



Using Complex Color Distributions as an Identification Tool

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WAY-2C Color Machine Vision

#TheVisionShow

Outline

- Introduction:
 - Example complex color-based identification applications
- What is color?
- A brief history including:
 - Color in machine vision
 - Color coordinate systems -why most are irrelevant here
- Color-based classification
 - How many classes can we distinguish?
 - Determining the most likely class
- What's the catch?
- Color-based anomaly detection



Some Identification Examples

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Sorting

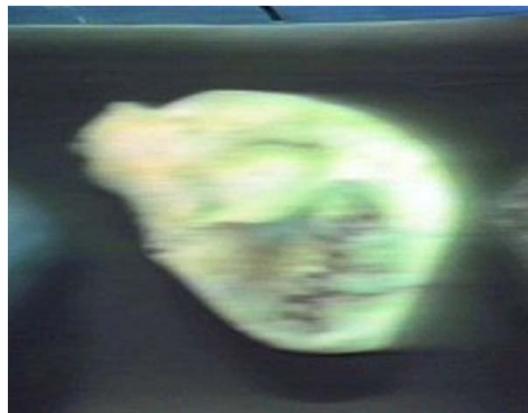
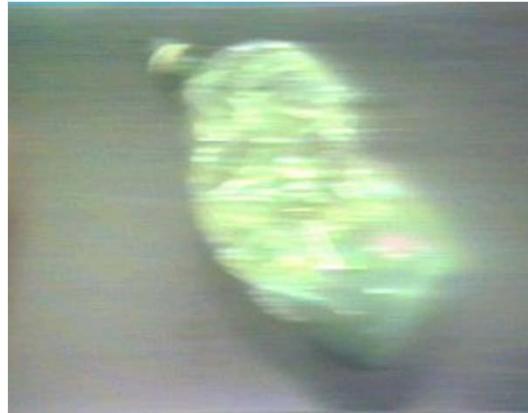
Cherry



Strawberry



Sorting



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Characterized by need for:

Speed in:

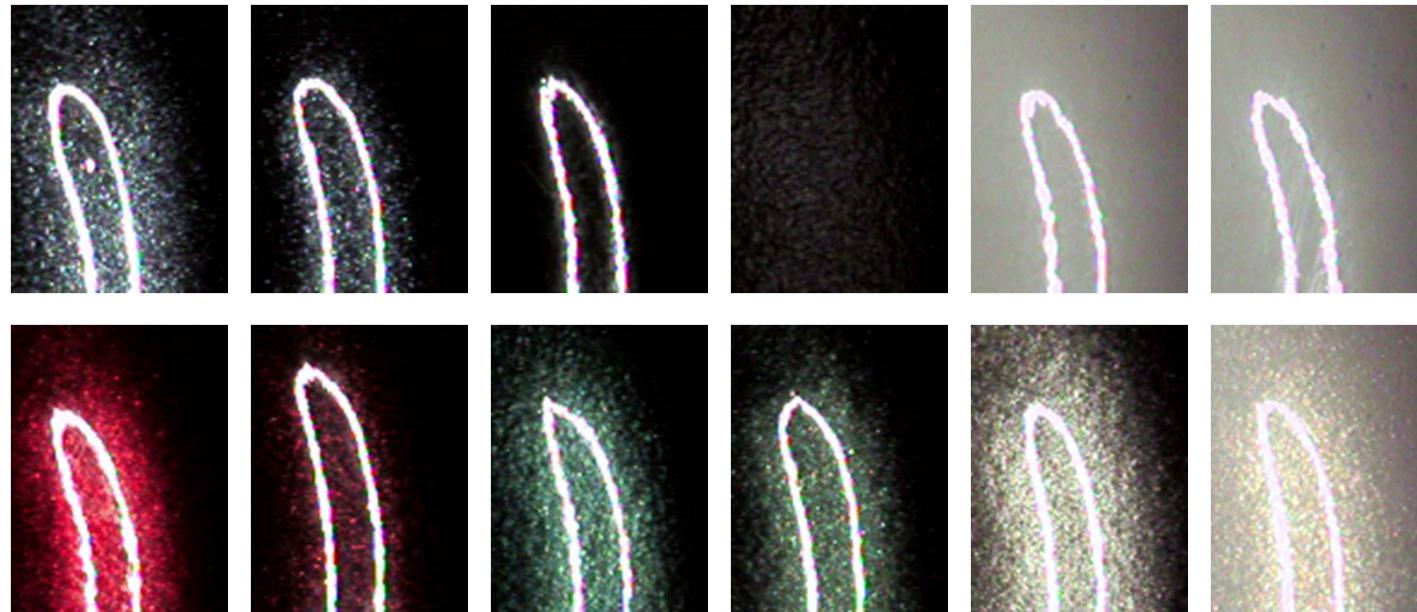
- **Training/Retrofitting**
(as conditions or items of interest change)
- **Testing**
(to verify training accuracy)
- **Processing**

