



Images as functions

- An image contains discrete number of pixels
 - A simple example
 - Pixel value:
 - "grayscale"
 - (or "intensity"): [0,255]





- An image contains discrete number of pixels
 - A simple example
 - Pixel value:
 - "grayscale"
 - (or "intensity"): [0,255]
 - "color"



- Lab: [L, a, b]
- HSV: [H, S, V]







Images as functions

- An Image as a function *f* from R² to R^M:
 - f(x, y) gives the **intensity** at position (x, y)







Vision for perception, interpretation





Related disciplines





The goal of computer vision

• To bridge the gap between pixels and "meaning"



What we see



What a computer sees

Computer Vision



• Make computers understand images and video.



What kind of scene?

Where are the cars?

How far is the building?

Every picture tells a story



• Goal of computer vision is to write computer programs that can interpret images



Human perception has its shortcomings...





Why computer vision matters





Safety



Health



Security



Comfort



Fun

How vision is used now



• Examples of **state-of-the-art**

Optical character recognition (OCR) مَامعة

Technology to convert scanned docs to text

• If you have a scanner, it probably came with OCR software





Digit recognition, AT&T labs http://www.research.att.com/~yann/

License plate readers http://en.wikipedia.org/wiki/Automatic number plate recognition

Face detection





- Many new digital cameras now detect faces
 - Canon, Sony, Fuji, ...

Smile detection



The Smile Shutter flow

Imagine a camera smart enough to catch every smile! In Smile Shutter Mode, your Cyber-shot® camera can automatically trip the shutter at just the right instant to catch the perfect expression.





3D from thousands of images ألفنارة



Object recognition (in supermarkets)

جَامعة المَـنارة

LaneHawk by EvolutionRobotics

"A smart camera is flush-mounted in the checkout lane, continuously watching for items. When an item is detected and recognized, the cashier verifies the quantity of items that were found under the basket, and continues to close the transaction. The item can remain under the basket, and with LaneHawk,you are assured to get paid for it... "



Vision-based biometrics





"How the Afghan Girl was Identified by Her Iris Patterns" http://www.cl.cam.ac.uk/~jgd1000/afghan.html





Login without a password...





Fingerprint scanners on many new laptops, other devices



Face recognition systems now beginning to appear more widely <u>http://www.sensiblevision.com/</u>



Object recognition (in mobile phones)



Google Goggles

Every picture tells a story











The Matrix movies, ESC Entertainment, XYZRGB, NRC

Special effects: shape capture





Pirates of the Carribean, Industrial Light and Magic







Smart cars





- Mobileye
 - Vision systems currently in high-end BMW, GM, Volvo models
 - By 2010: 70% of car manufacturers.

Google cars





https://www.nytimes.com/2010/10/10/science/10google.html

Interactive Games: Kinect





Vision in space



Vision systems (JPL) used for several tasks

- Panorama stitching
- 3D terrain modeling
- Obstacle detection, position tracking



NASA'S Mars Exploration Rover Spirit captured this westward view from atop a low plateau where Spirit spent the closing months of 2007.









Opportunity Launched 2003 Landed 2004 Curiosity Launched 2011 Landed 2012

Industrial robots







Vision-guided robots position nut runners on wheels



Home > Applications > Other Industries

Automotive Consumer Products Electronics Food & Beverage Logistics Medical Devices Pharmaceuticals Packaging Solar Web and Surface Inspection

Vision Guided Robot Key to First-Known Automated Lug Nut Fastening Application

Running down and torquing the lug nuts that hold the wheel to the hub is seemingly one of the simpler aspects of building an automobile, but it has proven one of the most difficult to automate. This is a difficult manual job, as well, because of the size and weight of the nutrunner and the need to tighten the nuts on two wheels in approximately 40 seconds. If the position of the lug nuts is known, a robot can easily position the nutrunner to deliver the needed torque. The problem is that typically the vehicle is only roughly positioned by a conveyor and the wheels themselves are free to rotate, tilt, and turn. Therefore an ordinary blind robot would never be able to find the nuts.

