intersection detection failures by drivers with hemianopia. In: Proceedings of the 8th International Driving Symposium on Human Factors in Driver Assessment, Training and Vehicle Design. Salt Lake City, Utah: University of Iowa, 239–245.
- Nasreddine, Z. S., Phillips, N. A., Bédirian, V., Charbonneau, S., Whitehead, V., Collin, I., Cummings, J. L., & Chertkow, H. (2005). The Montreal Cognitive Assessment, MoCA: a brief screening tool for mild cognitive impairment. *Journal of the American Geriatrics Society*, *53*(4), 695-699.

Schepens Eye Research Institute
Massachusetts Eye and Ear

The effects of simulated acuity and contrast sensitivity impairments on detection of pedestrian hazards

Harvard Medical School Affiliate

Garrett Swan[1], Maha Shahin[2], Jacqueline Albert[3], Joseph Herrmann[4], Alex Bowers[1]

[1] Schepens Eye Research Institute of Mass Eye and Ear, Harvard Medical School
[2] Ophthalmology, Mansoura University
[3] Southern California College of Optometry, Marshall B. Ketchum University
4 School of Medicine, Texas Tech University Health Sciences Center
contact: garrett_swan@meei.harvard.edu

Vision Sciences Society 2018

The effects of simulated acuity and contrast sensitivity impairments on detection of pedestrian hazards

Background

Driving is a highly visual task

Vision impairment may adversely affect safe driving (Owsley & McGwin 2010)

Visual acuity (VA) is the predominant measure used by states to determine whether someone is visually fit to drive (Peli 2008)

Eye disease may affect other aspects of vision while not reducing VA below state requirements for driving
- Cataracts, diabetes, and macular degeneration reduce both VA and CS

Contrast sensitivity (CS) is not measured by any state, yet has been shown to be a predictor of crash risk (Owsley et al., 2001)
- Better CS is a predictor of driving ability following cataract surgery (Wood & Carberry, 2006) and in drivers with macular disease(Alberti et al., 2014)

Studies utilizing simulated vision impairment have found that a large VA reduction is needed in order to produce a similar decrement in driving performance to a relatively small CS reduction (Higgins & Wood, 2005)

We explored the effect of simulated CS and VA reduction on reaction time and the proportion of timely responses to hazards
- Timely response = given the speed of the car and the time of detection, could the driver safely brake to avoid a collision?

Hypothesis: CS predicts detection performance better than VA

General methods


Participants drove in a highway setting that included oncoming traffic and curves in a high-fidelity driving simulator (FAAC Corp., Ann Arbor, MI)
- Participants completed two practice drives to acclimate to the simulator

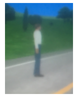
12 total pedestrians appeared equally to the left or right of the driver and ran toward the road along a collision course with the participant's vehicle
- Pedestrians appeared when the driver was 5s away

Participants were instructed to drive normally, maintain a speed of 100kph, and press the horn as soon as they saw a pedestrian

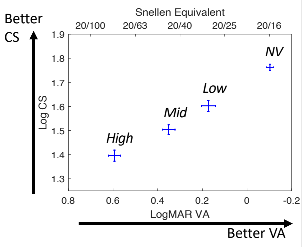
Experiment 1: Effects of VA and CS losses combined

Goal of Exp. 1:
How do simulated VA and CS deficits affect RT and timeliness?

Diffusing filters (Bangerter) were used to create CS reductions with VAs still within legal limits for driving (unrestricted or restricted license)


E.g. *High*

NV = normal vision
Low = low impairment
Mid = medium impairment
High = high impairment

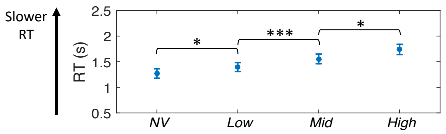


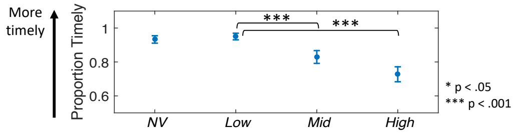
15 subjects, age = 26.9 (4.3) years, 6 males, 2+ years driving experience

Results from Experiment 1

	NV	*Low*	*Mid*	*High* Mean (SEM)
Prop. pedestrians detected	0.99 (0.02)	1.00 (0.00)	0.99 (0.02)	0.98 (0.03)
Car speed at horn press (kph)	93.47 (2.04)	93.05 (1.89)	92.89 (2.01)	93.73 (2.06)

Filters had no effects on detection rate or car speed at the time of the horn





As the strength of the diffusing filter increased,
RT significantly increased
and the proportion of timely responses was significantly reduced

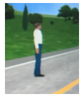
However, given that both CS and VA were reduced,
the individual effects of either a CS or VA reduction alone were not addressed

Experiment 2: Effects of VA and CS losses alone

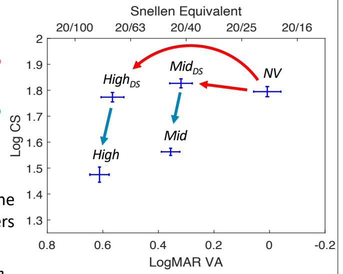
Goals of Exp. 2:
1) How does simulated VA alone affect RT and timeliness?
2) How does simulated CS alone affect RT and timeliness?

Blur (positive) lenses were used to reduce VA without reducing CS

Blur lenses were selected to match the VA of the *High* and *Mid* diffusing filters


E.g. *High*$_{DS}$

Mid$_{DS}$ matched to *Mid*
High$_{DS}$ matched to *High*
Same *Mid* from Exp. 1
Same *High* from Exp .1



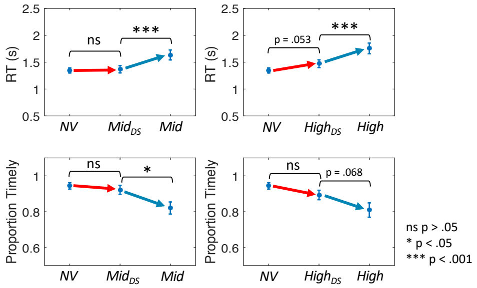
15 new subjects, age = 31.3 (10) years, 12 males, 2+ years driving experience

Results from Experiment 2

	NV	*Mid*$_{DS}$	*High*$_{DS}$	*Mid*	*High*
Prop. Pedestrians detected	1.00 (0.00)	0.99 (0.01)	0.99 (0.01)	0.99 (0.01)	0.99 (0.001)
Car speed at horn press (kph)	91.27 (1.72)	90.26 (1.94)	89.49 (1.78)	90.92 (1.97)	90.02 (2.01)

As in Experiment 1, neither the filters nor the blur lenses had any significant effects on detection rates or car speed

Results from Experiment 2 cont.



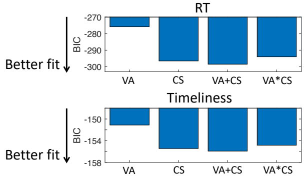
A VA loss alone did not significantly increase RT nor significantly reduce the proportion of timely responses

However, a CS loss alone did significantly increase RT and marginally reduced the proportion of timely responses

When comparing between the four visual impairment conditions, there was no significant interaction between VA and CS for either detection measure ($p > .6$)

Combining Experiment 1 and Experiment 2

To determine whether VA and/or CS is the best predictor of RT and proportion of timely responses, model comparison was used for 4 regression models:



VA = VA alone
CS = CS alone
VA+CS = VA and CS
VA*CS = VA and CS and the interaction

CS alone predicted RT (ΔBIC = 20.6) and timeliness (ΔBIC = 4.4) better than VA alone, and CS alone was not different from the best model (VS + CS, ΔBIC < 2)

General Discussion

In Experiment 1, a simulated VA and CS reduction impaired RT and timeliness

In Experiment 2, a CS reduction alone significantly impaired RT and timeliness, while a VA reduction alone had minimal effects

While there was no significant interaction between VA and CS on RT and timeliness, the model that best predicted behavior included VA and CS

These results are congruent with other studies which have reported that simulated CS reductions impair driving performance to a greater extent than simulated VA reductions (Higgins, Wood, & Tait, 1998)

Our findings suggest that CS, as well as VA, should be assessed when measuring vision for driving licensure
- This is especially true in eye diseases such as cataracts where VA may be within the legal limit, but CS is reduced

- Owsley, C., McGwin Jr, G. (2010). Vision and driving. *Vision Research, 50*(23), 2348-2361
- Peli, E. (2008). Driving with low vision: who, where, when, and why. *Albert and Jokobiec's Principles and Practice of Ophthalmology. Elsevier:* 4(2008): 5369-5376
- Owsley, C., Stalvey, B. T., Wells, J., Sloane, M. E., McGwin, G. (2001). Visual risk factors for crash involvement in older drivers with cataracts. *Archives of Ophthalmology, 119*(6), 881-887
- Wood, J., Troutbeck (1994). Effect of visual impairment on driving. *Human Factors, 36*(4), 476-487
- Wood, J. M., Carberry, T. P. (2006). Bilateral cataract surgery and driving performance. *British Journal of Ophthalmology, 90*(10), 1277-1280.
- Alberti, C. F., Horowitz, T., Bronstad, P. M., Bowers, A. R. (2014). Visual attention measures predict pedestrian detection in central field loss: a pilot study. *PloS one, 9*(2), e89381
- Higgins, K. E., Wood, J. M. (2005). Predicting components of closed road driving performance from vision tests. *Optometry and Vision Science, 82*(8), 647-656

Funded by:
R01-*EY025677*
T35-*EY007139*
S10-*RR028122*

Does an unexpected task reset the contents of visual working memory?