Maximum likelihood identification

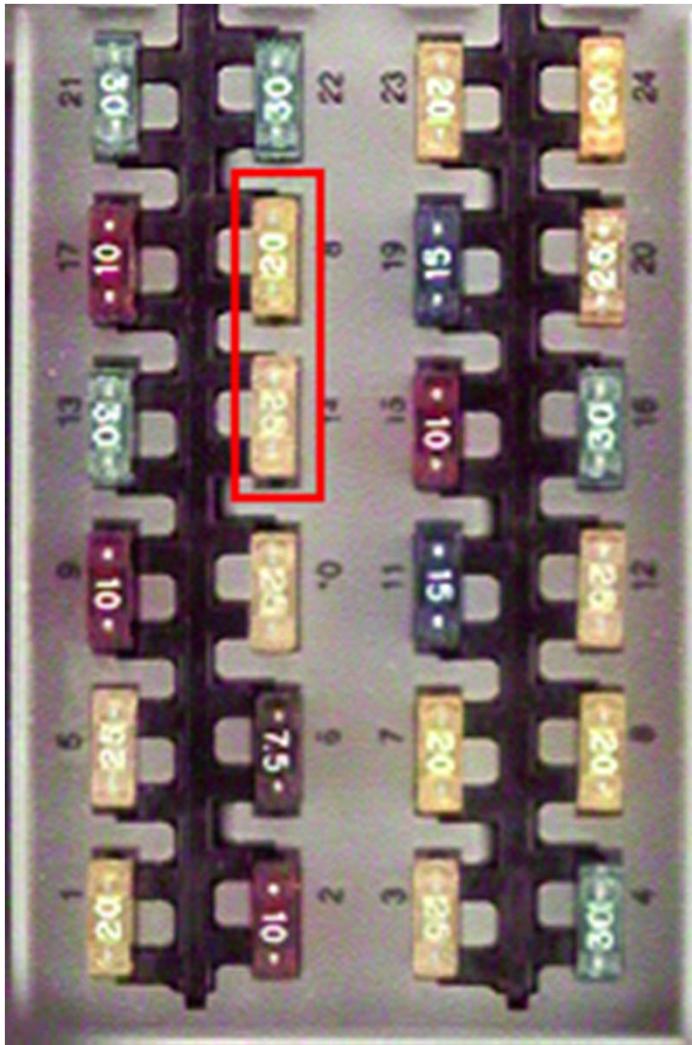
Sorting



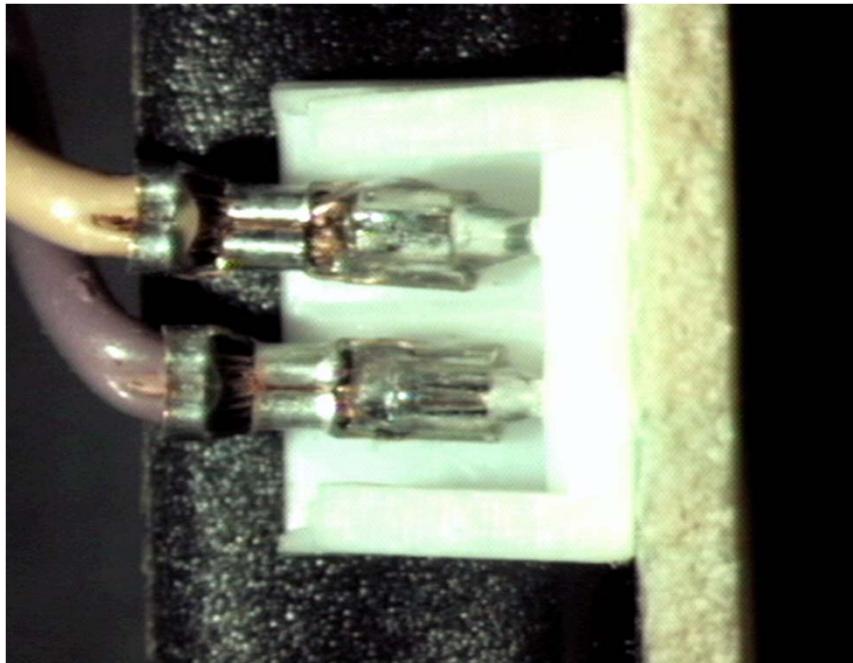
Auto Trim Parts Under White Ring Light



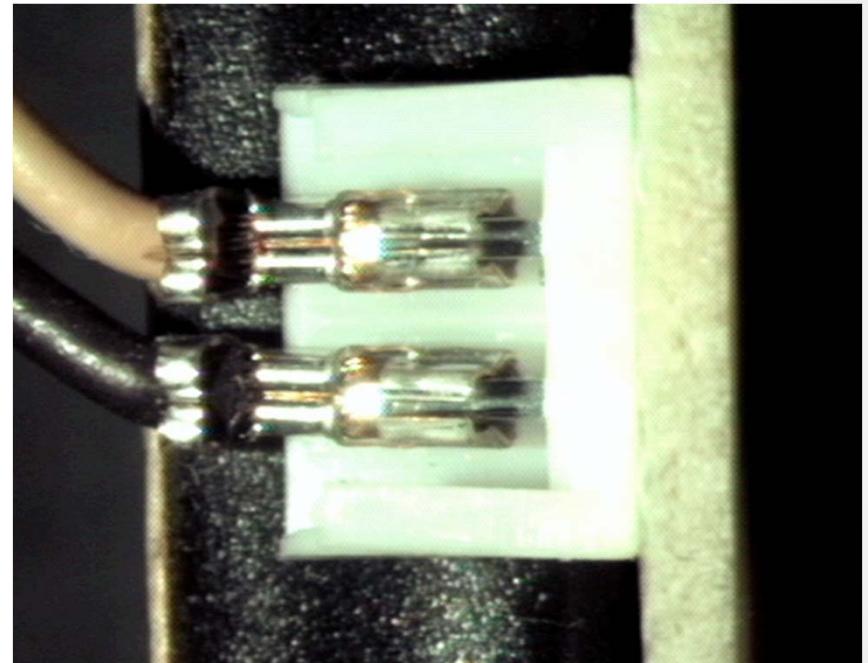
Assembly Inspection



Assembly Inspection



pass (solder)



fail (no solder)

Food Quality Assurance



?



under



under

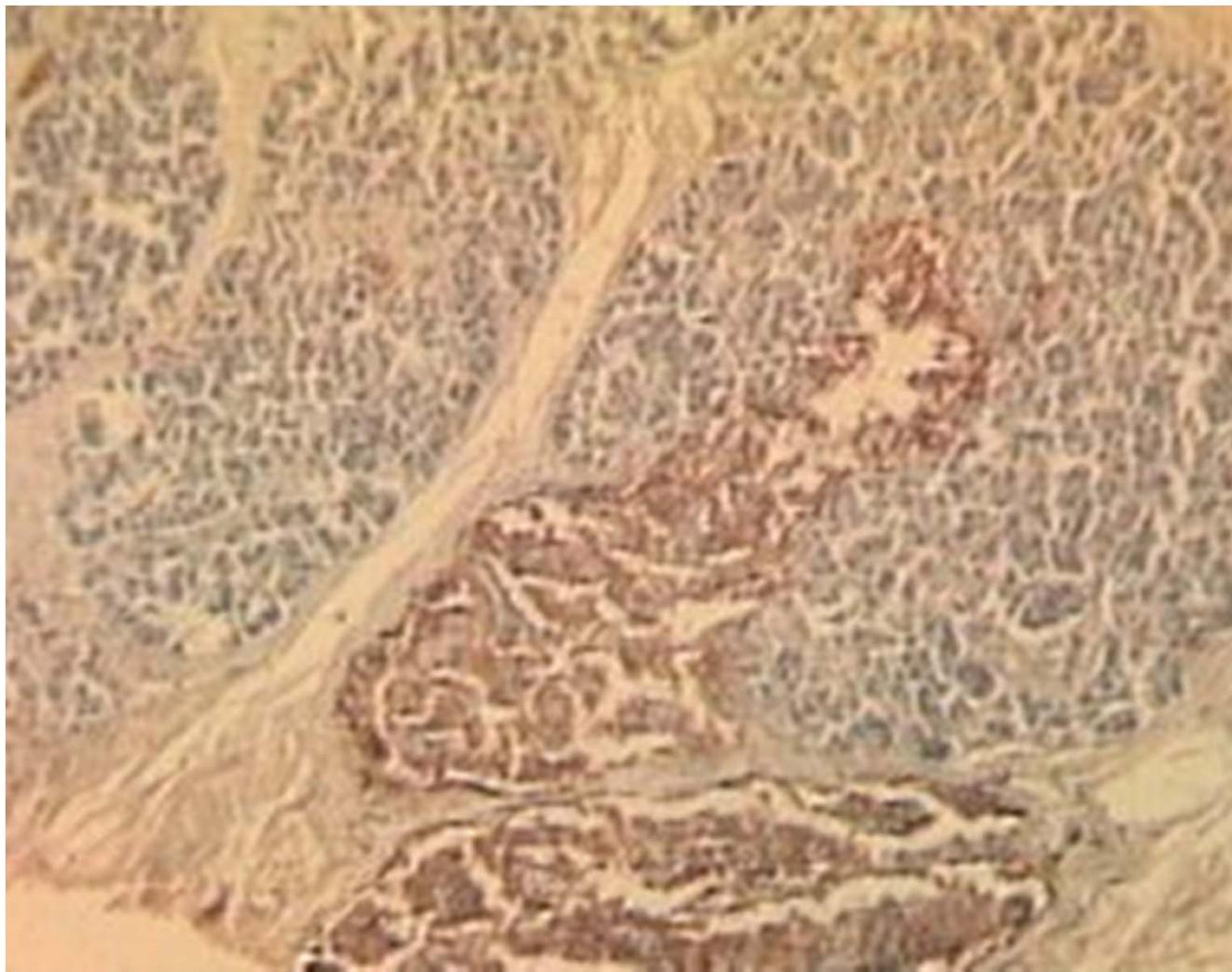


ok



over

Area Mapping



Area Mapping



Anomaly Detection



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Other: Pattern Translation





What Is Color?