Radix Controls, Oldcastle, Ontario, successfully automated this application by using a vision system to determine the position of the wheel including its fore and aft and side-to-side positions and three



Mobile robots





NASA's Mars Spirit Rover http://en.wikipedia.org/wiki/Spirit_rover



http://www.robocup.org/



Saxena et al. 2008 STAIR at Stanford



🗧) 🛞 stair.stanford.edu

STAIR: STanford Artificial Intelligence Robot

Artificial Intelligence Laboratory, Computer Science Department, Stanford University

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Since its birth in 1956, the AI dream has been to build systems that exhibit broadspectrum competence and intelligence. In the STAIR (STanford AI Robot) project, we are building a robot that can navigate home and office environments, pick up and interact with objects and tools, and intelligently converse with and help people in these environments.

Our single robot platform will integrate methods drawn from all areas of Al, including machine learning, vision, navigation, manipulation, planning, reasoning, and speech/natural language processing. This is in distinct contrast to the 30-year trend of working on fragmented Al sub-fields, and will be a vehicle for driving research towards true integrated Al.

Over the long term, we envision a single robot that can perform tasks such as:

- · Fetch or deliver items around the home or office.
- •
- Tidy up a room, including picking up and throwing away trash, and using the dishwasher.
- Prepare meals using a normal kitchen.
- Use tools to assemble a bookshelf.

A robot capable of these tasks will *revolutionize* home and office automation, and have important applications ranging from home assistants to elderly care. However, carrying out such tasks will require significant advances in integrating learning, manipulation, perception, spoken dialog, and reasoning.



Medical imaging



3D imaging MRI, CT





Image guided surgery Grimson et al., MIT

Earth viewers (3D modeling)









Computer Vision: Algorithms and Applications

© 2010 Richard Szeliski, Microsoft Research



http://szeliski.org/Book/



Computer graphics versus computer vision







- In **computer graphics** data are used to create pictures, for example, the case of computer-aided design (CAD).
- In **computer vision** one starts with a picture and attempts to abstract data from it.
- Usually experts in computer vision are also experts in computer graphics and use this expertise to create graphic user interfaces (GUIs) which make their vision products easier to use and more attractive.

2-D vision and 3-D stereo vision

- Almost all digital images are two-dimensional.
- In some applications it is necessary to reconstruct the three-dimensional scene from the image to obtain information in three dimensional coordinates.
- *Stereo-imaging* allows powerful 3-D imaging, as our own 3-D binocular vision illustrates.
- Stereo imaging involves two cameras with known vision and geometric properties arranged so that their 2-D pixels can be correlated. Various algorithms are then used to recognize objects and reconstruct some 3-D data.

Object Recognition



- In computer vision one must be clear which data are actually required in any particular case.
- Once this is known the engineer can choose the least expensive or most effective way of delivering that information (assuming it is possible).
- The simplest information one can demand of a vision system is *whether* an object is present or not.



Detecting insects in a digital image using neural networks

- In some cases the cost of **erroneous recognition** may be unacceptably high, and the vision system must be more discriminating than the simple infra-red sensor.
- To illustrate this point consider a machine whose purpose is to kill some undesirable insects by ultraviolet irradiation but not to kill other benign insects.



• Let us suppose that the insects of interest are the following, as illustrated in Figure





- How can we begin the job of recognizing these objects in an image?
- What information can we use?
- Of many possibilities, we might immediately think of characteristics such as colour, shape, size, movement pattern, speed, and so on.
- As always in computer vision, these things are easy to say but much more difficult to pin down in an explicit representation.



- For example, how would we represent the concept of insect shape within a computer?
- It can be done, but, of the various possibilities, **colour** is one of the easiest characteristics to represent.
- One of the first problems is distinguishing the objects of interest (the insects) from objects of no interest (the background).

As Figure shows, the background can be very complex, and in the case of flowers it can move around considerably.