Garrett Swan[1], Brad Wyble[1], and Hui Chen[2]

[1]Pennsylvania State University

[2]Zhejiang University

gsp.swan@gmail.com

bwyble@gmail.com

psychenhui@gmail.com

BCS-1331073

powered by Psychtoolbox

Vision Sciences Society 2017

Does an unexpected task reset the contents of visual working memory?

Visual working memory (VWM) describes the ability to encode, store, and retrieval information

Many studies have explored the contents of VWM by asking participants to report unexpected information in a surprise test
- Inattentional blindness (Mack & Rock, 1998)
- Attribute amnesia (Chen & Wyble, 2015)

Errors associated with these tasks are attributed to either failure of perception/ encoding (Mack & Rock, 1998) or forgetting (Wolfe, 1999)

Forgetting may be exacerbated by the demands of understanding and responding to a unexpected task
- Surprise tests often have increased reaction time

Does a surprise trial reset the contents of VWM? (Swan, Wyble, & Chen, 2017)
- We compared surprise trial performance for an attribute that participants **expected to report** versus an attribute they **did not expect to report**

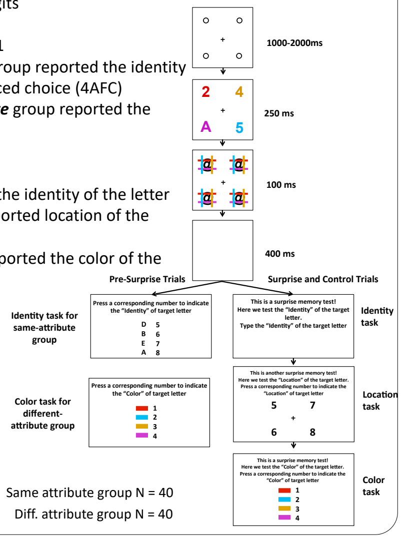
Experiment 1

In all trials, participants were searching for a target letter among 3 digits

Pre-surprise trials 1 to 11
- The ***same-attribute*** group reported the identity with 4 alternative forced choice (4AFC)
- The ***different-attribute*** group reported the color with 4AFC

Surprise trial 12
- Both groups recalled the identity of the letter
- Next, both groups reported location of the letter with 4AFC
- Lastly, both groups reported the color of the letter with 4AFC

Control trials 13 to 16
- Same as surprise trials



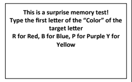
Same attribute group N = 40

Diff. attribute group N = 40

Experiment 2

Pre-surprise trials 1 to 11
- The *same-attribute* group reported color with 4AFC
- The *different attribute* group reported identity with 4AFC

Surprise question

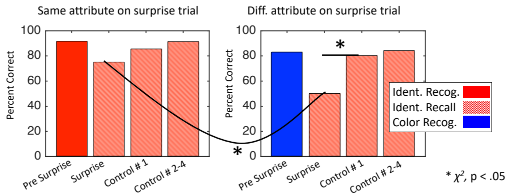


Same attribute group N = 40

Diff. attribute group N = 40

Surprise trial 12 and Control trials 13 to 16
- Both groups recalled the color of the target letter
- Next, both groups reported the location and then identity with 4AFC

Results from Experiment 1



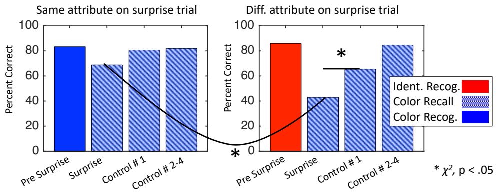
	Pre-sur	Surprise	Contr. 1	Contr. 2	Contr. 3	Contr. 4
Location	N/A	40%[2]	83%	90%	90%	95%
Color	N/A	35%[3]	85%	85%	75%	83%
Identity	91%	**75%[1]**	**85%**	95%	90%	88%

	Pre-sur	Surprise	Contr. 1	Contr. 2	Contr. 3	Contr. 4
Location	N/A	78%[2]	93%	88%	93%	98%
Color	83%	60%[3]	83%	80%	90%	88%
Identity	N/A	**50%[1]**	**80%**	75%	93%	83%

Superscript is the order of question

- Participants in both groups had to read the same unexpected question and type the letter
- However, participants in the *same-attribute* group had significantly better accuracy on the surprise trial than the *different-attribute* group

Results from Experiment 2



	Pre-sur	Surprise	Contr. 1	Contr. 2	Contr. 3	Contr. 4
Location	N/A	43%[2]	68%	80%	78%	90%
Color	83%	**68%[1]**	**80%**	85%	75%	83%
Identity	N/A	45%[3]	55%	73%	63%	73%

	Pre-sur	Surprise	Contr. 1	Contr. 2	Contr. 3	Contr. 4
Location	N/A	63%[2]	78%	73%	88%	85%
Color	N/A	**43%[1]**	**65%**	73%	88%	80%
Identity	85%	53%[3]	70%	78%	75%	78%

Superscript is the order of question

- These results replicated Experiment 1 using color instead of identity
- Participant were significantly more accurate in recalling color on the surprise trial in the *same-attribute* group than the *different-attribute* group

Combined results

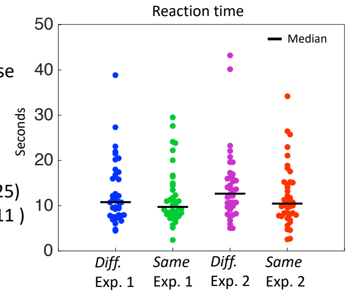
The results on the surprise trial of both experiments were compared using a log linear analysis

There was a significant effect of group (**G^2** = 11.5, p < .005), but no significant effect of experiment (**G^2** = .9, p = .33)

The combined analysis suggests that these results are a general property of memory and not a function of the specific attributes retrieved on the surprise trial

Were there differences in reaction time on the surprise trial between the groups?

There were no significant differences in RT
- Exp. 1 (t (78) = .68, p = .25)
- Exp. 2 (t (78) = 1.3, p = .11)



General Discussion

Results show that attributes already stored in visual working memory can be retrieved despite interference from an unexpected task

Results support fractionation of working memory into different stores (e.g. Baddeley, 2003) because reading did not strongly affect memory responses on the surprise trial

Results show the *content-addressability* of memory, which is the ability to access memories by their content (e.g. Swan & Wyble, 2014) even with an incorrect expectation of how information will be retrieved

Results also show that the inability to report information on the surprise trial is influenced by the strength of encoding (Chen & Wyble, 2016) and not merely forgetting

Swan, G., Wyble, B., & Chen, H. (2017). Working memory representations persist in the face of unexpected task alterations. *Attention, Perception, & Psychophysics*, 1-7.

- Baddeley, A. (2003). Working memory: looking back and looking forward. Nature reviews neuroscience, 4(10), 829-839.
- Chen, H., & Wyble, B. (2015). Amnesia for object attributes failure to report attended information that had just reached conscious awareness. *Psychological Science*, *26*(2), 203-210
- Chen, H., & Wyble, B. (2016). Attribute amnesia reflects a lack of memory consolidation for attended information. *Journal of Experimental Psychology: Human Perception and Performance*, *42*(2), 225
- Mack, A., & Rock, I. (1998). *Inattentional blindness* (Vol. 33). Cambridge, MA: MIT press.
- Swan, G., & Wyble, B. (2014). The binding pool: A model of shared neural resources for distinct items in visual working memory. *Attention, Perception, & Psychophysics*, *76*(7), 2136-2157.
- Wolfe, J. M (1999). Inattentional amnesia. In V. Coltheart (Ed.), *Fleeting Memories*(pp.71-94). Cambridge, MA: MIT Press.

BCS-1331073

Testing Predictions of the Binding Pool model

Garrett Swan and Brad Wyble
Pennsylvania State University

Psychonomics Society 2016

Testing Predictions of the Binding Pool model

Visual working memory (VWM) describes the ability to encode, store, and retrieval visual information

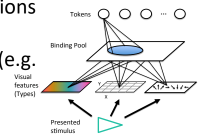
Testing predictions of models of VWM motivates new research and tests the model's validity

- Correct predictions = supports model
- Incorrect predictions = suggests model needs to be revised or replaced

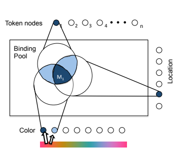
Here, we tested published predictions of the Binding Pool model

Binding Pool model 2.0 (based on Swan & Wyble, 2014):

- Token nodes index stored representations akin to object-files
- Types represent a stimulus's features (e.g. color, orientation)
- The binding pool is a shared resource pool where stimuli are stored as distributed representations

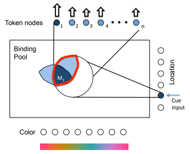


Encoding



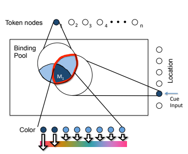
A memory is the serial conjunction of a type and a token node

Retrieval stage 1



First, a cue is used to retrieve a token node

Retrieval stage 2



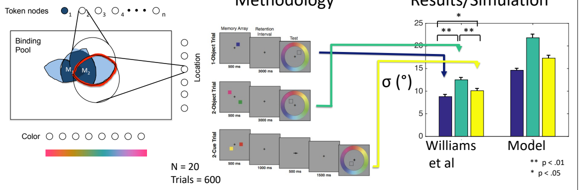
Next, the cue and retrieved token node are used to retrieve the desired feature

Note for all simulations, model parameters were unchanged

Prediction 1: Forgetting one object will increase the precision of another object in memory