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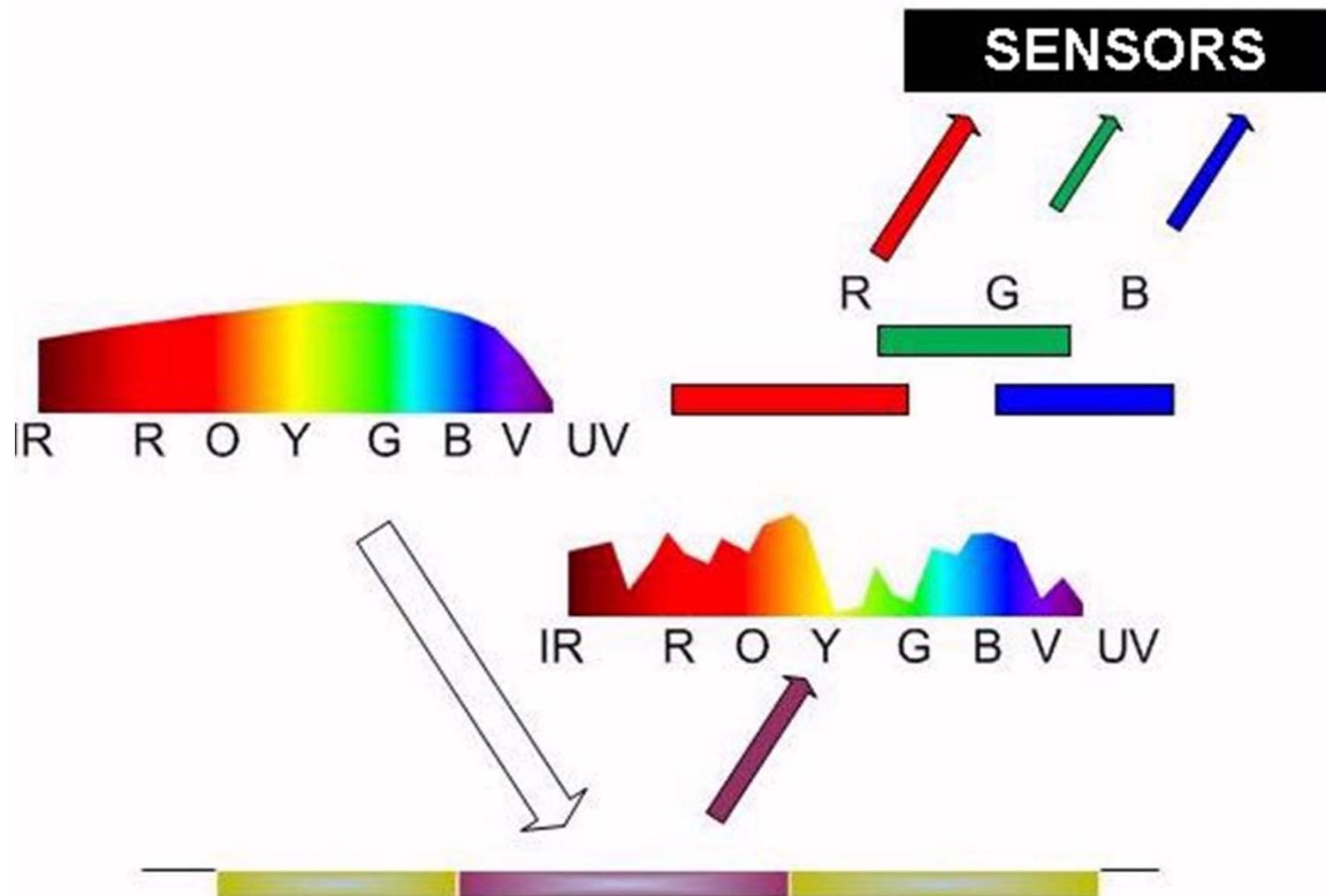
Color is NOT a Physical Property **- It is a Perception**

A function of a long chain of independent properties and processes that include among other things the spectral properties of the material of which the object is made.

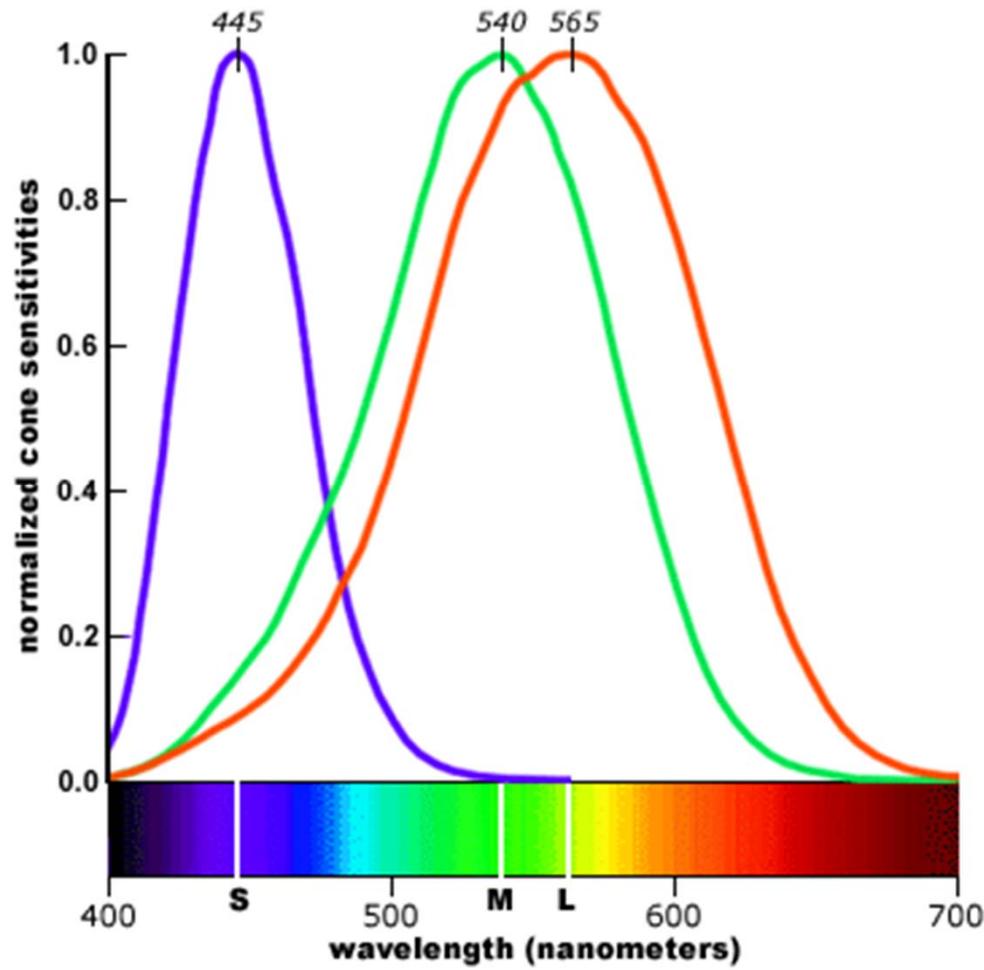
Can differ among:

