Computational Vision
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Lecture 24: Object recognition, background

Initialize

```
Off[General::spell];
```

Outline

Last time

Object recognition overview

Today

Object recognition: finishing up compensating for viewpoint changes

Recognition, background variation, segmentation & learning objects

Variation over view: review

From the previous lecture...

Background context, clutter, and occlusion

Background/context for "indexing"

Background can provide prior information, that could be called "index" cues, to narrow down the space of possible objects to be recognized. E.g see: Oliva et al. (2003), Torralba et al. (2006) (pdf).

One of the first demonstrations of the role of background information for human perception was:

Biederman I (1972) Perceiving real-world scenes. Science 177:77-80.

Background (clutter) as a confound

Variation over background (clutter) is challenging, very important, yet poorly understood.

Need a better understanding of local image cues, as well as how high-level models can be used to disambiguate local information

Natural image statistics:

The same image of an object appearing at different locations will produce quite different local responses in spatial filters.

Place the antlers

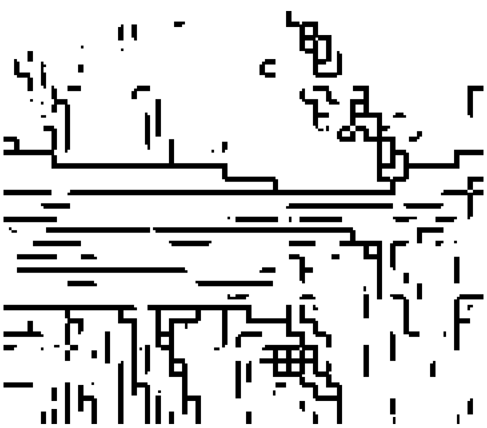
on background location 1

or on background location 2

Compare the local information in the following blow ups for location 1

and location 2

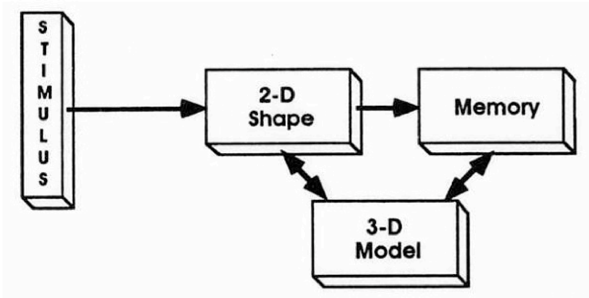
Here are examples of edge detector outputs for the two conditions:

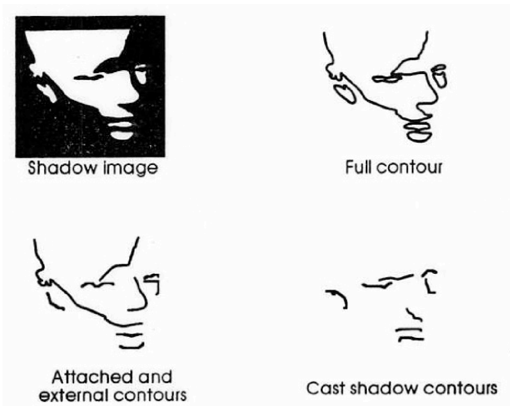


Konishi SM, Yuille AL, Coughlan JM, Zhu SC (2003) Statistical edge detection: Learning and evaluating edge cues. IEEE Transactions on Pattern Analysis and Machine Intelligence 25:57-74.

■ The solution?

Feedforward and feedback: Use high-level information to predict input and to compare with actual input





From: Cavanagh P (1991) What's up in top-down processing? In: Representations of Vision: Trends and tacit assumptions in vision research (Gorea A, ed), pp 295-304. Cambridge, UK: Cambridge University Press.

Information from high-level model (in memory) can be used to "explain away" the cast shadow contours.

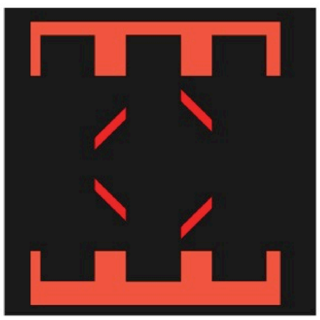
See too: Sinha P, Poggio T (2001) High-level learning of early perceptual tasks. In: Perceptual Learning (Fahle M, ed). Cambridge, MA: MIT Press.