The first problem in computer vision: discriminating objects of interest from" the background clutter



- Thus the problem of deciding if the image contains a bee is compounded by the problem of knowing what else the image contains.
- A simple solution to the problem of *background clutter* is to constrain the system so that the background is fixed and simple.
- So suppose that the machine will have a platform on which the insects will walk, and suppose that this platform will be of a constant light blue colour which allows the pixels to be classified as either background or insect with reasonable fidelity.
- In practice, of course, some pixels are misclassified so that in the following experiments some background pixels have their data included in the 'insect' statistics, while some genuine insect pixels have got lost in the background.



 Having abstracted a set of 'insect pixels' from the image, suppose that the greyscale values from a colour camera can be used to classify the pixels into one of the following colours:

| Red | Green |
|--------|-------|
| Yellow | Ochre |
| Black | White |

• So that each insect will have its pixels assigned to these six classes.



جَـامعة الـمَــنارة PIXEL FREQUENCIES BY COLOUR FOR SIX PAIRS OF INSECTS

| Object | Red | Green | Yellow | Ochre | Black | White | Unclassified |
|---------------|-------|-------|--------|-------|-------|-------|--------------|
| Ladybird 1 | 12872 | 554 | 423 | 291 | 9107 | 223 | 145 |
| | 13009 | 483 | 243 | 314 | 8728 | 364 | 403 |
| Ladybird 2 | 18579 | 842 | 228 | 28 | 16879 | 917 | 283 |
| | 18402 | 938 | 229 | 25 | 16880 | 969 | 218 |
| Fly 1 | 2775 | 3383 | 1845 | 294 | 16566 | 368 | 1966 |
| | 2831 | 3417 | 1878 | 334 | 16675 | 285 | 1482 |
| Fly 2 | 1399 | 2322 | 3875 | 375 | 13271 | 3445 | 5924 |
| - | 1414 | 2378 | 3797 | 384 | 13398 | 3316 | 5685 |
| Bee 1 | 3669 | 4821 | 1281 | 2576 | 21829 | 693 | 779 |
| | 3594 | 4542 | 1336 | 2762 | 21442 | 632 | 762 |
| Bee 2 | 3695 | 3037 | 535 | 2021 | 18198 | 344 | 266 |
| | 3623 | 3173 | 621 | 2102 | 18086 | 333 | 256 |
| Wasp 1 | 2314 | 3590 | 12753 | 1686 | 8386 | 2846 | 2330 |
| | 2269 | 3834 | 12675 | 1608 | 8540 | 2724 | 2155 |
| Wasp 2 | 3097 | 5034 | 15124 | 3626 | 9599 | 4406 | 845 |
| | 2756 | 3814 | 15018 | 3159 | 8936 | 6701 | 1556 |
| Greenbottle 1 | 1678 | 6797 | 1207 | 106 | 15737 | 1402 | 1891 |
| | 1691 | 6734 | 1152 | 98 | 15831 | 1371 | 1356 |
| Greenbottle 2 | 842 | 7931 | 3192 | 63 | 14925 | 3287 | 3113 |
| | 873 | 7900 | 3183 | 57 | 14708 | 3254 | 3142 |
| Blowfly 1 | 1801 | 4033 | 432 | 231 | 24722 | 24 | 1185 |
| | 2161 | 3994 | 412 | 240 | 25271 | 27 | 1143 |
| Blowfly 2 | 3958 | 3578 | 212 | 153 | 29592 | 11 | 458 |



- The ladybirds have the highest numbers of red pixels.
- The wasps have the highest numbers of yellow pixels.
- The greenbottles have the highest numbers of green pixels, and so on.
- However, not all the insects can be classified by having predominance in one colour.
- For example, honey bees are mostly black but have a yellowy-brown 'ochre' colour. Even though this colour characterizes the bees, their ochre count is less than that of the wasps whose bright yellow becomes this ochre colour in certain lights and shadows.