- Species
- Individuals
- Genders

Color Sensing Chain



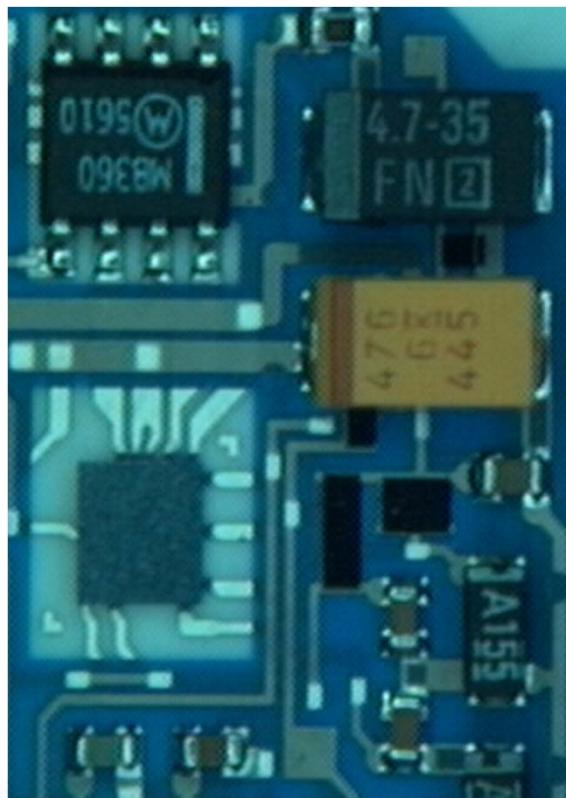
Human “RGB” Color Filters



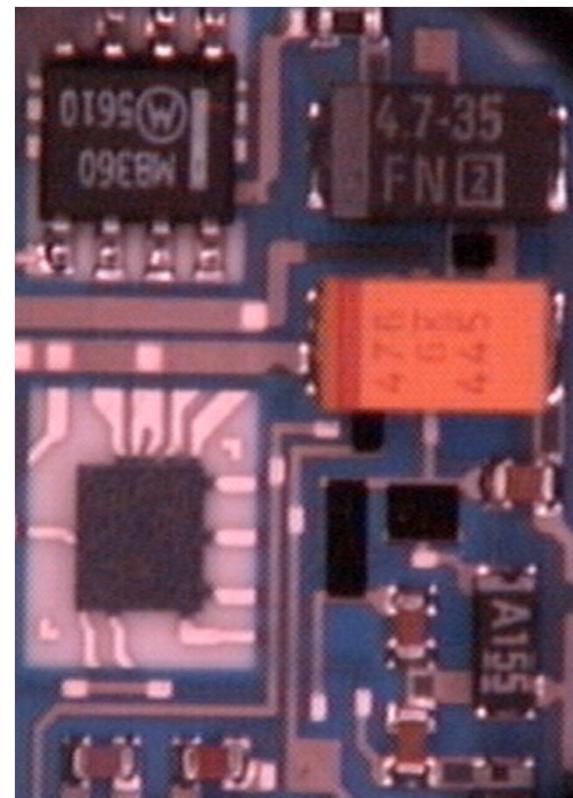
Can differ among:
• Individuals

Source Spectrum Effects

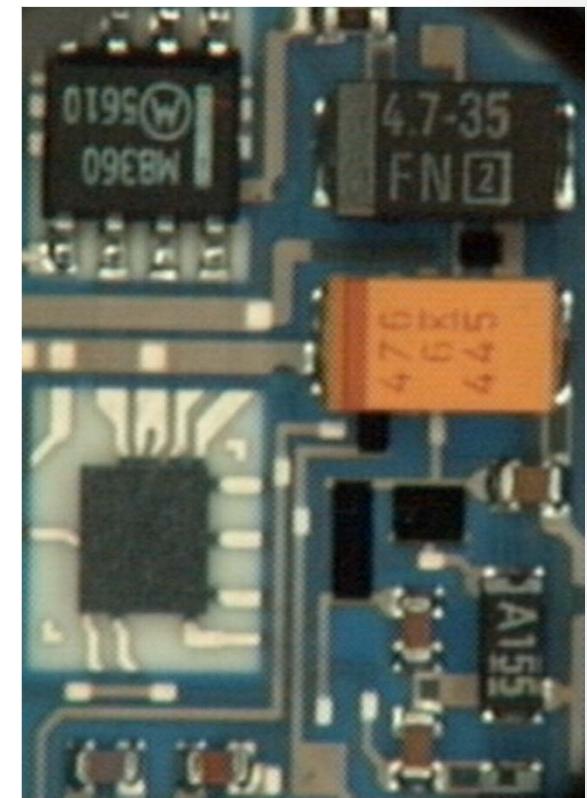
Fluorescent



Tungsten Halogen



Color Balanced



Courtesy Visual*Sense*Systems

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Brief Oversimplified History

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Brief Oversimplified History

Hundreds of millions of years:

Creatures use color information to reduce uncertainty re food, shelter, mates, predators, etc.

Tens of thousands of years:

Humans use color to create art, dye fabrics.

Hundreds of years

Qualitative understanding for printing, painting and dyeing.

Last hundred years:

Quantification: for color matching, video display, video transmission.

Last few decades

Machine vision: uses video, borrows quantification from above.

Last Hundred Years

Color Quantification – 3 components

Color perception
matching:

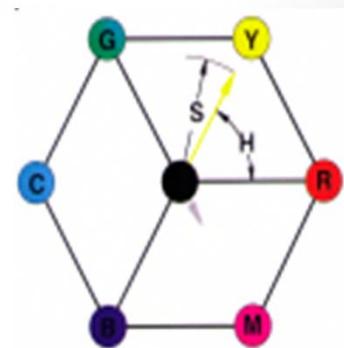
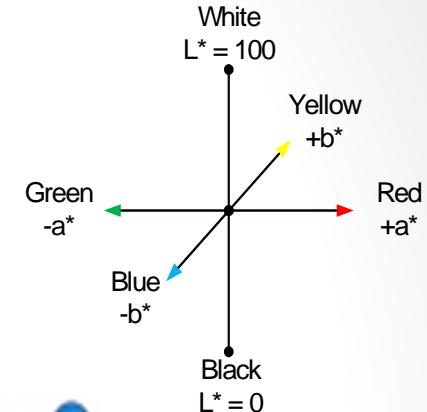
CIE, LAB,
CIELAB,
 $L^*a^*b^*$, ...

Color creation
-video displays:

RGB

Video transmission
encoding:

HSI, HSV,



Last few decades

Machine vision:

Gauging, shape, area based identification:

BW and gray scale, highest resolution, mature tools.

If necessary, filters to enhance color contrasts.

Hue-based segmentation for gray scale conversion:

Assumes single color items.

Hue is relatively independent of lighting intensity

Image using hue alone allows use of gray scale tools.



High-speed color measurement:

Assumes items should be perceived as a single specified color.

For perception specification L*a*b* coordinates best.

Requires great care for lighting uniformity and stability, camera stability.

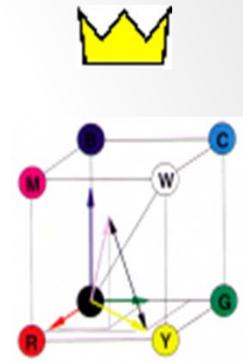
General (multi)color-based identification:

Typically time-consuming training, target-specific, threshold setting or “color picking”.

RGB coordinates best

Our experience shows that, contrary to conventional wisdom, RGB coordinates work best for general color based recognition based on complex color distributions.

- L*a*b* and HSI require extra computational load while offering no advantage for multiple colored objects.
- HSI offers best color resolution for vivid (saturated) colors but very poor resolution for unsaturated colors near the black-white axis.



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Color-Based Identification: Classification

Which of several specified
classes does item most likely
belong to?

More information in color images than gray-scale images



Courtesy Marathon Sports, Inc.

How many classes can we distinguish based on color alone?

For m -color objects, if we can distinguish n colors then we can distinguish

$$\frac{n!}{m!(n-m)!}$$

classes.