- Directed forgetting

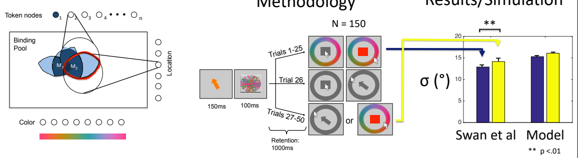
Why? By 'forgetting' or deleting memory M_2, there is less noise during the retrieval of M_1, but also less binding pool neurons coding for M_1



Results from Williams et al. (2013) supported this prediction

Prediction 2: Storing more features reduces memory precision

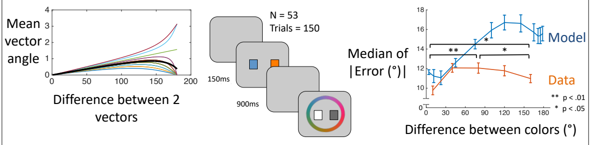
Why? Adding features increases the amount of noise in the binding pool, which means less binding pool neurons to represent that object



Results from Swan, Collins, and Wyble (2016) supported this prediction

Prediction 3: Similarity in feature space affects memory precision

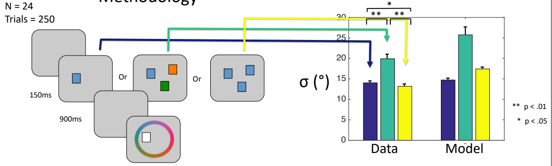
Why? The 'n' shaped function is caused by how retrieved type activity is decoded (i.e. averaging activation vectors)



Results qualitatively supports the prediction for precision, but the model overestimates the magnitude

Prediction 4: Three repetitions are less precise than a single object

Why? Each repeated object is bound to its own token node, which increases the amount of noise in the binding pool

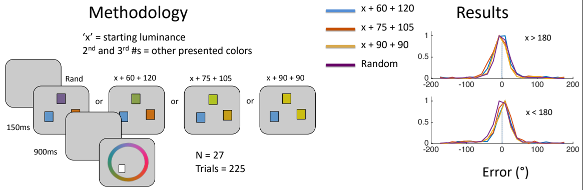


Results fail to support the model's prediction

- Precision for 3 repeated objects was better than a single object
- Found the same results using sequential presentation

Prediction 5: The similarity of two objects will determine the magnitude of the bias of a third object's response distribution

Why? Like Pred. 3, this is caused by how retrieved type activity is decoded (i.e. averaging activation vectors)



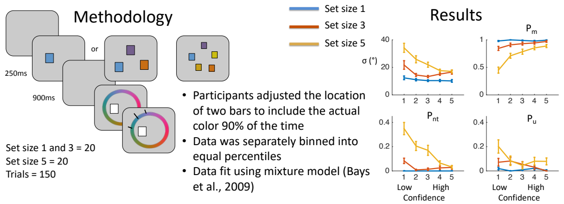
The results do show a bias towards non-targets

However, the results fail to support the model's prediction

- The model predicts that repetitions pull significantly more than non-repetitions
- Found same result using luminance instead of color

Prediction 6: Participants should have high confident retrieval errors

Why? Some retrieval errors are caused by incorrectly retrieving a token bound to a distractor, resulting in a high confident swap



These results suggest that some participants do guess and make retrieval errors despite high levels of confidence

- However, there isn't a u-shaped function for P_{nt}, which fails to support the prediction of the model

General discussion:

Predictions of the Binding Pool model were tested:

- **Prediction 1**: provides an account of directed forgetting
- **Prediction 2**: supports the model's mechanisms for encoding objects and features
- **Prediction 3**: suggest opponent colors interfere less in memory
- **Prediction 3 and 5**: failure to support these predictions indicate that the decoding of retrieved type activity is incorrect
- **Prediction 4**: failure to support this prediction indicates that repetitions are coded differently
    - Idea: Repetitions are bound to the same token
- **Prediction 6:** results suggest that the model's current implementation of confidence could be improved
    - This will likely change as a result of how type activity is decoded in future iterations of the model

- Bays, P. M., Catalao, R. F., & Husain, M. (2009). The precision of visual working memory is set by allocation of a shared resource. *Journal of Vision*, 9(10), 7-7
- Swan, G., & Wyble, B. (2014). The binding pool: A model of shared neural resources for distinct items in visual working memory. *Attention, Perception, & Psychophysics*, 76(7), 2136-2157.
- Swan, G., Collins, J., & Wyble, B. (2016). Memory for a single object has differently variable precisions for relevant and irrelevant features. *Journal of vision*, 16(3), 32-32.
- Williams, M., Hong, S. W., Kang, M. S., Carlisle, N. B., & Woodman, G. F. (2013). The benefit of forgetting. *Psychonomic bulletin & review*, 20(2), 348-355.

Testing Predictions of the Binding Pool model

Garrett Swan and Brad Wyble
Pennsylvania State University

BCS-1331073

Vision Sciences Society 2016

Testing Predictions of the Binding Pool model

Visual working memory (VWM) describes the ability to encode, store, and retrieval visual information

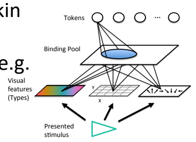
Testing predictions of models of VWM motivates new research and tests the model's validity

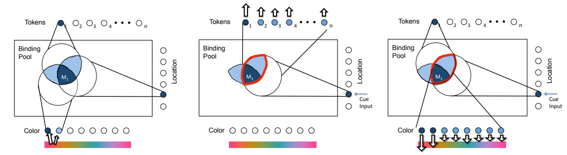
- Correct predictions = supports model
- Incorrect predictions = suggests model needs to be revised or replaced

Here, we tested published predictions of the Binding Pool model

Binding Pool model 2.0 (based on Swan & Wyble, 2014):

- Tokens index stored representations akin to object-files
- Types represent a stimulus's features (e.g. color, orientation)
- The binding pool is a shared resource pool where stimuli are stored as distributed representations





A memory is the serial conjunction of a type and a token

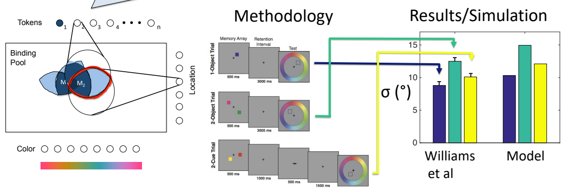
First, a cue is used to retrieve a token

Next, the cue and retrieved token are used to retrieve the desired feature

Prediction 1: Forgetting one object will increase the precision of another object in memory

- Directed forgetting

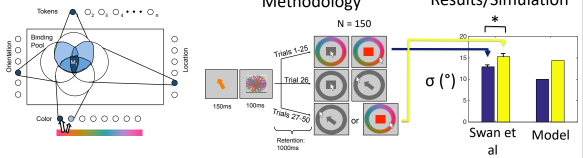
Why? By 'forgetting' or deleting memory M_2, there is less noise during the retrieval of M_1, but also less binding pool neurons coding for M_1



Results from Williams et al. (2013) supported this prediction

Prediction 2: Storing more features reduces memory precision

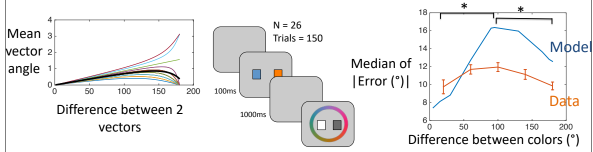
Why? Adding features increases the amount of noise in the binding pool, which means less binding pool neurons to represent that object



Results from Swan, Collins, and Wyble (2016) supported this prediction

Prediction 3a and 4: Similarity in feature space affects memory precision and confidence

Why? The 'n' shaped function is caused by how retrieved type activity is decoded (i.e. averaging activation vectors)

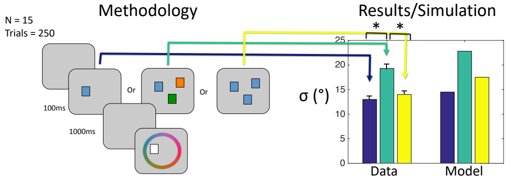


Results qualitatively supports the prediction for precision, but the model overestimates the magnitude

- Prediction for retrieval confidence was not supported (uniform)

Prediction 3b: Three repetitions are less precise than a single object

Why? Each repeated object is bound to its own token, which increases the amount of noise in the binding pool

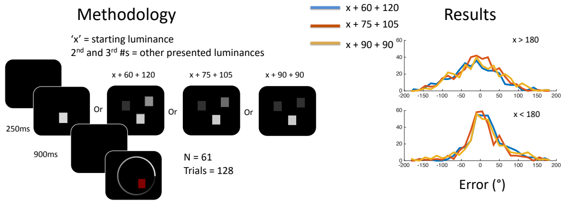


Results fail to support the model's predictions

- Precision for 3 repeated objects was not significantly differently from a single object

Prediction 5: The similarity of two objects will determine the magnitude of the bias of a third object's response distribution

Why? Like Pred. 3, this is caused by how retrieved type activity is decoded (i.e. averaging activation vectors)

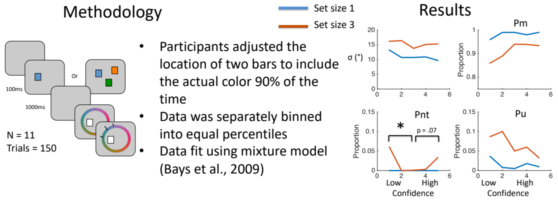


The results fail to support the prediction of the model

- The model predicts that repetitions pull significantly more than non-repetitions