Bootstrapped learning of object models in clutter

Brady MJ, Kersten D (2003) Bootstrapped learning of novel objects. J Vis 3:413-422.

http://gandalf.psych.umn.edu/users/kersten/kersten-lab/camouflage/digitalembryo.html

Occlusion



The solution?

Efficient grouping based on similarity. But that may not be enough. One can also use occlusion information to "explain away" missing features.

Consistent with the Bayesian idea of "explaining away".

Next

- **Perceptual integration, perception as "puzzle solving".**
- **Learning object categories**
- **Spatial layout**
- **Visual skill acquisition and video games**

Appendix

- **Writing Packages**

The basic format is straightfoward:

```
BeginPackage["Geometry`Homogeneous`"]
XRotationMatrix::"usage" =
 "XRotationMatrix[phi] gives the matrix for rotation about
   x-axis by phi degrees in radians"
YRotationMatrix::"usage" =
 "YRotationMatrix[phi] gives the matrix for rotation about
   y-axis by phi degrees in radians"
ZRotationMatrix::"usage" =
 "ZRotationMatrix[phi] gives the matrix for rotation about
   z-axis by phi degrees in radians"
ScaleMatrix::"usage" =
 "ScaleMatrix[sx,sy,sz] gives the matrix to scale a vector by
   sx,sy, and sz in the x, y and z directions, respectively."
TranslateMatrix::"usage" =
 "TranslateMatrix[x,y,z] gives the matrix to translate coordinates
   by x,y,z."
ThreeDToHomogeneous::"usage" =
 "ThreeDToHomogeneous[sx,sy,sz] converts 3D coordinates to 4D
   homogeneous coordinates."
HomogeneousToThreeD::"usage" =
 "HomogeneousToThreeD[4Dvector] converts 4D homogeneous
   coordinates to 3D coordinates."
ZProjectMatrix::"usage" =
 "ZProjectMatrix[focal] gives the 4x4 projection matrix to map
```

```
   a vector through  the origin to an image plane at focal
   distance from the origin along the z-axis."
ZOrthographic::"usage" =
 "ZOrthographic[vector] projects vector on to the x-y plane."
Begin["`private`"]
XRotationMatrix[theta_] :=
  {{1, 0, 0, 0}, {0, Cos[theta], -Sin[theta], 0},
   {0, Sin[theta], Cos[theta], 0}, {0, 0, 0, 1}};
YRotationMatrix[theta_] :=
  {{Cos[theta], 0, Sin[theta], 0}, {0, 1, 0, 0},
   {-Sin[theta], 0, Cos[theta], 0}, {0, 0, 0, 1}};
ZRotationMatrix[theta_] :=
  {{Cos[theta], -Sin[theta], 0, 0}, {Sin[theta], Cos[theta], 0, 0},
   {0, 0, 1, 0}, {0, 0, 0, 1}};
ScaleMatrix[sx_, sy_, sz_] :=
  {{sx, 0, 0, 0}, {0, sy, 0, 0}, {0, 0, sz, 0}, {0, 0, 0, 1}};
(*TranslateMatrix[x_,y_,z_]:=
  {{1,0,0,x},{0,1,0,y},{0,0,1,z},{0,0,0,1}};*)
TranslateMatrix[x_, y_, z_] :=
  {{1, 0, 0, 0}, {0, 1, 0, 0}, {0, 0, 1, 0}, {x, y, z, 1}};
ThreeDToHomogeneous[vec_] := Append[vec, 1];
HomogeneousToThreeD[vec_] := Drop[vec/vec[[4]], -1];
ZProjectMatrix[focal_] :=
  {{1, 0, 0, 0}, {0, 1, 0, 0}, {0, 0, 1, 0}, {0, 0, N[1/focal], 0}};
ZOrthographic[vec_] := Take[vec, 2];
End[]
EndPackage[]
```

```
Geometry`Homogeneous`
```

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