How many classes can we distinguish
based on color alone?

$$\frac{n!}{m!(n-m)!}$$

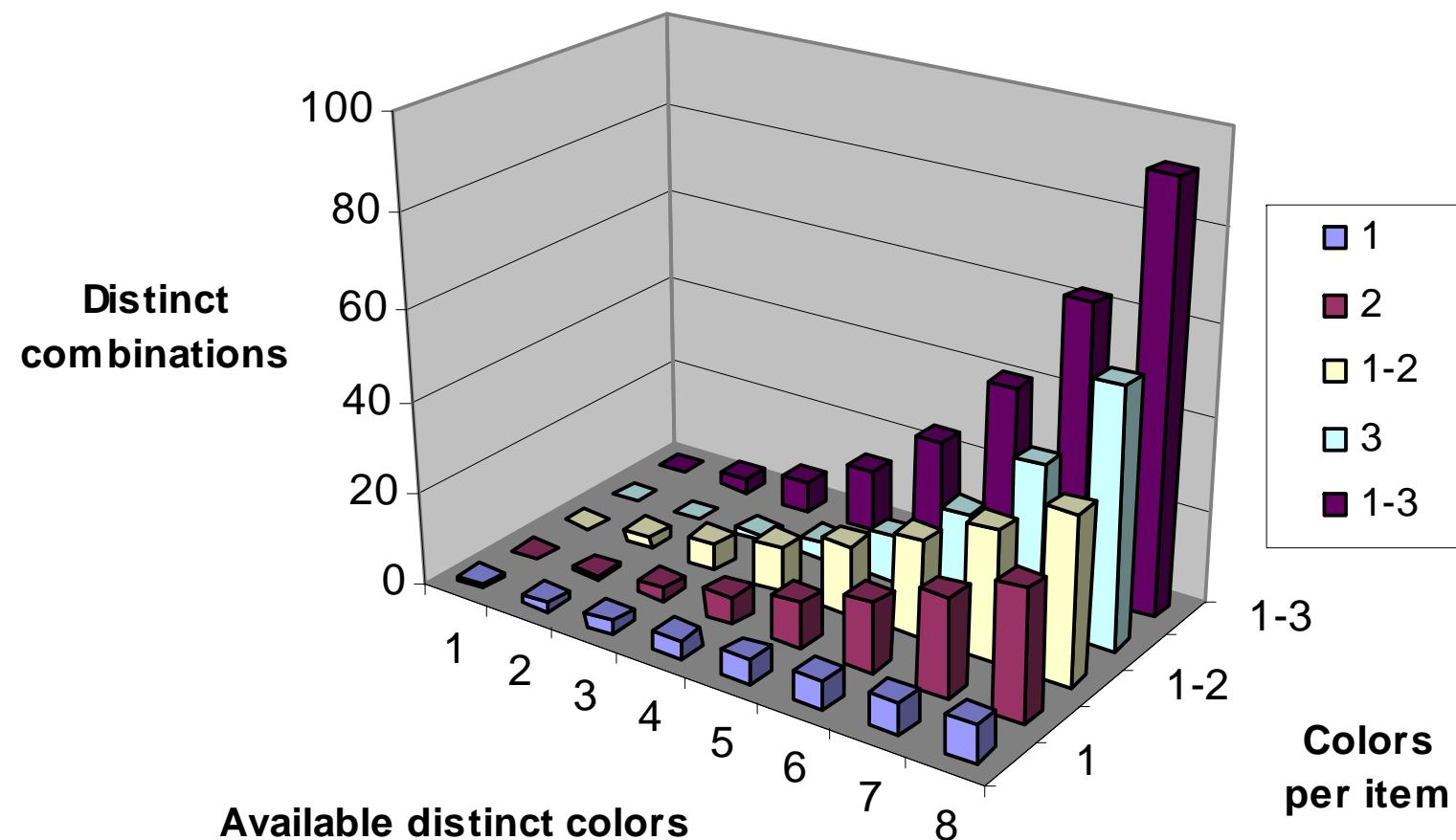
For single color objects, if we can distinguish n colors then we can distinguish n classes.

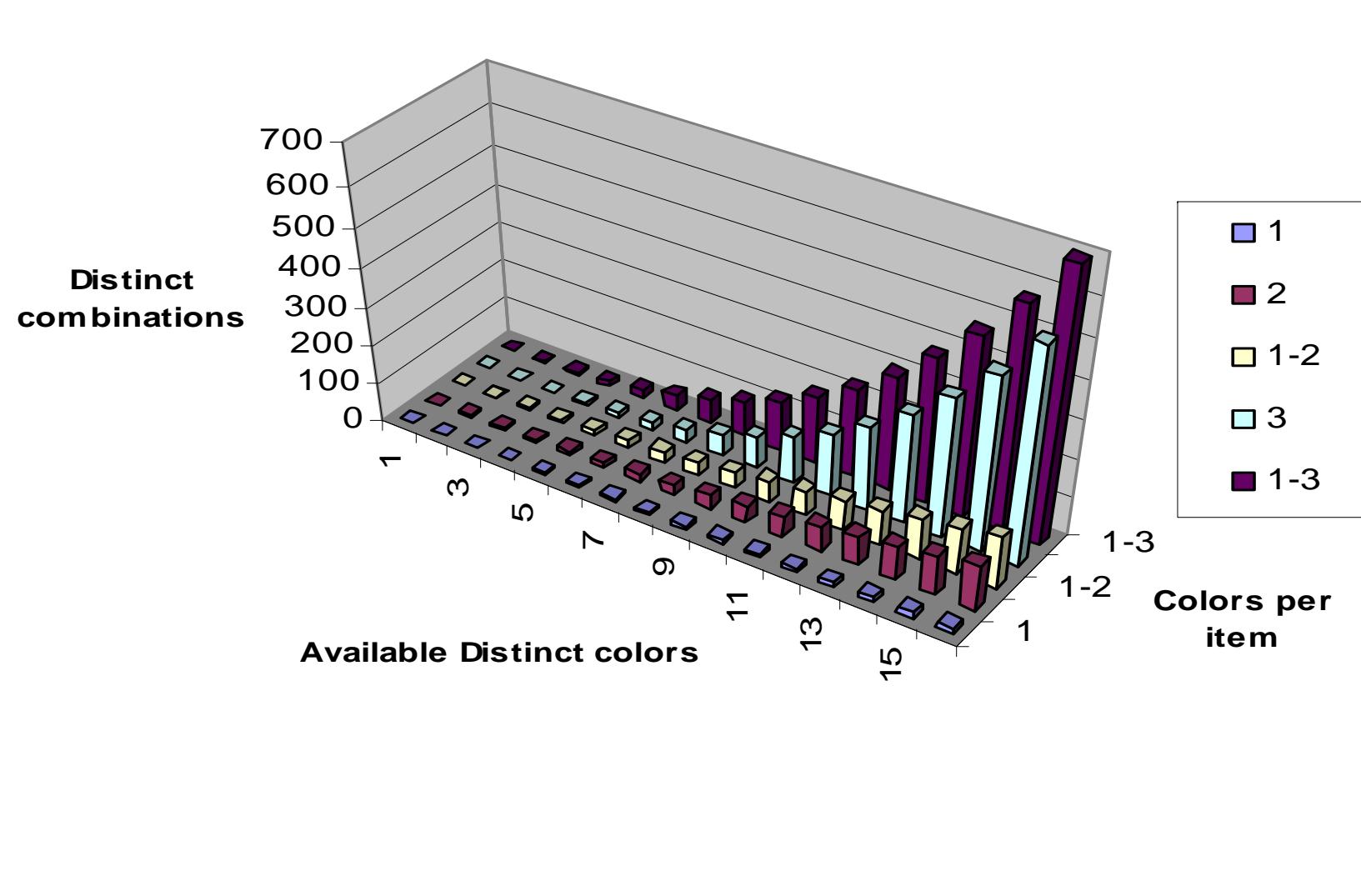
e.g. if we can distinguish 8 colors we can
distinguish 8 classes.

