Lost and Confused: Measuring Uncertainty in Navigation

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Introduction

• Navigation is difficult, so people often rely on navigational aids. However, navigational aids (e.g. GPS) can impair learning an environment.[1] If we can measure how lost a person is in real time, we can differentially deploy navigational aids at the appropriate time. This way a person still learns the environment, but also gets help when they need it most.

• Colloquially, we understand that a person is lost when they are frequently looking around. So, one of our basic premises is that we can measure disorientation by how much a person looks around.

• Our previous work[2] showed that *heading entropy*, a new measure of looking around behavior, is a better predictor of overall navigational success than *circular variance*.

• The current study aimed to replicate our previous findings[2] and generalize them to 1) situation when someone studies a map prior to navigation and 2) to a smaller environment.

Research Question

Relate navigational success to how a person looks around.
This compares how people's entropy changes across trials.

Analytic Goal

Compare different "looking around" measures -- heading entropy and circular variance -- as predictors of disorientation and learning.

Methods

Materials:

• *Virtual Environment (VE):* developed with a commercially available video game editor (Unreal Engine 2, Epic Games, Raleigh, NC); measures approximately 68,400m^2 and contains 16 generic landmarks

• "Map": aerial view of VE (1050x1050px) with labeled landmark locations

Sample and procedure:

• n = 110 (undergraduate students), 75 female

❶ Study the aerial view of VE for 60 seconds

❷ Navigate 10 trials (walk landmark-to-landmark within VE)

• **Measurements:**

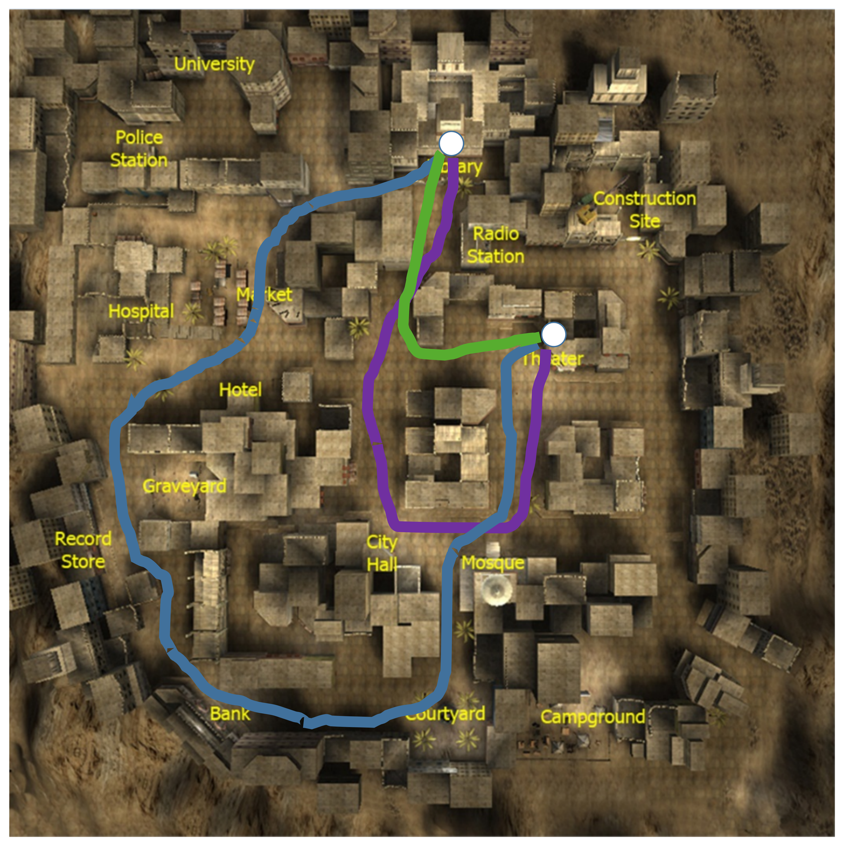
→ navigational success: *path efficiency* (PE) in distance

→ disorientation measures, calculated from yaw (compass heading):

→ *circular variance* (CV)

→ *heading entropy* (HE)

Path Efficiency



Path Efficiency = 1.0

Path Efficiency = 0.7

Path Efficiency = 0.4

PE compares the length of the actual path traveled with optimal path length:

