Computer Vision in Agriculture

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Past v. Present-day farmers

Figure: Past farmers

Figure: Present-day farmers

Rise of computers in agriculture

- Recently, computers and peripheral devices are readily available
  1. High computational power and sensors
  2. Low cost
- Increasing demand for various foods as population grows
  - Both quantity and quality
- Manual labour is insufficient for the task
  - Repetitive work, prone to mistakes

Consequences

Computers come into play

- Managing resources on large scale farms
  - Vegetation
  - Livestock
  - etc.
- Optimal food composition and ingredients
- Optimal feeding and milking times
- Using GPS guided tractors
- Not to mention genetic engineering...
- Last but not least: Computer Vision

Figure: Devices in modern farming

Computer Vision in Agriculture

- Monitoring product quality
- Classification and sorting
  - Crops
  - But also ready made meals

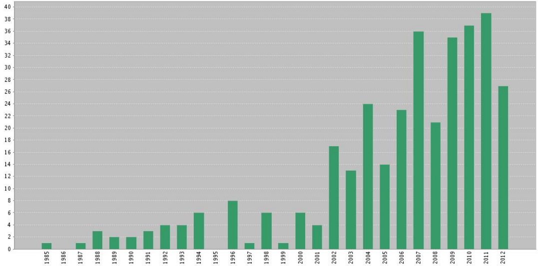


Figure: Increasing amount of publications in the last decade[1]

[1] Graph generated by Web of Knowledge

Computer Vision in Agriculture

In many aspects - ideal for computer vision

- Required methods
  - Segmentation
  - Classification
  - Edge detection
  - Feature extraction
  - Texture recognition
- Adjustable environment
  - Lighting
  - Amount and type of targets
  - Background
  - Movement
  - Equipment
  - Evaluation and training data

Automatic inspection process

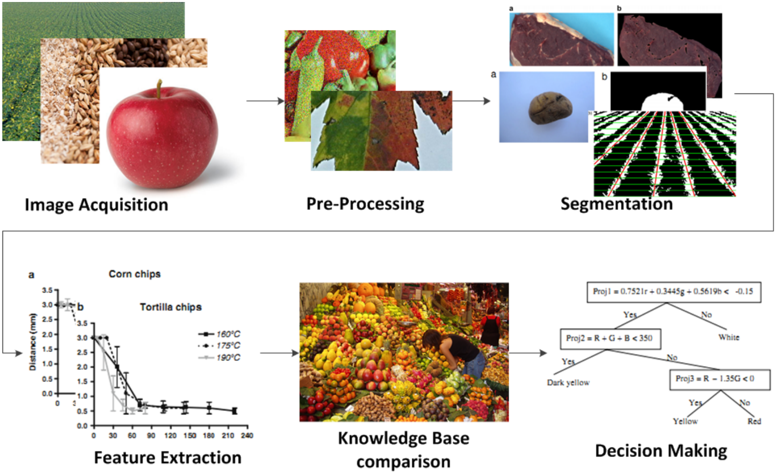


Figure: Processing diagram

Vegetables

Desired functions:

- Defect analysis
- Size, shape, color

1. Crops
    - Minimizing effects of pesticides
    - Detecting composition of a specific area
        - How much is weed, how much is crops?
2. Potatoes
3. Grains
    - Cereals, wheat

Fruits

- Various types of fruit
  - Apple, tomato, orange, olive, mango, pomegranate

Figure: Fruits

Other products

Meat and fish

- Color and texture indicate quality and degradation
  - Pork, ham
  - Beef
  - Fish

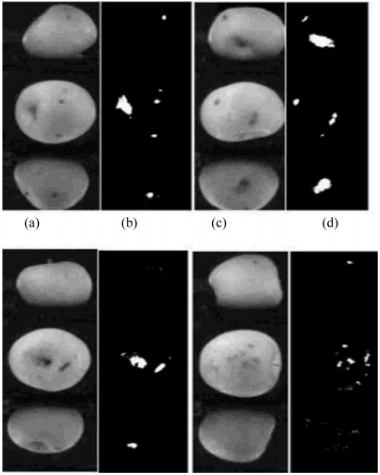
Industrialized products

- Potato chips
- Pizza
- Wine
- Ready meals

Fruits

Quick survey of papers

Apples - 2002, China. NN with fractals, yielding 93% success rate on 40 apples.



(a) (b) (c) (d)

(e) (f) (g) (h)

Fruits

Quick survey of papers

Citrus - 2007, Spain. Segmentation by incrementally growing patches, yielding 95% success rate on 635 fruits.

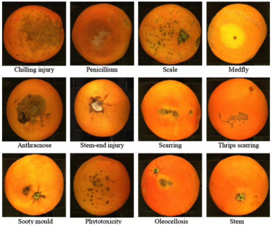


Figure: Defective oranges

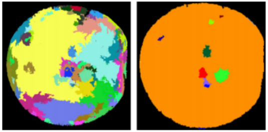


Figure: Orange segmentation

Fruits

Quick survey of papers

Olives - 2007, Spain. LDA by statistical features, yielding 90% success rate on most of 260 olives.