How many classes can we distinguish based on color alone?

$$\frac{n!}{m!(n-m)!}$$

For two-color objects, if we can distinguish n colors then we can distinguish $n(n-1)/2!$ classes.
e.g. if we can distinguish only 8 colors we can distinguish 28 classes.





Determining most likely class ...



should be simple and very reliable



general purpose with few controls to tweak.

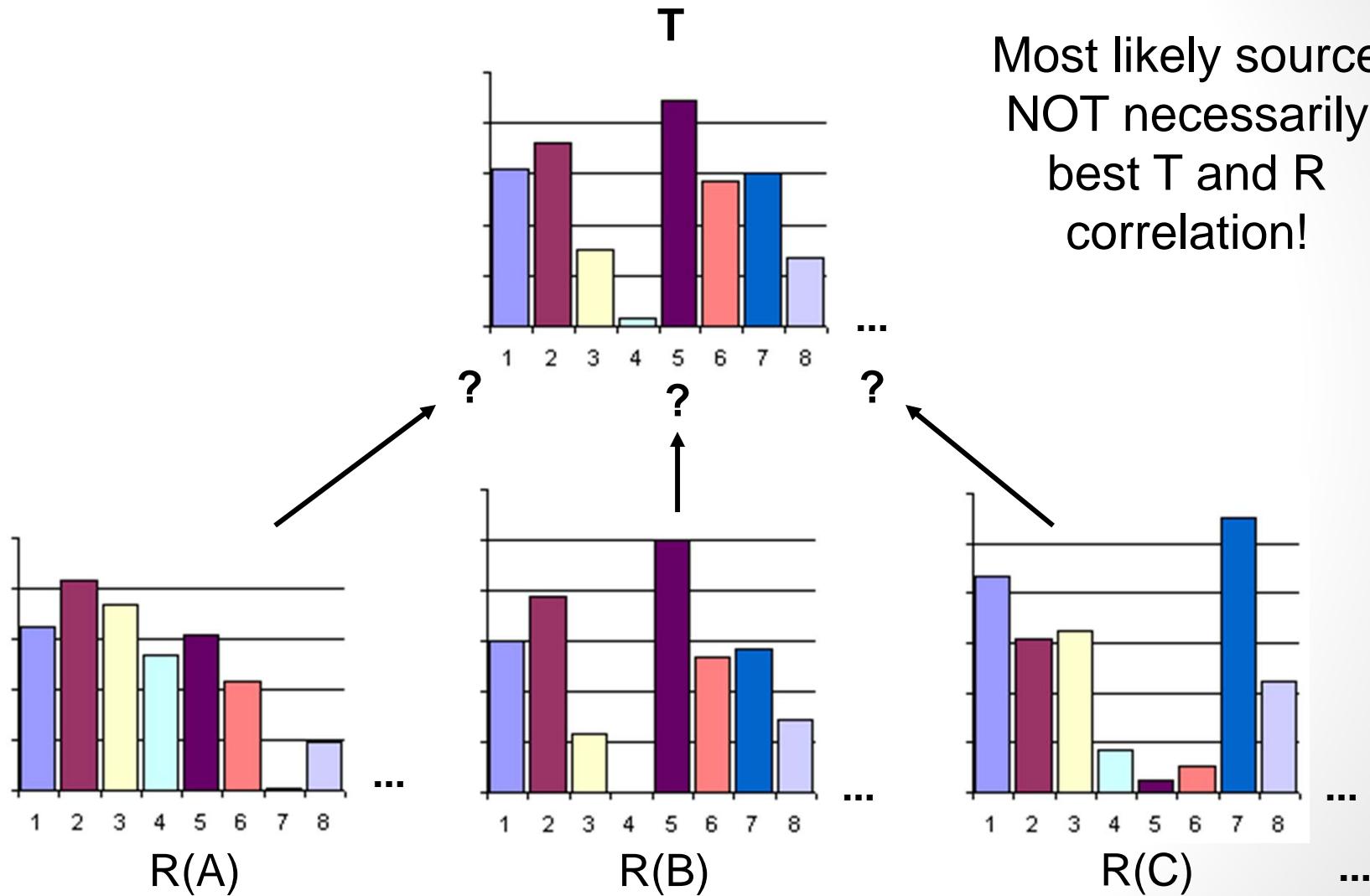
"Most likely" implies probability

- Quantity of interest is not color difference, it's the probability that the "correct" class has been chosen.
- Requires a classification method that will make this probability as high as possible.
- This puts tight restrictions on the overall method used, but few on the actual hardware/software implementation.

Probability distributions req'd

- To make most likely selection based on colors requires probability distributions covering all colors for each class of interest.
- This generally means building representative “3-D” reference color histograms for each class in which each color value is assigned to a unique cell.
- If the histograms for the different classes differ from one another, then a test sample must be assigned to the class whose reference distribution is most likely to have generated it.

Determine most likely source



Most likely source
NOT necessarily
best T and R
correlation!

While information theory can be an aid in developing commercial software,

... it is not necessary for understanding the principles.

Prob. of test T given source A

$$P(T | A) = e^{-N_T \sum_i p_{iT} \ln(p_{iA})}$$

N_T total number of independent samples in the test region T.

p_{iT} probability of a color associated with cell i for the test histogram.

p_{iA} probability of color associated with cell i for the reference histogram for class A.

Relative source prob. given test

$$\frac{P(A | T)}{P(B | T)} = e^{N_T \sum_i p_{iT} (\ln(p_{iA}) - \ln(p_{iB}))}$$

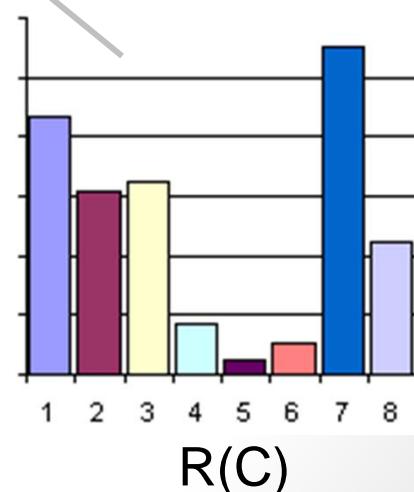
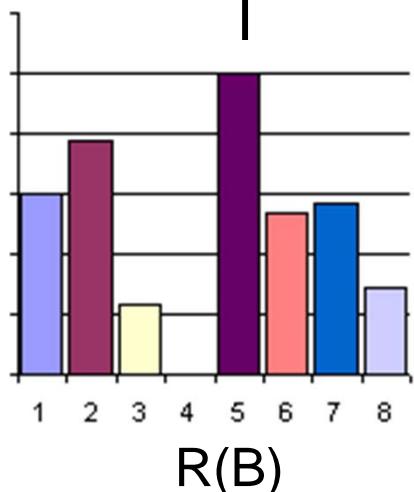
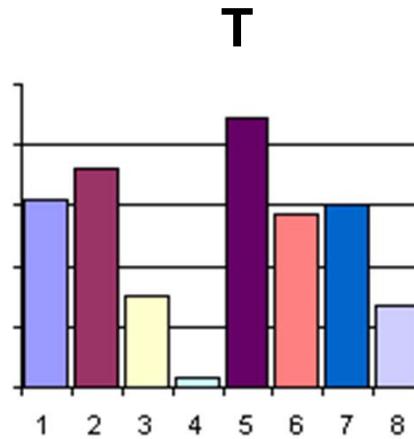
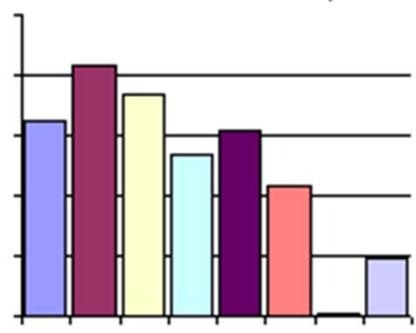
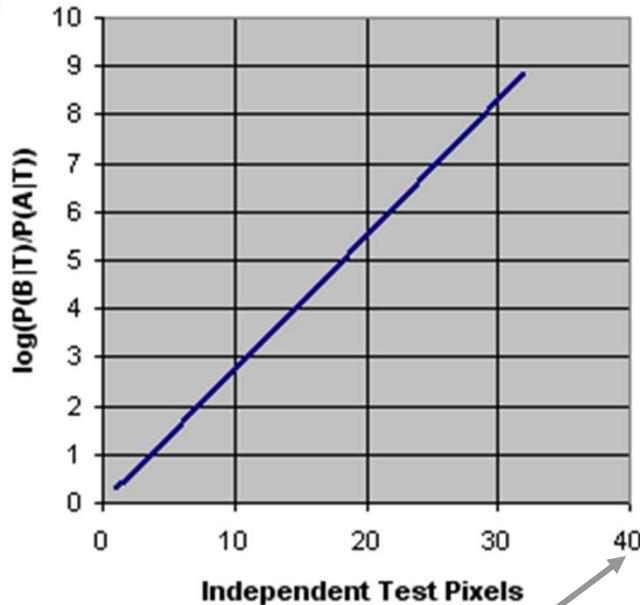
Even though $P(T | A)$ and $P(T | B)$ may each be very small the above ratio can be very large. If so, the likelihood that the test data set T belongs to class A rather than class B is very large.