• Thus every insect is represented by six numbers: the number of its pixels classified as red, the number classified as green, the number classified as yellow, the number classified as ochre, the number classified as black, and the number classified as white.



• For example, for the first ladybird the numbers can be arranged as a sequence, or *vector:*

| red | green | yellow | ochre | black | white |
|----------|-------|--------|-------|-------|-------|
| (12872, | 554, | 423, | 291, | 9107, | 223) |

• while for the second ladybird the statistics are:

| red | green | yellow | ochre | black | white |
|---------|-------|--------|-------|--------|-------|
| (18579, | 842, | 228, | 28, | 16879, | 917) |



- Having established a pre-processing procedure which maps the various insects into this colour/frequency space, the computer vision task can be completed in a number of ways.
- This case is particularly well suited to the application of **neural networks**.
- The training data for the network are the vectors of colour frequencies as inputs, and the insect classes as outputs.
- So we might use a six-input and six-output network with six nodes in the hidden layer.
- The pattern recognition was very successful in correctly assigning new insects to their class.



- In this application of neural networks we exploit some of their useful features:
 - 1. no two insects have exactly the same pixel colour frequencies and so the generalization of the network to 'similar' data is essential.
 - 2. ability to cope with redundancy in the data. It happens that there is very little useful information in the frequency of white pixels. This is because the wings of the insects, although transparent in some lights, are highly reflective and can produce quite large 'white' responses in rather a random way.



Once the insect has been recognized - or more precisely, classified
the system can take whatever action is appropriate according to

- the system can take whatever action is appropriate according to its specification.



- The kind of object recognition in the last section is of the 'yes/no', 'it-ishere-or not' kind.
- In many applications of computer vision much more than this is required.
- Apart from knowing that an image contains an object, more information about that object may be needed.