Prediction 6: Participants should have high confident retrieval errors

Why? Some retrieval errors are caused by incorrectly retrieving a token bound to a distractor, resulting in a high confident swap



These results suggest there may be increased swaps at higher confidence relative to medium levels of confidence

- However confidence does not predict higher set sizes, which limits the applicability of this confidence metric for this task

General discussion:

Predictions of the Binding Pool model were tested:

- **Prediction 1**: provides an account of directed forgetting
- **Prediction 2**: supports the model's mechanisms for encoding objects and features
- **Prediction 3a, 4 and 5**: failure to support these predictions indicate that the decoding of retrieved type activity is incorrect
- **Prediction 3b**: failure to support this prediction indicates that repetitions are coded differently
  - Idea: Repetitions are bound to the same token
- **Prediction 6:** the marginal significance suggests the model's current implementation of confidence could be improved
  - This will likely change as a result of how type activity is decoded in future iterations of the model

- Bays, P. M., Catalao, R. F., & Husain, M. (2009). The precision of visual working memory is set by allocation of a shared resource. *Journal of Vision*, *9*(10), 7-7
- Swan, G., & Wyble, B. (2014). The binding pool: A model of shared neural resources for distinct items in visual working memory. *Attention, Perception, & Psychophysics*, *76*(7), 2136-2157.
- Swan, G., Collins, J., & Wyble, B. (2016). Memory for a single object has differently variable precisions for relevant and irrelevant features. *Journal of vision*, *16*(3), 32-32.
- Williams, M., Hong, S. W., Kang, M. S., Carlisle, N. B., & Woodman, G. F. (2013). The benefit of forgetting. *Psychonomic bulletin & review*, *20*(2), 348-355.

Object Perception, visual Attention, and visual Memory conference 2015

Coarse-coding of task irrelevant features of multiple objects

Coarse-coding of task irrelevant features of multiple objects

Garrett Swan and Brad Wyble

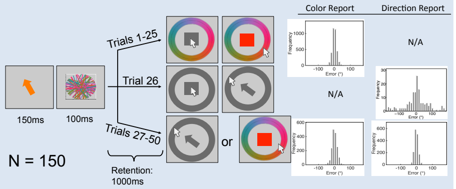
BCS-1331073

Background

In a typical visual working memory (VWM) task, you may be asked to remember the color of an object. This visual object would then have both relevant (color) and irrelevant features (e.g. shape, size)

What happens to the irrelevant features?

We have previously shown that task irrelevant features are ***coarsely coded***, using a surprise test methodology **(Swan, Collins, & Wyble, in review)**



Direction: Surprise trial: SD = 27.1, pM = .59; First post-surprise trial: SD = 12.2, pM = .92

Color: Pre-surprise trials: SD = 12.9 (.27), pM = .98 (.01); Post-surprise trials: SD = 14.9 (.45), pM = .96 (.01)

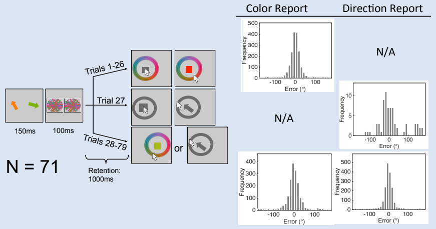
SD = std. dev. in degrees, pM = percent in memory (Zhang & Luck, 2008)

Direct measure (Direction):
Surprise trial SD for direction is less precise than participants' SD on the first post-surprise direction trial

Indirect measure (Color):
Memory for color becomes less precise when direction becomes relevant in the post-surprise trials

Experiment

Question: Is there coarse coding of irrelevant features when multiple objects are presented or is it a special property of a single object?



Direction: Surprise trial: SD = 23.4, pM = .60; First post-surprise trial: SD = 20.9, pM = .82

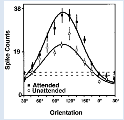
Color: Pre-surprise trials: SD = 19.2 (.54), pM = .91 (.02); Post-surprise trials: SD = 22.0 (.81), pM = .85 (.02)

Replicates both the direct and the indirect results from the single-object experiment above

Coarse coding of an irrelevant feature appears to be a general property of memory in this task

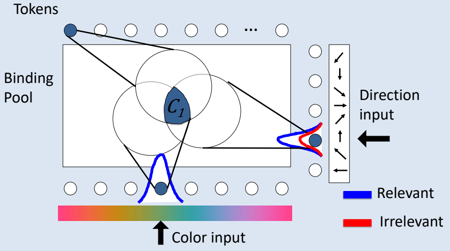
Binding Pool model (Swan & Wyble, 2014)

Potential mechanism: attention to a feature changes the amplitude of its activation (McAdams & Maunsell, 1999)



Binding Pool model components

- Types = features (e.g. color, direction, location)
- Tokens = index representations
- Binding pool = pool of neurons
- Encoding = binding of token and types
- Type activation strength = task relevance



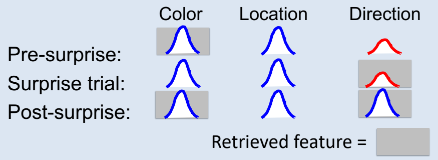
C_1 = activated cell assembly is ***product of input***

$$BP = \sum_{j=1}^{K} (BP + (Token_j * Token_{conn_j})\prod_{i=1}^{L}(Type_{j,i} * Type_{conn_{j,i}}))$$

K = number of items L = number of type layers

Simulating Experiment with Binding Pool model

Type activation strength is changed depending on trial



Direction: Surprise trial: SD = 28.1 (1.2), pM = .65 (.90); First post-surprise trial: SD = 27.1 (1.0), pM = .64 (.02)

Color: Pre-surprise trials: SD = 26.6 (.2), pM = .62 (.01); Post-surprise trials: SD = 26.8 (.2), pM = .65 (.01)

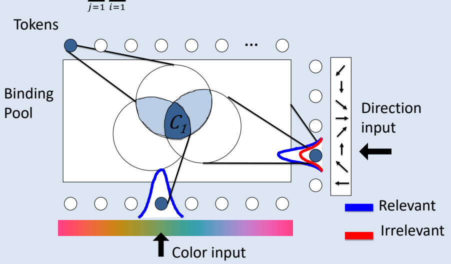
Model can neither simulate the coarse memory nor the cost to color for making direction relevant

Why? There is no additional interference in the binding pool when direction becomes relevant because the amount of active BP neurons do not change with feature relevance

Binding Pool model 2.0

New encoding mechanism: Features are bound to a token independently (Vul & Rich, 2010)

$$BP = \sum_{j=1}^{K}\sum_{i=1}^{L}(BP + (Token_j * Token_{conn_j})(Type_{j,i} * Type_{conn_{j,i}})$$



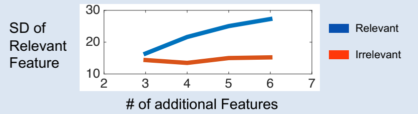
Direction: Surprise trial: SD = 54.7 (3.3), pM = .74 (.04); First post-surprise trial: SD = 23.6 (.90), pM = .82 (.02)

Color: Pre-surprise trials: SD = 20.9 (.2), pM = .84 (.01); Post-surprise trials: SD = 22.9 (.2), pM = .83 (.01)

This change to encoding more accurately simulates coarse memories and the cost of adding relevant features to memory

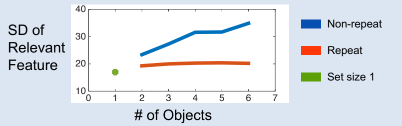
Predictions

Prediction 1: The effect of increasing the number of irrelevant features on relevant feature retrieval



The model predicts that many irrelevant features can be coarsely coded without affecting the precision of the relevant feature

Prediction 2: The effect of repeating features of different objects on relevant feature retreival



The model predicts that repeated features can be retrieved more precisely than if the features were not repeated, although not as well as when there is only a single object

Swan, G., & Wyble, B. (in review). Memory for a single object has distinct levels of precision for relevant and irrelevant features.
Swan, G., & Wyble, B. (2014). The binding pool: A model of shared neural resources for distinct items in visual working memory. *Attention, Perception, & Psychophysics*
Zhang, W., & Luck, S. J. (2008). Discrete fixed-resolution representations in visual working memory. *Nature*
Bays, P. M., Catalao, R. F., & Husain, M. (2009). The precision of visual working memory is set by allocation of a shared resource. *Journal of vision*
McAdams, C. J., & Maunsell, J. H. (1999). Effects of attention on orientation-tuning functions of single neurons in macaque cortical area V4. *The Journal of Neuroscience,*
Vul, E., & Rich, A. N. (2010). Independent sampling of features enables conscious perception of bound objects. *Psychological Science,*

Vision Sciences Society 2015

Measuring the memory quality of a task irrelevant feature of an attended object

Measuring the memory quality of a task irrelevant feature of an attended object

Garrett Swan and Brad Wyble

Department of Psychology, Pennsylvania State University

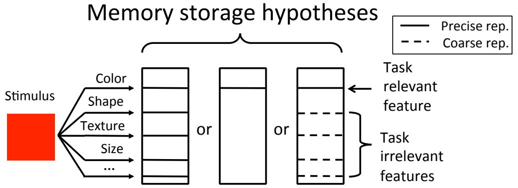
BCS-1331073

In a typical visual working memory (VWM) study, subjects are asked to remember features of an object (e.g.):

Yet, we know little about the memory of an object's irrelevant features.

Given memory's limited resources, it is vital to know what information is stored to fully understand memory's capacity.