Relative source probabilities

$$\frac{P(A | T)}{P(B | T)} = e^{N_T \sum_i p_{iT} (\ln(p_{iA}) - \ln(p_{iB}))}$$

When the probabilities of each color are known for each of a pair of possible classes, the likelihood of the correct class being selected increases exponentially with number of independent samples (pixels) in the histogram for the test region.

Relative source probability



Relative source probabilities

$$\frac{P(A | T)}{P(B | T)} = e^{N_T \sum_i p_{iT} (\ln(p_{iA}) - \ln(p_{iB}))}$$

- Puts no constraints on how histograms are constructed other than good separation of classes will occur only when histograms for different classes differ significantly.
- Therefore puts no constraints on color coordinate systems used for histogram building.

HSI offers no advantage!

$$\frac{P(A | T)}{P(B | T)} = e^{N_T \sum_i p_{iT} (\ln(p_{iA}) - \ln(p_{iB}))}$$

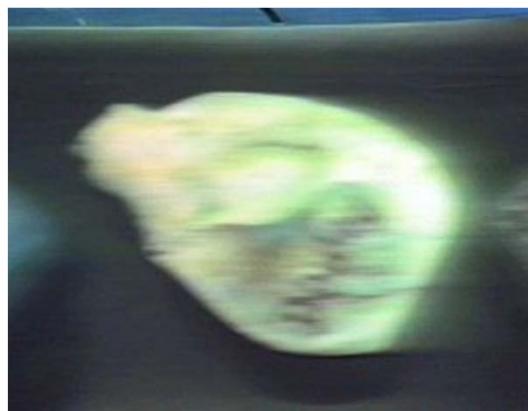
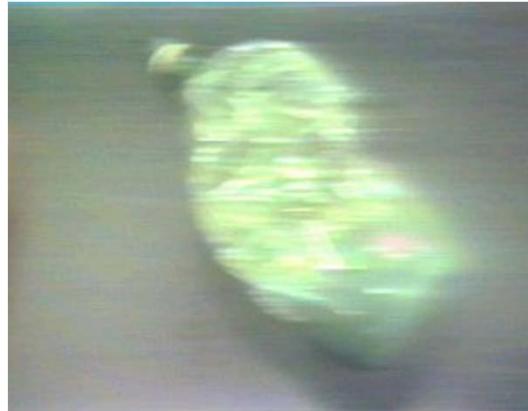
- With no constraints on coordinate systems used for histogram building. Advantage to coordinate systems that are easiest to implement and distribute colors likely to be encountered reasonably uniformly over available space.
- In contrast to conventional wisdom for other methods, our experience has never shown HSI or other coordinate system to offer any advantage over RGB.

Additional advantages:

This probability approach has several advantages:

- Histograms can be easily and quickly constructed.
- Histogram building can be easily automated.
- No need to pick individual colors or set thresholds.
- RGB color space usually best.
- Seems to closely mimic human results.

Sorting class examples



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Characterized by need for:



Maximum likelihood identification

Speed in:

- **Training/Rerunning
(as conditions change)**
- **Testing
(to verify training accuracy)**
- **Processing**

Automated procedures:



- **Training/Rerunning:**

For each class, system prompts operator to send training bottles to build reference histograms.

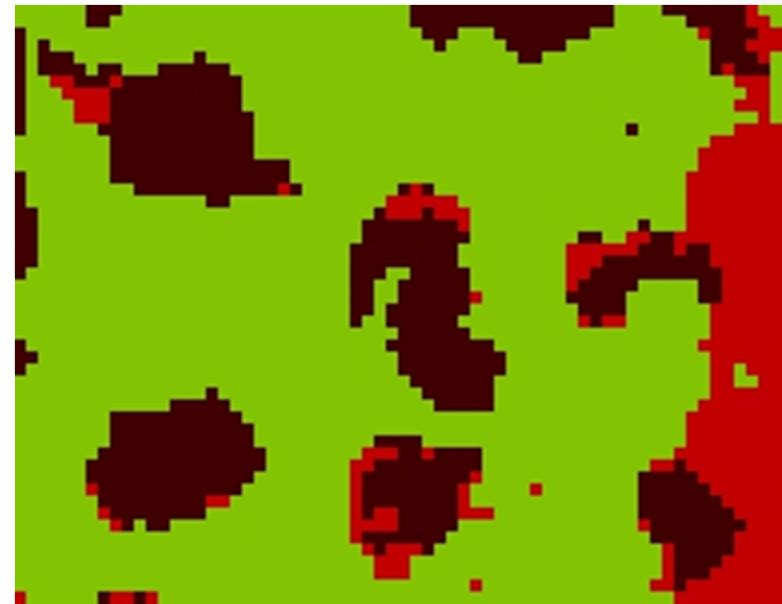
- **Testing:**

System prompts operator to send one bottle of each class; allows processing only if one arrives in each bin.

- **Processing:**

Starts automatically after test passed.

Area Mapping



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What's been shown

- Complex multicolor items contain potentially far more identification information than single color items.
- Harvesting this identification information is straightforward. One need only:
 - Construct reference histograms.
 - See which reference histogram is most likely to have generated test data. (NOT which reference histogram most closely matches test histogram or which reference histogram correlates best with test histogram.)
- In general HSI and other coordinate systems offer no advantage over RGB.
- Probability method is quick and easy to train and test.
- The probability method produces robust maximum likelihood results whose reliability increases exponentially with the number of independent samples and the difference between reference histograms.

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What's the catch?

Academic some years ago:

“That’s nothing new. We’ve tried it and it doesn’t work.”

We understand –practical implementation presents quite a few obstacles. It took years of effort by several experienced researchers and engineers to overcome these and actually make it work. Among the obstacles:

- Algorithms to efficiently handle test region sizes varying from one pixel to millions of pixels.
- How to handle color distribution differences varying from barely perceptible to extreme.
- Measures to quickly predict classification success from training results.
- ~100K lines of debugged and documented code.

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Color-Based Identification: Anomaly Detection

Does item fall within expectations
for specified class?

Anomaly Detection



Only one training class

A Measure of Anomalousness

Uses only one reference histogram. The quantity

$$-\sum_i (p_{iT} - p_{iR}) \ln(p_{iR})$$

is similar to the exponent term in the classification probability equations.