| 172 | 169 | 173 | 168 | 172 | 175 | 175 | 172 | 172 | 169 | 172 | 166 | 166 | 166 | 166 | 167 | 168 | 169 | 166 | 169 | 175 | 171 | 166 | 169 | 168 | 169 | 166 | 171 | 165 | 172 | 171 | م امع |
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| 170 | 176 | 173 | 162 | 166 | 170 | 176 | 170 | 168 | 165 | 173 | 172 | 172 | 164 | 170 | 177 | 174 | 171 | 172 | 170 | 166 | 171 | 173 | 174 | 170 | 177 | 189 | 172 | 170 | 172 | 169 | |
| 177 | 169 | 166 | 167 | 176 | 165 | 170 | 167 | 168 | 169 | 171 | 166 | 170 | 171 | 168 | 169 | 173 | 171 | 170 | 171 | 165 | 168 | 167 | 168 | 165 | 173 | 178 | 180 | 169 | 173 | 175 | المعارة |
| 166 | 169 | 170 | 161 | 168 | 171 | 171 | 168 | 169 | 163 | 171 | 168 | 166 | 163 | 168 | 169 | 170 | 170 | 165 | 163 | 165 | 186 | 166 | 170 | 165 | 171 | 166 | 169 | 166 | 174 | 171 | |
| 172 | 167 | 170 | 166 | 170 | 168 | 170 | 165 | 170 | 168 | 168 | 165 | 168 | 163 | 165 | 167 | 168 | 169 | 172 | 170 | 164 | 168 | 168 | 169 | 164 | 176 | 175 | 172 | 186 | 168 | 165 | |
| 170 | 169 | 169 | 167 | 168 | 172 | 177 | 166 | 166 | 171 | 177 | 169 | 166 | 165 | 168 | 169 | 178 | 173 | 186 | 163 | 164 | 166 | 163 | 169 | 170 | 171 | 167 | 172 | 166 | 172 | 173 | |
| 171 | 170 | 166 | 166 | 172 | 168 | 171 | 170 | 176 | 171 | 172 | 170 | 174 | 170 | 171 | 174 | 172 | 168 | 186 | 170 | 170 | 189 | 162 | 163 | 168 | 174 | 166 | 168 | 164 | 170 | 168 | |
| 169 | 164 | 163 | 166 | 169 | 167 | 175 | 166 | 165 | 168 | 172 | 167 | 170 | 168 | 164 | 165 | 168 | 171 | 170 | 166 | 164 | 167 | 162 | 164 | 165 | 172 | 165 | 168 | 166 | 170 | 169 | |
| 176 | 171 | 172 | 166 | 172 | 170 | 174 | 169 | 166 | 166 | 172 | 170 | 172 | 168 | 161 | 154 | 160 | 171 | 172 | 173 | 170 | 168 | 151 | 160 | 163 | 168 | 166 | 170 | 168 | 171 | 176 | |
| 174 | 167 | 167 | 165 | 171 | 170 | 174 | 169 | 172 | 169 | 172 | 176 | 172 | 154 | 146 | 142 | 142 | 156 | 174 | 176 | 169 | 170 | 163 | 166 | 169 | 174 | 161 | 169 | 171 | 174 | 170 | |
| 176 | 166 | 168 | 169 | 172 | 166 | 175 | 168 | 167 | 171 | 183 | 179 | 160 | 133 | 115 | 112 | 114 | 131 | 160 | 173 | 169 | 170 | 167 | 168 | 170 | 174 | 172 | 175 | 171 | 174 | 170 | |
| 174 | 170 | 170 | 165 | 167 | 163 | 170 | 166 | 168 | 168 | 175 | 173 | 165 | 124 | 78 | 71 | 83 | 114 | 144 | 163 | 165 | 161 | 161 | 167 | 170 | 175 | 189 | 171 | 167 | 172 | 170 | |
| 169 | 163 | 167 | 163 | 167 | 164 | 170 | 165 | 164 | 166 | 170 | 167 | 156 | 114 | 59 | 45 | 65 | 100 | 139 | 162 | 159 | 163 | 165 | 185 | 167 | 174 | 169 | 171 | 169 | 171 | 166 | |
| 172 | 168 | 169 | 167 | 173 | 168 | 172 | 166 | 167 | 167 | 175 | 168 | 165 | 134 | 66 | 1 | 69 | 130 | 150 | 158 | 165 | 170 | 167 | 168 | 171 | 178 | 173 | 172 | 187 | 173 | 175 | |