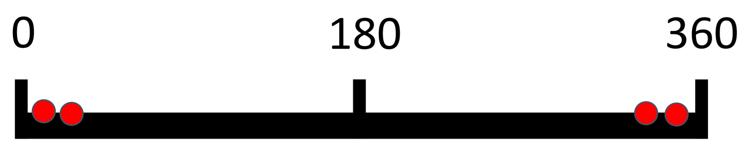
$$PE = \frac{PL_O}{PL_A}$$

Highest path efficiency is 1.0, and infinitely approaches zero

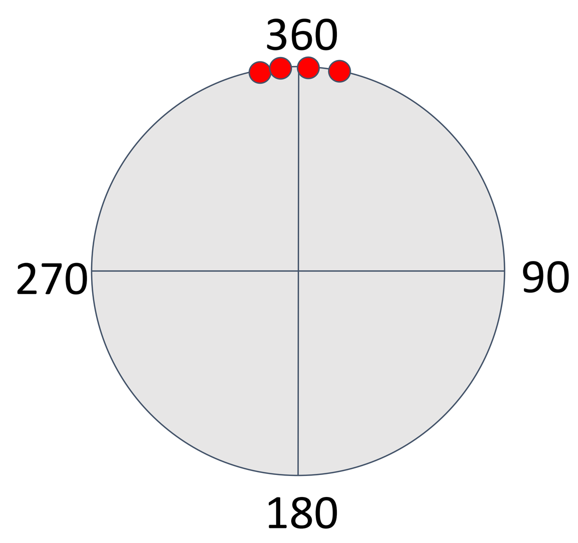
Measures of Disorientation

Traditional descriptive statistics do not capture looking around or directional pointing data very well. Consider you ask four people to point north and record their response in degrees (using a field compass):

Data: [3, 350, 5, 355]



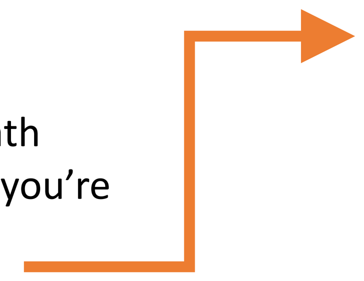
Linear μ = 178.25 degrees



Circular μ = 358.25 degrees

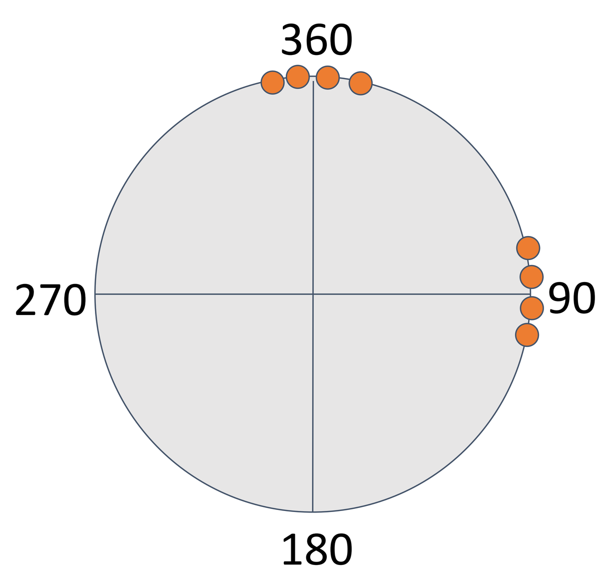
Same data (same numbers), but interpreting the distance between them is dramatically different.

Consider another hypothetical: you walked a familiar path represented by the arrow to the right. You know where you're going so don't need to look around to follow this path.



Your heading data would be tightly clustered at 360° and 90°. Clearly you are well-oriented. However, CV data would not accurately capture your well-oriented behavior.

HE captures the tight clustering of data and represents good orientation along the path's turns. HE is based on probability (via information theory[4]), so it weighs each value equivalently.



Therefore HE should be better represent well-oriented behavior than CV.[1]

Heading Data Calculations

Raw data: compass heading observations (1-360°)

Heading Entropy[2]: $\mathrm{H} = -\sum p(x)\log p(x)$

Circular variance[3]: change heading values to radians, transform them to points on the unit circle, vector average these values, and take one minus this mean resultant vector to get the circular variance.

Predicting Path Efficiency with Disorientation Measures

% Trial Time	R^2	Beta coefficients: Heading Entropy	Beta coefficients: Circular Variance
5%	.23	-.435 >	-.075
10%	.26	-.574 >	.224
25%	.37	-.638 >	.048
50%	.62	-.460 >	-.383

= p < .05

= n.s.

• Multiple linear regression, predicting overall PE by HE and CV of percentage of trial

• PE variance predicted by model (R^2) increases across all time percentages

• HE consistently better predictor than CV, at all time percentages

• HE and CV highly collinear at 100% of trial

Since each optimal path is a different length, we measure entropy and circular variance based on percentage of a trial

Discussion

• Replicated results from (2): HE consistently better than CV in predicting PE

• Extended to map study prior to navigation and to a smaller environment

• Reasons why we accounted for less variance than (2)
  • environment size, layout
  • memory component – map study
  • rotational vs translational movement (the strafing effect)

Future Directions

• How can we incorporate *a priori* measures of HE, to measure during navigation how lost a person is? We don't know how long 5%, 10%, etc. is going to be until the person has finished navigating.

• Considering pace per distance (time/distance) as a normalizing measure.

• Can we incorporate this type of "lostness" measure into navigational feedback technology?

• Testing looking around behavior in more naturalistic scenarios (e.g. virtual reality headsets).

References

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(2) Brunyé, T. T., Haga, Z. D., Houck, L. A., & Taylor, H. A. (in press) You look lost: Understanding uncertainty and representational flexibility in navigation. In J. Zacks and H. A. Taylor (Eds.). *Representations in mind and world*. Psychology Press.

[3] Berens, P. (2009). CircStat: a MATLAB toolbox for circular statistics. *Journal of Statistical Software*, 31(10), 1-21.

(4) Shannon, C. E. (2001). A mathematical theory of communication. *ACM SIGMOBILE Mobile Computing and Communications Review*, 5(1), 3-55.