If this quantity:

≤ 0 test color distribution falls “inside” reference
 > 0 “outside” “

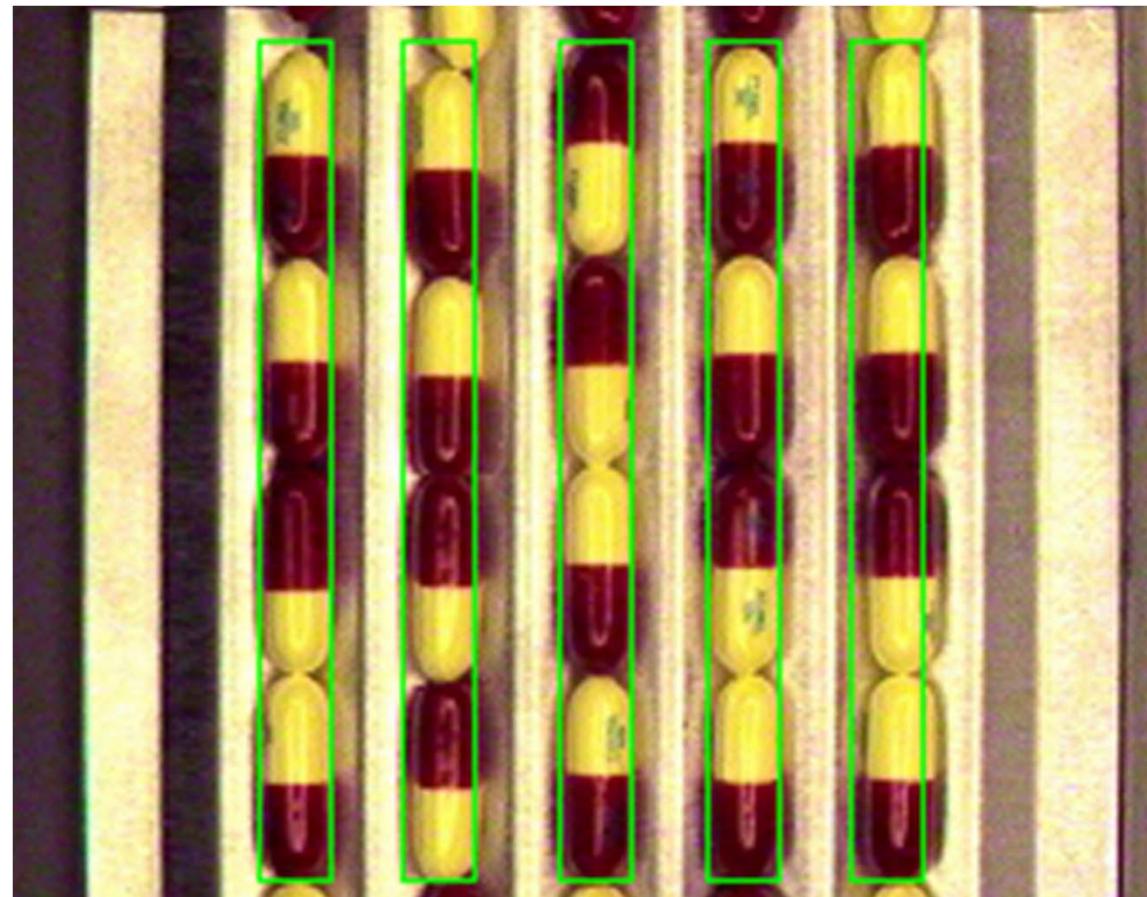
Anomaly Detection

Issues:

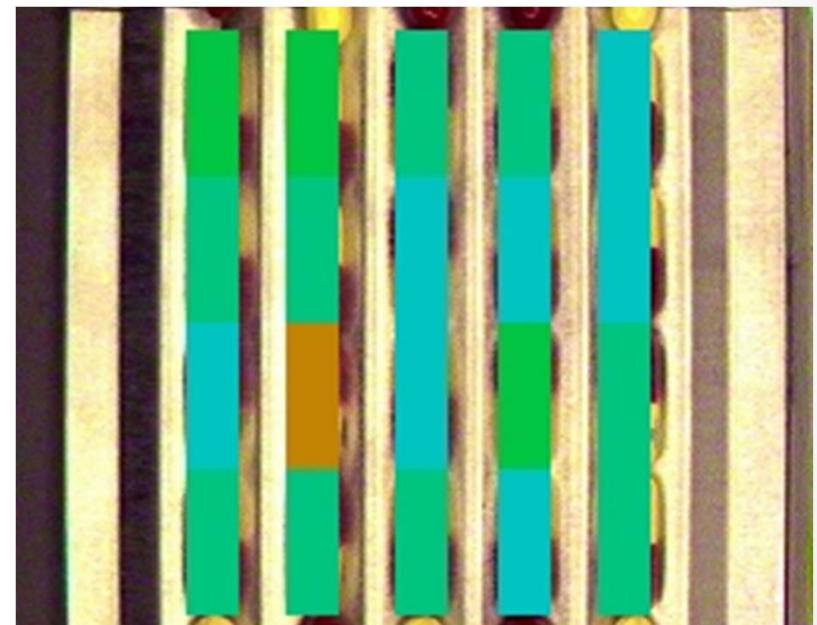
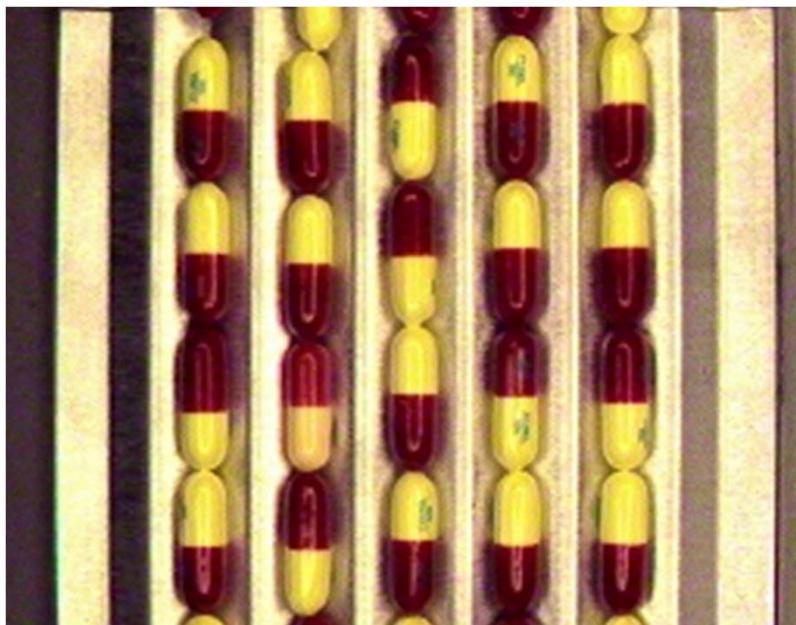
- Multiple colors
- Glints
- Shadows
- Printing (or not)
- Random orientation



Training Regions



Anomalousness



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The Future:

?

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Some source links

Color perception	http://www.handprint.com/HP/WCL/color1.html
HSI, HSV, etc. color spaces	http://en.wikipedia.org/wiki/HSL_and_HSV
$L^*a^*b^*$ color space	http://en.wikipedia.org/wiki/Lab_color_space

WAY-2C

Robert K. McConnell, PhD

President

WAY-2C Color Machine Vision

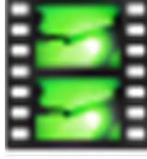
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Video Links

Bottle sorting	
Capsule anomaly	
Pizza	
Fuse block inspection	
Apple orchard	 