| 170 | 167 | 172 | 166 | 174 | 169 | 175 | 172 | 167 | 163 | 176 | 172 | 174 | 150 | 77 | ٥ | 74 | 150 | 165 | 163 | 171 | 174 | 168 | 166 | 167 | 173 | 167 | 169 | 171 | 173 | 174 | |
| 171 | 168 | 169 | 166 | 173 | 171 | 178 | 173 | 166 | 166 | 177 | 174 | 173 | 159 | 88 | 0 | 81 | 151 | 168 | 159 | 164 | 172 | 186 | 168 | 186 | 172 | 167 | 166 | 184 | 170 | 168 | |
| 178 | 172 | 172 | 168 | 167 | 163 | 173 | 170 | 178 | 169 | 178 | 181 | 183 | 162 | 88 | 2 | 53 | 152 | 170 | 182 | 167 | 172 | 167 | 165 | 168 | 173 | 170 | 172 | 167 | 169 | 168 | |
| 169 | 170 | 178 | 171 | 177 | 174 | 175 | 171 | 169 | 168 | 177 | 175 | 183 | 171 | 102 | 2 | 51 | 185 | 176 | 166 | 164 | 172 | 173 | 172 | 167 | 175 | 175 | 173 | 171 | 178 | 174 | |
| 174 | 170 | 172 | 168 | 173 | 168 | 177 | 172 | 165 | 170 | 181 | 175 | 177 | t70 | 95 | t | 58 | 154 | 172 | 164 | 166 | 172 | 167 | 166 | 165 | 170 | 172 | 173 | 167 | 1/2 | 173 | |
| 167 | 164 | 167 | 165 | 174 | 169 | 175 | 172 | 170 | 169 | 178 | 174 | 180 | 168 | 99 | 4 | 33 | 150 | 172 | 159 | 162 | 158 | 169 | 170 | 170 | 175 | 178 | 178 | 169 | 157 | 1/0 | |
| 176 | 170 | 169 | 168 | 176 | 169 | 176 | 171 | 165 | 169 | 178 | 173 | 177 | 165 | 97 | 2 | 43 | 151 | 176 | 164 | 164 | 173 | 173 | 173 | 174 | 176 | 171 | 170 | 10/ | 170 | 100 | |
| 172 | 166 | 174 | 171 | 180 | 175 | 181 | 175 | 168 | 168 | 177 | 177 | 183 | 169 | 106 | 0 | 38 | 152 | 175 | 154 | 168 | 178 | 1/4 | 1/3 | 171 | 1/4 | 171 | 173 | 109 | 175 | 172 | |
| 173 | 168 | 167 | 171 | 177 | 168 | 176 | 171 | 171 | 168 | 178 | 173 | 178 | 165 | 96 | <u> </u> | 39 | 150 | 1// | 163 | 160 | 173 | 175 | 1/3 | 1/1 | 170 | 173 | 174 | 171 | 177 | 172 | |
| 173 | 167 | 174 | 168 | 170 | 170 | 176 | 166 | 164 | 170 | 1/6 | 1// | 182 | 168 | 111 | 1 | 2/ | 147 | 1/0 | 109 | 100 | 170 | 160 | 107 | 163 | 175 | 169 | 174 | 169 | 173 | 172 | |
| 171 | 166 | 168 | 168 | 1/3 | 164 | 1/3 | 169 | 16/ | 169 | 178 | 111 | 1.63 | 107 | 105 | 3 | 28 | 140 | 170 | 102 | 160 | 168 | 100 | 187 | 168 | 178 | 171 | 173 | 170 | 176 | 174 | |
| 175 | 171 | 173 | 172 | 174 | 108 | 176 | 1/2 | 106 | 104 | 173 | 175 | 100 | 170 | 102 | 7 | 10 | 141 | 170 | 185 | 184 | 172 | 188 | 169 | 165 | 173 | 171 | 175 | 171 | 178 | 174 | |
| 175 | 171 | 173 | 171 | 178 | 109 | 132 | 174 | 170 | 10/ | 170 | 176 | 100 | 170 | 11.0 | L'A | 10 | 140 | 172 | 150 | 1.64 | 170 | 168 | 168 | 167 | 173 | 169 | 170 | 167 | 170 | 186 | |
| 1/1 | 100 | 108 | 10/ | 172 | 100 | 175 | 180 | 160 | 167 | 179 | 170 | 170 | 179 | 126 | 2 | 12 | 137 | 176 | 160 | 157 | 168 | 167 | 168 | 165 | 175 | 167 | 171 | 173 | 172 | 167 | |
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- Inspection of the greyscale numbers in Figure shows there is a marked vertical column of low values in the centre of the image.
- This suggests there is a **dark object** against a lighter background.