Memory storage hypotheses

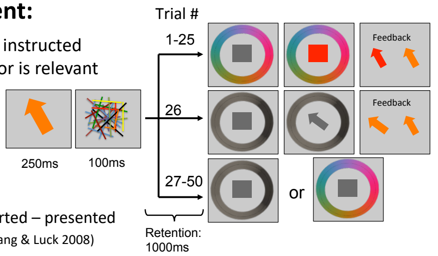


- Object-based encoding (Eitam et al., 2015)
  - An irrelevant feature memory is as precise as a relevant feature memory
- Only relevant memories (Awh et al., 2006)
  - No memory of an irrelevant feature
- Coarse coding
  - Coarse memory for an irrelevant feature

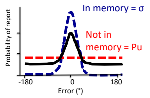
To test these models, we coupled delayed estimation with a surprise test (Rock et al., 1992)

Experiment:

-Participants instructed that only color is relevant



Analysis:
- Error = reported – presented
- σ and Pu (Zhang & Luck 2008)



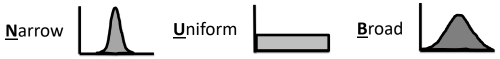
N = 139

Trials 1-25 = pre-surprise (only color report)

Trial 26 = surprise trial (direction report)

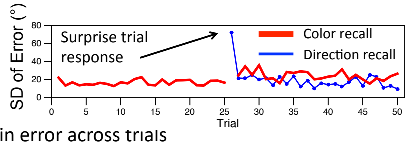
Trial 27-50 = post-surprise (color or direction)

Predictions for irrelevant feature memory quality:



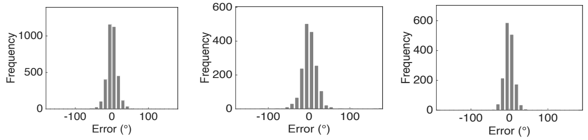
Object-based | Only relevant | Coarse coding

Results:



- Variance in error across trials

Memory for relevant features:



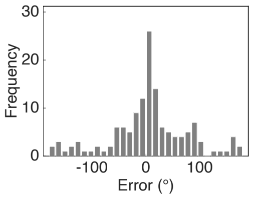
Pre-surprise color	Post-surprise color	Post-surprise direction
σ = 12.8 (SE: .3)	σ = 17.6 (.5)	σ = 13 (.5)
Pu = .02	Pu = .03	Pu = .02

$p < .0001$

-There's a cost to color memory when direction is relevant

Memory for irrelevant feature:

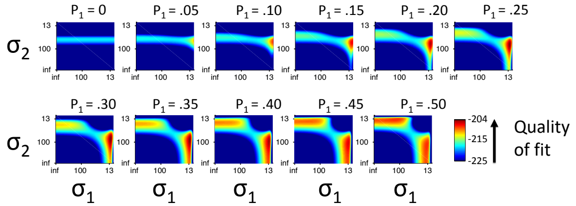
- Note: one data point per subject



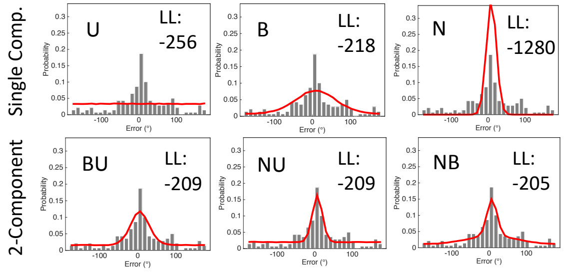
-To determine whether this distribution is N, U, B, or some combination (e.g. NU, BU, or NB), we used maximum likelihood estimation

- 4 parameters were varied:
  - Width of a von Mises distribution--------------- (σ_1: [1° to 180°, inf])
  - Width of a second von Mises distribution----- (σ_2: [1° to 180°, inf])
  - Proportion of first von Mises--------------------- (P_1: [0 to 1])
  - Bias of both von Mises distributions------------ (μ: [0° to 15°])

Log likelihood (LL) function with μ fixed at 8°



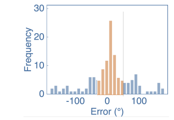
- Slices of this 4-D space correspond to the different models, with the maximum fits displayed below (see Suppl. for full fits) :



- 2-comp. models fit better than single comp., with NB fitting best.

Conclusions:

- Subjects varied in their memory of an irrelevant feature with most having a coarse memory of direction on the surprise trial
- For subjects with a coarse memory of direction, the cost may have been greater when fully encoding direction.



- In a permutation test comparing the ratio (Blue/Red) of the cost ratios (post/pre), we find a greater penalty for subjects who had poor direction memory on the surprise trial ($p < .04$)

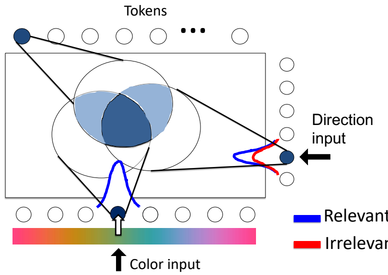
How can we simulate changes in relevancy?

Swan & Wyble (2014)

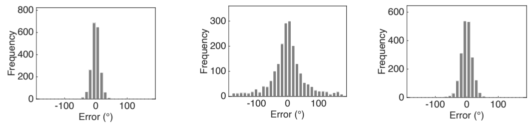
Special issue on VWM

- Binding Pool model components:
  - Types = features (e.g. color, direction)
  - Tokens = index representations
  - Binding pool = pool of neurons
- Encoding = binding of token and types
  - Type activation strength = task relevance

Encoding



Simulating Retrieval



Pre surprise (Relevant): SD: 13.	Surprise trial (Irrelevant): NB	Post surprise (Relevant): SD: 17.5

Discussion:
- Irrelevant features are encoded with reduced quality
- Increasing precision for one feature comes at the expense of other features
- This is true even for a set size of 1

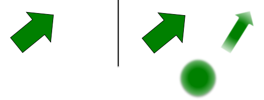
- **Swan, G., & Wyble, B. (2014). The binding pool: A model of shared neural resources for distinct items in visual working memory. *Attention, Perception, & Psychophysics*, 1-22.**
- Eitam B, Shoval R, Yesurun Y (2015) Seeing without knowing: Task relevance dissociates between visual awareness and recognition. *Ann N Y Acad Sci* 1339(1):125-137
- McAdams CJ, Maunsell JH (1999) Effects of attention on orientation-tuning functions of single neurons in macaque cortical area V4. *The Journal of Neuroscience*, *19*(1):431-441.
- Rock I, Linnett CM, Grant P, Mack A (1992). Perception without attention: Results of a new method. *Cognitive Psychology*, *24*(4), 502-534.
- Suchow JW, Brady TF, Fougnie D, Alvarez GA (2013). Modeling visual working memory with the MemToolbox. *Journal of vision*, *13*(10), 9.
- Zhang W, Luck SJ (2008) Discrete fixed-resolution representations in visual working memory. *Nature* 353(7192): 233-235
- Awh E, Vogel EK, Oh SH (2006) Interactions between attention and working memory. *Neuroscience*, 139(1):201-208

Psychonomics Society 2014

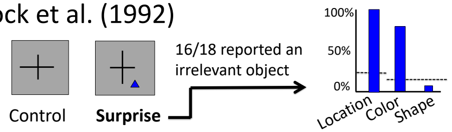
Testing a model of visual working memory: can extra features be stored without a cost?

In a typical visual working memory (VWM) study, subjects are asked to remember features of an object. We know little about what is actually remembered about an object's irrelevant features.

Task:	Presented object:	Memory trace?
Remember color		

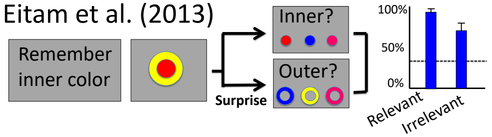


Rock et al. (1992)



- Some memory for task irrelevant features of a task ***irrelevant*** object

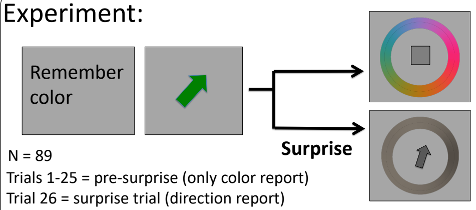
Eitam et al. (2013)



- Some memory for task irrelevant features of a task ***relevant*** object

Q1: How is irrelevant information coded?
Q2: Is there a cost to encoding additional relevant features for one object?

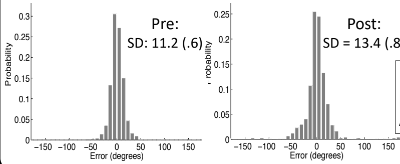
Experiment:



N = 89
Trials 1-25 = pre-surprise (only color report)
Trial 26 = surprise trial (direction report)
Trial 27-50 = post-surprise (either color or direction report)

Q2: Is there a cost to encoding additional relevant features for one object?

- Compared color memory precision of pre-surprise (1-feature) to post-surprise (2-feature) trials



Paired t-test:
$p < .0001$
Answer: YES

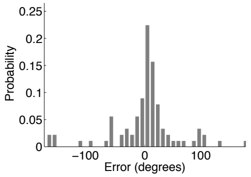
Testing a model of visual working memory: can extra features be stored without a cost?

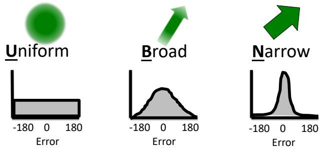
Garrett Swan and Brad Wyble

PENNSTATE 1855
NSF BCS-1331073

Q1: How is the irrelevant information coded?