- conventional attempts at edge detection have not been very successful because they depend on thresholding.
- Figure shows the results of a new method of edge detection .
- Using this method, the geometric 'edges' of the pin have been detected to sub-pixel accuracy approaching one-tenth of a pixel.

| 172 | 169 | 173 | 168 | 172 | 171 | 175 | 172 | 172 | 169 | 172 | 166 | 166 | 166 | 166 | 167 | 168 | 169 | 166 | 169 | 175 | 171 | 166 | 169 | 168 | 168 | 166 | 171 | 165 | 172 | 171 |
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| 177 | 169 | 166 | 167 | 176 | 165 | 170 | 167 | 168 | 169 | 171 | 166 | 170 | 171 | 168 | 169 | 173 | 171 | 170 | 171 | 165 | 168 | 167 | 168 | 165 | 173 | 176 | 180 | 169 | 173 | 175 |
| 166 | 169 | 170 | 161 | 168 | 171 | 171 | 168 | 169 | 163 | 171 | 168 | 166 | 163 | 168 | 169 | 170 | 170 | 165 | 163 | 165 | 166 | 166 | 170 | 168 | 171 | 186 | 169 | 166 | 174 | 171 |
| 172 | 167 | 170 | 166 | 170 | 168 | 170 | 165 | 170 | 168 | 168 | 165 | 168 | 163 | 165 | 167 | 168 | 169 | 172 | 170 | 164 | 168 | 168 | 169 | 164 | 176 | 175 | 172 | 166 | 168 | 165 |
| 170 | 169 | 169 | 167 | 168 | 172 | 177 | 166 | 166 | 171 | 177 | 169 | 166 | 165 | 168 | 169 | 178 | 173 | 166 | 163 | 164 | 166 | 163 | 169 | 170 | 171 | 167 | 172 | 166 | 172 | 173 |
| 171 | 170 | 166 | 166 | 172 | 168 | 171 | 170 | 176 | 171 | 172 | 170 | 174 | 170 | 171 | 174 | 172 | 168 | 166 | 170 | 170 | 189 | 162 | 163 | 168 | 174 | 166 | 168 | 164 | 170 | 168 |
| 169 | 164 | 163 | 166 | 169 | 167 | 175 | 166 | 165 | 168 | 172 | 167 | 170 | 166 | 164 | 165 | 168 | 171 | 170 | 166 | 164 | 167 | 162 | 164 | 165 | 172 | 165 | 168 | 166 | 170 | 169 |
| 176 | 171 | 172 | 166 | 172 | 170 | 174 | 169 | 185 | 186 | 172 | 170 | . 172 | 168 | 161 | 154 | 160 | 171 | 172 | 173 | 170 | 168 | 161 | 160 | 163 | 168 | 166 | 170 | 168 | 171 | 176 |
| 174 | 167 | 167 | 165 | 171 | 170 | 174 | 169 | 172 | 169 | 172 | 176 | 172 | 154 | 146 | 142 | 142 | 156 | 174 | 176 | 169 | 170 | 163 | 166 | 169 | 174 | 161 | 169 | 171 | 174 | 170 |
| 176 | 166 | 168 | 169 | 172 | 166 | 175 | 168 | 167 | 171 | 183 | 179 | 160 | 133 | 115 | 112 | 114 | 131 | 160 | 173 | 189 | 170 | 167 | 168 | 170 | 174 | 172 | 175 | 171 | 174 | 170 |
| 174 | 170 | 170 | 165 | 167 | 163 | 170 | 166 | 168 | 168 | 175 | 173 | 165 | 124 | 78 | 71 | B3 | 114 | 144 | 163 | 165 | 161 | 161 | 167 | 170 | 175 | 169 | 171 | 167 | 172 | 170 |
| 169 | 163 | 167 | 163 | 167 | 164 | 170 | 165 | 164 | 166 | 170 | 167 | 156 | 114 | 59 | 45 | 65 | 100 | 139 | 162 | 159 | 163 | 165 | 165 | 167 | 174 | 189 | 171 | 169 | 171 | 166 |
| 172 | 168 | 169 | 167 | 173 | 168 | 172 | 166 | 167 | 167 | 175 | 168 | 165 | 134 | 66 | 1 | 69 | 130 | 150 | 158 | 165 | 170 | 167 | 168 | 171 | 176 | 173 | 172 | 167 | 173 | 175 |
| 170 | 167 | 172 | 166 | 174 | 169 | 175 | 172 | 167 | 163 | 176 | 172 | 174 | 150 | 77 | 0 | 74 | 150 | 165 | 183 | 171 | 174 | 168 | 166 | 167 | 173 | 167 | 169 | 171 | 173 | 174 |
| 171 | 168 | 169 | 166 | 173 | 171 | 178 | 173 | 166 | 166 | 177 | 174 | 173 | 159 | 88 | 0 | 61 | 151 | 168 | 159 | 164 | 172 | 166 | 168 | 166 | 172 | 167 | 166 | 164 | 170 | 168 |
| 178 | 172 | 172 | 168 | 167 | 163 | 173 | 170 | 170 | 169 | 178 | 181 | 183 | 162 | 88 | 2 | 53 | 122 | 170 | 162 | 167 | 172 | 167 | 165 | 166 | 173 | 170 | 172 | 167 | 169 | 168 |
| 169 | 170 | 176 | 171 | 177 | 174 | 175 | 171 | 169 | 168 | 177 | 175 | 183 | 171 | 102 | 2 | 51 | 155 | 176 | 166 | 164 | 172 | 173 | 172 | 167 | 175 | 175 | 173 | 171 | 178 | 174 |
| 174 | 170 | 172 | 168 | 173 | 168 | 177 | 172 | 165 | 170 | 181 | \$75 | 177 | 170 | 96 | 1 | 58 | 154 | 172 | 164 | 166 | 172 | 167 | 186 | 165 | 170 | 172 | 173 | 167 | 172 | 173 |
| 167 | 164 | 167 | 165 | 174 | 169 | 175 | 172 | 170 | 169 | 178 | 174 | 180 | 168 | 99 | 4 | 33 | 150 | 172 | 159 | 162 | 168 | 169 | 170 | 170 | 175 | 176 | 178 | 169 | 167 | 170 |
| 176 | 170 | 169 | 168 | 176 | 169 | 176 | 171 | 165 | 169 | 178 | 173 | 177 | 166 | 97 | 2 | 43 | 151 | 176 | 164 | 164 | 173 | 173 | 173 | 174 | 176 | 171 | 170 | 167 | 170 | 168 |
| 172 | 166 | 174 | 171 | 180 | 175 | 181 | 175 | 168 | 168 | 177 | 177 | 183 | 169 | 106 | a | 38 | 152 | 175 | 164 | 168 | 178 | 174 | 173 | 171 | 174 | 171 | 173 | 169 | 175 | 172 |
| 173 | 168 | 167 | 171 | 177 | 168 | 175 | 171 | 171 | . e | døes | s det | ecte | d | 98 | 1 | 39 | 50 | . e | dves | s det | ecte | d | 173 | 171 | 178 | 171 | 173 | 171 | 175 | 171 |
| 173 | 167 | 174 | 168 | 170 | 170 | 176 | 166 | 164 | Ĺ | to s | ub-p | ixel | - | 111 | 1 | 27 | 147 | Ľ | to s | ub-p | ixel | _ | 167 | 165 | 175 | 173 | 174 | 171 | 177 | 172 |
| 171 | 168 | 168 | 168 | 173 | 164 | 173 | 169 | 167 | | ac | cura | cy — | | 105 | 3 | 29 | 145 | accuracy | | | | | | 163 | 171 | 189 | \$71 | 169 | 173 | 172 |
| 175 | 171 | 173 | 172 | 174 | 168 | 176 | 172 | 168 | 164 | 173 | 175 | 177 | 173 | 112 | 2 | 29 | 141 | 170 | 161 | 160 | 168 | 169 | 167 | 168 | 176 | 171 | 173 | 170 | 176 | 174 |
| 175 | 171 | 173 | 171 | 178 | 169 | 172 | 174 | 170 | 167 | 175 | 176 | 180 | 170 | 123 | 7 | 18 | 141 | 176 | 165 | 164 | 172 | 168 | 168 | 165 | 173 | 171 | 175 | 171 | 178 | 174 |
| 171 | 166 | 168 | 167 | 172 | 165 | 175 | 173 | 170 | 171 | 177 | 175 | 178 | 173 | 116 | 0 | 19 | 140 | 172 | 159 | 158 | 170 | 168 | 168 | 167 | 173 | 169 | 170 | 167 | 170 | 166 |



- By this method the measurement is that the pin is **2.5 pixels** across.
- At 100 pixels per inch this means that the diameter measurement of the pin is 0.025 inches.