Surprise trial:
- Direction report
- Note: one data point per subject

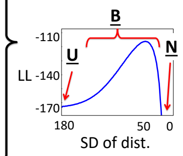


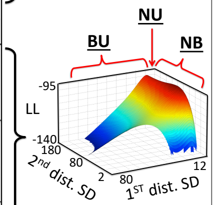


Single component Models			
Hypothesis	Best fit	LL	AIC
U	M = 0	-163	327
B	M = 2	-116	236
N	M = 1	-1094	2190
2 component Mixture Models			
BU	M = 3	-98.6	203.2
NU	M = 2	-100.6	205.2
NB	M = 3	-95.3	196.6

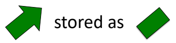
LL = log likelihood
AIC = Akaike information criterion
M = number of parameters

LL functions

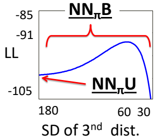




What if some subjects encoded the orientation, but not the direction?



3 component Mixture Models			
$NN_{\pi}U$	M = 3	-98.3	202.6
$NN_{\pi}B$	M = 4	-91.2	190.4



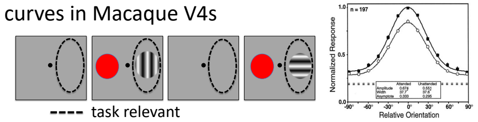
Q1: How is irrelevant information coded?

- Half of the participants have a coarse encoding of the irrelevant feature relative to a relevant feature
  - The relative likelihood of $NN_{\pi}U$ to $NN_{\pi}B$ is .0022

How can we simulate changes in relevancy?

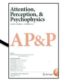
McAdams & Maunsell (1999)

- Attention modulates the amplitude of tuning curves in Macaque V4s



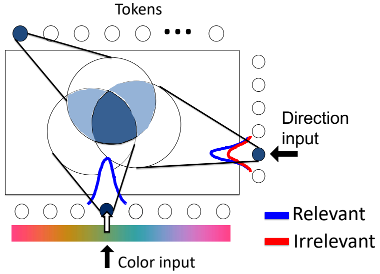
Swan & Wyble (2014)

Special issue on VWM

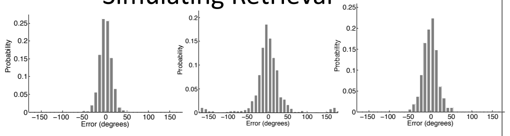


- Binding Pool model components:
  - Types = features (e.g. color, direction)
  - Tokens = index representations
  - Binding pool = pool of neurons
- Encoding = binding of token and types
  - Type activation strength = task relevance

Encoding



Simulating Retrieval



Pre surprise (relevant):	Surprise trial (irrelevant):	Post surprise (Relevant):
SD: 13.6 (.6)	$NN_{\pi}B$	SD: 17.6 (1)

Discussion:
- Irrelevant features are encoded with variable quality
- Increasing precision for one feature comes at the expense of other features

- **Swan, G., & Wyble, B. (2014). The binding pool: A model of shared neural resources for distinct items in visual working memory. *Attention, Perception, & Psychophysics*, 1-22.**
- Eitam, B., Yeshurun, Y., & Hassan, K. (2013). Blinded by irrelevance: Pure irrelevance induced "blindness". *Journal of experimental psychology: human perception and performance*, *39*(3), 611.
- McAdams, C. J., & Maunsell, J. H. (1999). Effects of attention on orientation-tuning functions of single neurons in macaque cortical area V4. *The Journal of Neuroscience*, *19*(1), 431-441.
- Rock, I., Linnett, C. M., Grant, P., & Mack, A. (1992). Perception without attention: Results of a new method. *Cognitive Psychology*, *24*(4), 502-534.
- Suchow, J. W., Brady, T. F., Fougnie, D., & Alvarez, G. A. (2013). Modeling visual working memory with the MemToolbox. *Journal of vision*, *13*(10), 9.

The Binding Pool model of VWM: A model for storing individuated objects in a shared resource pool

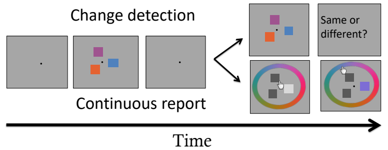
Garrett Swan and Brad Wyble
Pennsylvania State University

Vision Sciences Society 2014

The Binding Pool model of VWM: A model for storing individuated objects in a shared resource pool

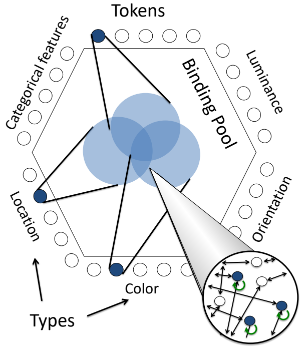
We are building a model of visual working memory (VWM).

The Binding Pool model is a mechanistic model that accounts for both the quality and quantity of representations in VWM (Swan & Wyble, 2014)



Model components:

- Tokens index stored representations as object-files
- Types represent a stimulus' features (e.g. color, orientation, etc.)
- The binding pool is a shared resource pool of distributed representations in which multiple stimuli are stored



- Neural Units
  Active Inactive
- Bidirectional connections
- Randomized weights
- No synaptic modification
- Storage of information occurs through sustained activity in the binding pool

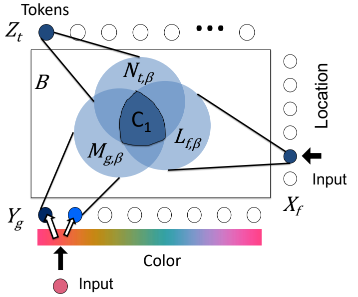
Encoding:

- One token is activated per item
- Types and tokens both project to the binding pool
- Binding pool nodes receiving convergent input are activated

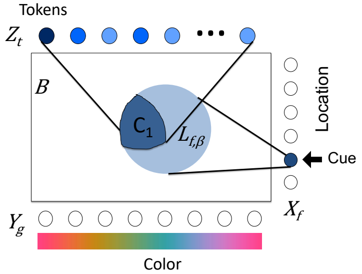
The activated nodes store the connection between active Type and Token nodes.

- C_1 = activated cell assembly

Encoding 1 object with 2 features



$$B_\beta = B_\beta + Z_t N_{t,\beta} \sum_{f=1}^{n} X_f L_{f,\beta} \sum_{g=1}^{n} Y_g M_{g,\beta}$$



$$Z_t = \sum_{\beta=1}^{n} B_\beta N_{t,\beta} \sum_{f=1}^{n} X_f L_{f,\beta}$$

Token retrieval:

The cued feature is projected into the binding pool

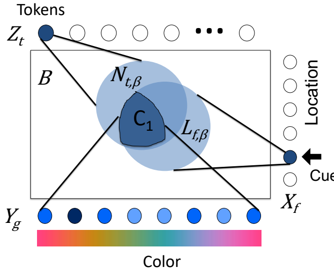
The subset of binding pool nodes then summate their activity at the token layer

- Strongly active
- Weakly active

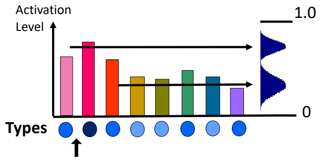
Type retrieval:

The cued feature and the retrieved token project to the binding pool

The subset of binding pool nodes then summate their activity at the type layer



$$Y_g = Z_t \sum_{\beta=1}^{n} B_\beta M_{g,\beta} N_{t,\beta} \sum_{f=1}^{n} X_f L_{f,\beta}$$



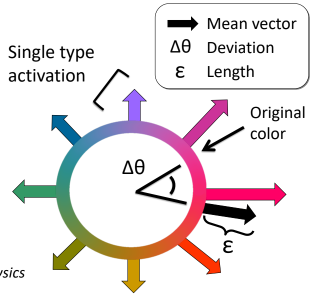
Type activity after retrieval of information from a token is a noisy reconstruction of the original type representation

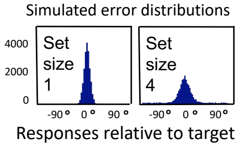
Type activity is converted to vectors

Mean vector is then computed

Mean vector has two properties:

- Location = retrieved color value
- Vector length = 'confidence'





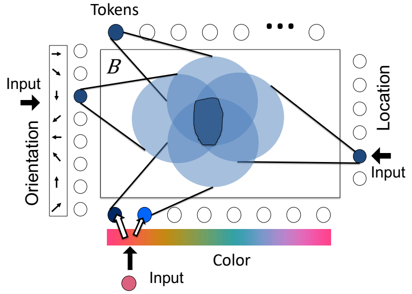
Storing more items increases the variance of retrieved type activity for each item

Prediction:

Retrieval variability increases as more features are encoded per item

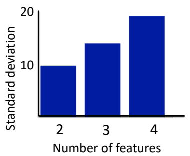
This is a controversial prediction (Fougnie et al., 2010; Oberauer et al., 2013; vs. Vogel et al., 2001)

Encoding 1 object with 3 features



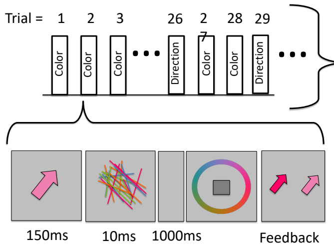
Simulation:

One object with 2, 3, and 4 features



Testing predicted cost of adding a feature

- Subjects shown 1 stimulus (arrow) with both a color and a direction
- First block, reported consistently color or direction (between subj.)
- Second block, reported either feature at random
- Control group reported consistently the same feature



Condition	Block 1 SD (SE)	Block 2 SD (SE)
Control	12.6(.7)	13.5(.9)
Exp.	13.5(.6) Color	17.7(.9) Color, 9.5(.4) Dir.

Condition	Block 1	Block 2
Control	8.4(.6)	8.5(.7)
Exp.	8.1(.5) Dir.	16.6(.6) Color, 9.4(.7) Dir.

Results and Discussion:

Significant main effect of starting feature ($p < .0001$) and condition ($p < .0001$), and interaction between the two ($p < .05$)

The cost of adding one additional feature on one object is detectable

These results support the prediction of the model that there is a cost when storing more features of a complex object

These results suggest that features are selectively encoded according to task demands

- Flexible encoding models can avoid the combinatorial explosion problem in representational space

Swan, G., & Wyble, B. (2014). The binding pool: a model of shared neural resources for distinct items in visual working memory. *Attention, Perception, & Psychophysics*
Fougnie, D., Asplund, C. L., Marois, R. (2010). What are the units of storage in visual working memory? *Journal of Vision*
Oberauer, K., & Eichenberge, S. (2013). Visual working memory declines when more features must be remembered for each object. *Memory & Cognition*
Vogel, E. K., Woodman, G. F., & Luck, S. J. (2001). Storage of features, conjunctions, and objects in visual working memory. *JEP: Human Perception and Performance*

The Binding Pool Model of Visual Working Memory

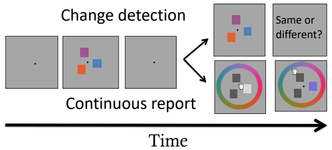
Garrett Swan and Brad Wyble
The Pennsylvania State University

Psychonomics Society 2013

The Binding Pool Model of Visual Working Memory

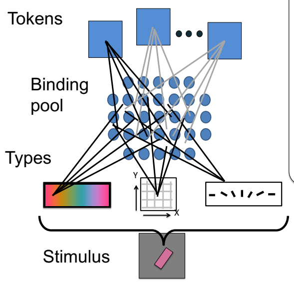
We are building a model of visual working memory (VWM).

The Binding Pool model is a mechanistic model that accounts for both the quality and quantity of representations in VWM.



Model components:

- Tokens index stored representations as object-files
- Types represent a stimulus' features
- The Binding Pool is a shared resource pool of distributed representations in which multiple stimuli are stored

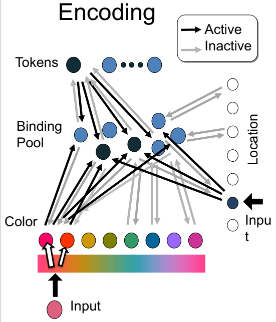


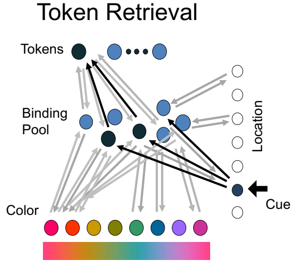
- • Neural Unit
- Bidirectional connection
- Randomized weights
- No synaptic modification
- Storage of information occurs through sustained activity in the binding pool

Encoding:

- One token is activated per item
- Encoding is serial
- Types and tokens both project to the binding pool
- Binding pool nodes receiving convergent input are activated

The activated nodes store the connection between active Type and Token nodes



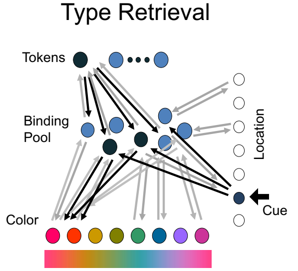


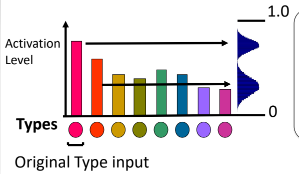
Token retrieval
The cued feature is projected into the binding pool

The subset of binding pool nodes then summate their activity at the token layer

Type retrieval
The cued feature and the retrieved token project to the binding pool

The subset of binding pool nodes then summate their activity at the type layer





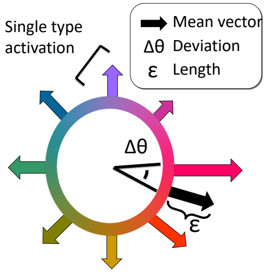
Type activity after retrieval of information from a token is a noisy reconstruction of the original type representation

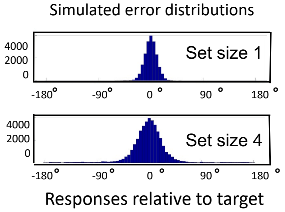
Type activity is converted to vectors

Mean vector is then computed

Mean vector has two properties:

- Location = retrieved color value
- Vector length = 'confidence'

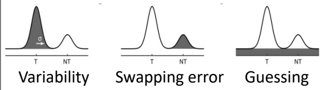




Storing more items increases the variance of retrieved type activity for each item

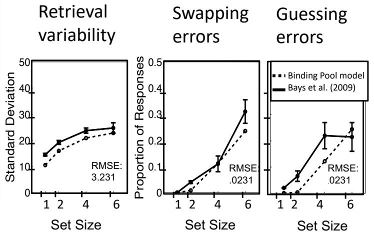
Simulations

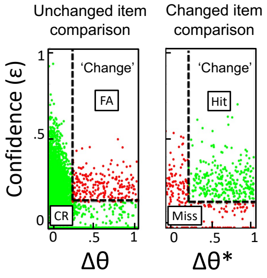
The model data was analyzed with a mixture model (Bays et al., 2009)



Continuous report task

As set size increases, the model's retrieval variability and the chance of swap and guessing errors increase





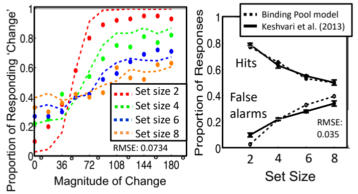
Change detection task

Each item in the probe display is compared to the retrieved item at that location

FA = false alarm
CR = correct rejection
Δθ = retrieved location – unchanged item
Δθ* = retrieved location – changed item
- - - = threshold

The probability of the model reporting a 'change' is dependent upon the magnitude of change

As set size increases, the model's performance degrades



There are two forms of capacity in the Binding Pool model:
-***Fixed capacity of information storage***: the quality of all memories is dependent upon the size of the binding pool.
-***Variable number of items***: The quantity of items stored per trial is variable: reflecting attentional fluctuations and encoding duration.

The precision of each memory trace results from the combination of these two limits on each trial. These limits enable the model to simulate existing data and generate predictions.

- Bays, P. M., Catalao, R. F. G., & Husain, M. (2009). The precision of visual working memory is set by allocation of a shared resousce. *Journal of Vision*. 9(10). 1-11
- Keshvari, S., van den Berg, R., & Ma, W. J. (2013). No evidence for an item limit in change detection. *PLoS Computational Biology*, 9(2)

Simultaneously and sequentially presented colors exhibit similar within-task interference for working memory representations

Garrett Swan and Brad Wyble
The Pennsylvania State University

Vision Sciences Society 2013

Simultaneously and sequentially presented colors exhibit similar within-task interference for working memory representations

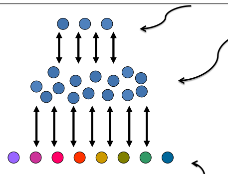
Visual working memory (VWM) is a complex process of encoding and retrieving information. Current models provide a theoretical framework for understanding how information is stored[1,2], but few models are explicit about the underlying neural mechanisms of VWM.
A neural simulation can generate more explicit predictions about the structure of memory and the time course of encoding.

Model architecture:

- Tokens index stored representations
- Types represent stimulus features
- The Binding pool is a shared resource pool of distributed representations in which multiple stimuli are stored

Tokens = tokens project to overlapping subsets of the binding pool

Binding Pool = stores distributed Type representations, sustains activity during retention interval



- Neural Unit
- Bidirectional connection
- Randomized weights
- No synaptic modification
- Storage of information occurs through sustained activity in the binding pool

Types = points within a color dimension (or any other)

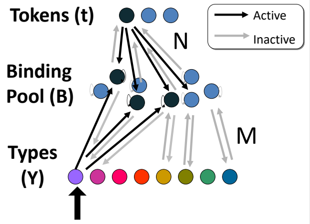
Encoding and retrieval of a single Type:

Encoding:

- One token is activated per item
- Encoding is serial
- Types and tokens both project to the binding pool
- Binding pool nodes receiving convergent input are activated

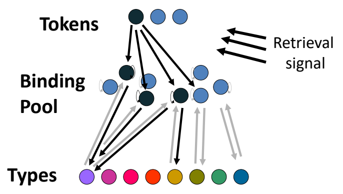
The activated nodes maintain the connection between active Type and Token nodes.

Encoding



$$B_\beta = B_\beta + \sum_{\alpha=1}^{n} M_{\alpha,\beta}\, N_{t,\beta}\, Y_\alpha$$

Retrieval of Type



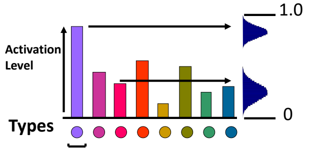
$$Y_\alpha = Y_\alpha + \sum_{\beta=1}^{n} M_{\alpha,\beta}\, N_{t,\beta}\, B_\beta$$

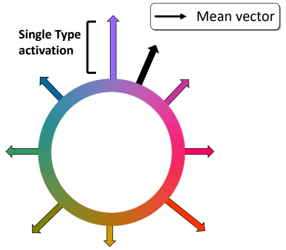
Retrieval:
Information stored in a given Token can be reconstructed at the Type layer.

The same connections which had been used to encode the type representation into the binding pool are now activated in the reverse direction

The distributed nature of the Binding Pool results in a noisy retrieval of the original Type representation.

Typically, the original Type input is activated to a higher degree than other Type nodes.

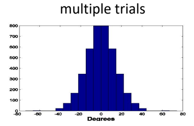




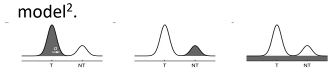
Type nodes are treated as vectors in a color wheel. The population mean is computed by adding the vectors.

- Location = retrieved color value
- Vector length = 'confidence' of retrieval

Error distribution over multiple trials



In order to better understand the different types of responses, the model output was analyzed with a mixture model[2].



Simulations of Bays et al. 2009

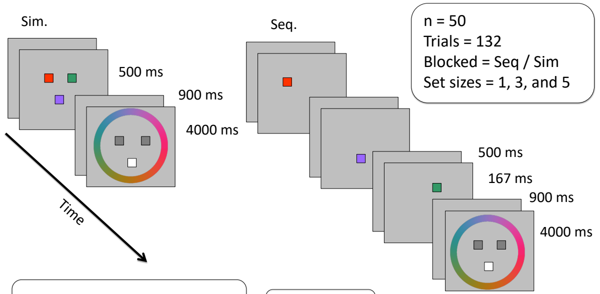
The number of tokens on each trial is drawn from a uniform distribution from 2 to 6. If the set size exceeds this capacity, then one or more Types fail to be encoded.

Free parameters:

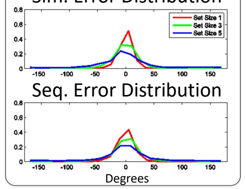
- Binding Pool size = 750
- Token overlap = 7.5%
- Token capacity = U(2,6)

Experiment:
Sequential vs. simultaneous presentation

A property of this model is that simultaneously presented stimuli are encoded serially.
Thus, a prediction is that encoding of simultaneous and sequential stimuli should produce similar patterns of errors.

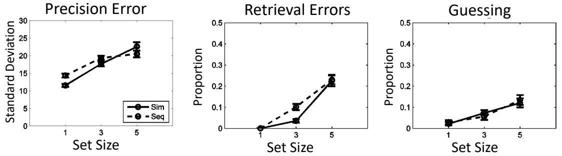


n = 50
Trials = 132
Blocked = Seq / Sim
Set sizes = 1, 3, and 5



Results

2x3 ANOVA : No significant main effects for Block or interactions after Bonferroni corrections.



The null pattern of results from the behavioral data lends credence to the serial encoding inherent in the model.

The model can also simulate errors in change detection paradigms and can reproduce ensemble statistic effects (see supplemental).

Future work will generate predictions to be tested empirically.

1.) Luck, S., & Vogel, E. (1997). The capacity of visual working memory for features and conjunctions. Nature
2.) Bays, P., Catalao, R., & Husain, M. (2009). The precision of visual working memory is set by allocation of a shared resource. Journal of Vision

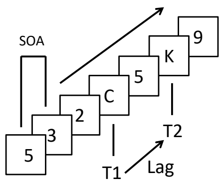
Model and behavioral data were analyzed using code from Paul Bays at www.bayslab.com

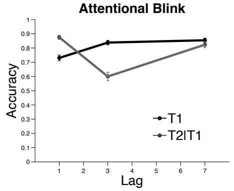
Psychonomics Society 2012

Exploring Localized Attentional Interference in the Context of a Multiple Location RSVP Task.

Garrett Swan and Brad Wyble
The Pennsylvania State University

Introduction: Rapidly presented targets produce changes in the deployment of attention



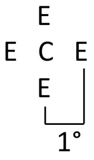


Attentional blink: T1 processing reduces T2 processing within 200 to 500 ms

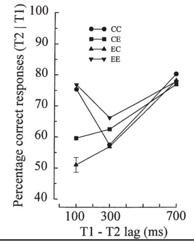
Is lag 1 sparing present in spatially offset stimuli?

Visser et al (1999)

-RSVP stream
-4 conditions (CC, EE, CE, EC)
-**Found no Lag 1 sparing with spatial offset**

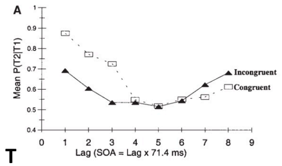


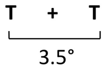
E = eccentric
C = Centric



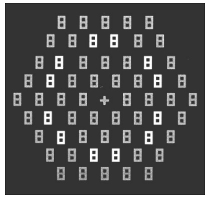
Shih (2000)

-Dual RSVP streams
-2 conditions (same or different loc.)
-**Found Lag 1 sparing with spatial offset**

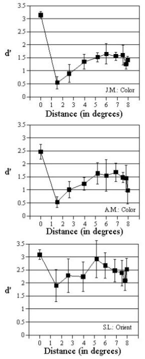




One possible explanation: Localized attentional interference (Mounts 2000)

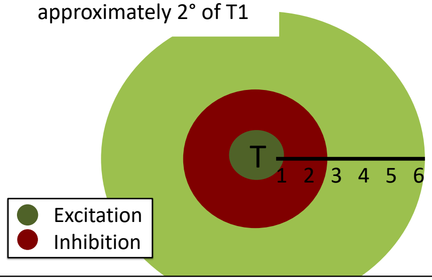


Target array



-2 targets presented in highlighted locations at 67ms temporal offset
-T2 performance varied as a function of T1 proximity

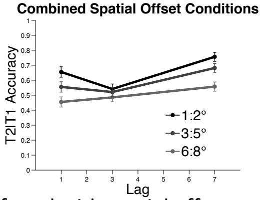
Hypothesis: LAI interferes with T2 perception at lag 1 when T2 appears within approximately 2° of T1



Experiment 1: Parametrically measure the extent of an attentional window

Methods: Replicated Visser et al (1999) paradigm with increased eccentricities (1-8°)
n = 51
SOA = 100 ms

Results:
Lag ($p < .001$)
DVA ($p <.001$)
Lag x DVA ($p < .001$)

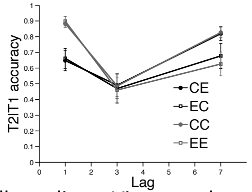


Conclusions: LAI was not found with spatial offset at lag 1.

Experiment 2: Attempt to replicate Visser et al (1999)

Methods: White stimuli on dark background
n = 12

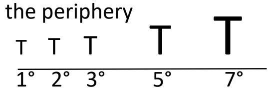
Results:
Lag ($p < .001$)
Condition ($p < .007$)
Lag x Condition ($p < .001$)



Conclusions: Failure to fully replicate Visser et al (1999). Found lag 1 sparing with spatial offset.

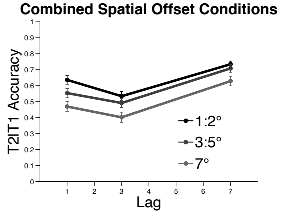
Experiment 3: Compensating for decreased perceptual acuity in the periphery

Stimuli:



Methods: n = 75

Results:
Lag ($p < .001$)
DVA ($p < .001$)
Lag x DVA ($p = .38$)

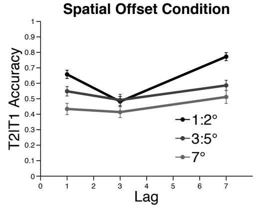


Conclusions: Increased stimuli size relative to eccentricity increased peripheral perception.

Experiment 4: Minimize potential practice effects from block design.

Methods: CE and CC appear within-block.
n = 54

Results:
Lag ($p < .001$)
DVA ($p < .001$)
Lag x DVA ($p < .001$)

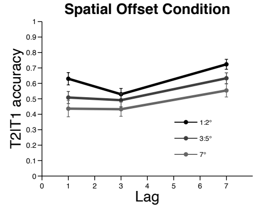


Conclusions: In a within-block design, LAI was not found with spatial offset at lag 1.

Experiment 5: Emulating Mounts (2000) which used a salient T1

Methods: Red T1

Results:
Lag ($p < .001$)
DVA ($p < .001$)
Lag x DVA ($p < .007$)



Conclusions: A salient T1 was not sufficient to produce a LAI with spatial offset at lag 1.

General conclusions:

-Experiments 1-5 no LAI with spatial offset at lag 1
-Experiment 2 failed to replicate Visser et al (1999)
-Experiment 3 found lag 1 sparing and Attentional blink in periphery
-Experiments 4-5 demonstrates that expectation did not produce LAI with spatial offset at lag 1
-Experiment 5 demonstrates that saliency did not produce LAI at lag 1

Discussion:

-In RSVP, categorically defined targets are not sufficient to produce LAI
-Lag 1 sparing is not limited by immediate spatial proximity
-In RSVP, salient targets are not sufficient to produce LAI

Future Direction:

-Add perceptual noise to paradigm to find the boundary condition of LAI

References:

Mounts, Jeffrey. 2000. Evidence for suppressive mechanisms in attentional selection: Feature singletons produce inhibitory surrounds. *Perception & Psychophysics* 62(5), 969 – 983

Shih, Shui-I. 2000. Recall of two visual targets embedded in RSVP streams of distractors depends on their temporal and spatial relationship. *Perception & Psychophysics*, 62(7), 1348-1355

Visser, Troy, Zuvic, Samantha, Bischof, Walter, & Di Lollo, Vincet. 1999. The attentional blink with targets in different spatial locations. *Psychonomics: Bulletin & Review*, 6(3), 432-436

Exploring Localized Attentional Interference in the Context of a Multiple Location RSVP Task.