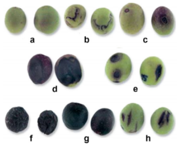


Figure: Defective olives

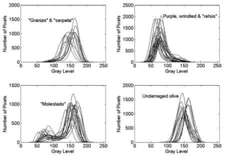
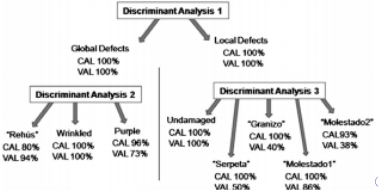


Figure: R-G histograms



Fruits

Quick survey of papers

Strawberries - 2009, China. K-means, yielding shape class accuracy of over 90% on 50 strawberries.

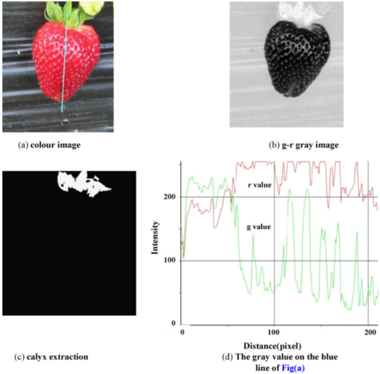


Figure: Strawberry analysis

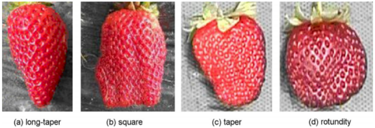


Figure: Strawberry shapes

Example: Potato inspection

Fourth most important crop, with an annual consumption rate increase of 4.5%. Requirements:

- Defect detection
- Size sorting
- Automation

Figure: Potatoes

Example: Potato inspection

Requirements:

- Defect detection
- Size sorting
- Automation

Methods:

- Machine Learning - SVM
- Color analysis
- Two-step method:
  1. Segmentation
  2. Defect classification

Example: Potato inspection

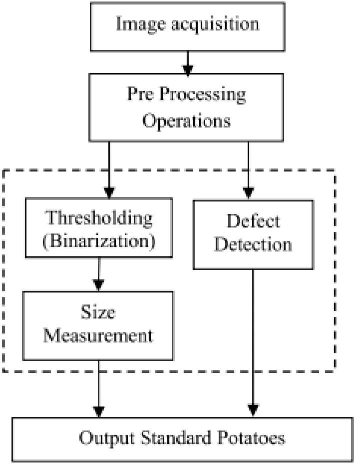


Figure: System diagram

Example: Potato inspection

Process details

Image acquisition

- 50 bags of potatoes were used
- 500 Jpeg images of size 224×168

Pre-Processing

- Contrast enhancement
- Thresholding using Otsu's method
- Filling and closing

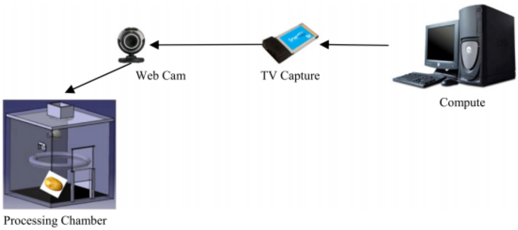


Figure: Image acquisition system

Example: Potato inspection

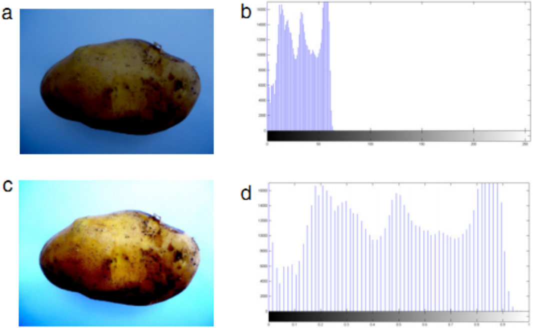


Figure: Contrast enhancement

Figure: Filling and closing

Example: Potato inspection

Process details

Size sorting

1. Using edge detection techniques to find the maximal and minimal diameters
2. Comparing the diameters and diameter ratio to US Agriculture dept. standards
3. Classification of misshapen or otherwise unacceptable potatoes.

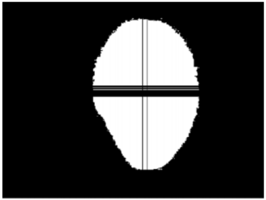


Figure: Potato diameter

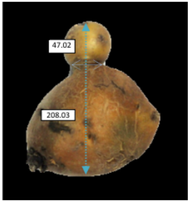


Figure: A misshapen potato

Example: Potato inspection

Process details

Defect detection

- Using supervised classifiers
  - SVM - SMO based
  - KNN
  - MLP - Multi layer perceptrons
- Potato colors exploited to classify defects

Example: Potato inspection

Results

Table 1
Classification comparison of performance in the presented methods.

	Method					
	Knn	MLP	SVM-linear kernel	SVM-poly nominal kernel	SVM-quadratic kernel	***SVM-SMO based***
CDR (%)	91.25	95	95	95	95	***95***
FAR (%)	6	2	3	3	3	***4***
FRR (%)	2.75	3	2	2	2	***1***

Figure: Classification result

Example: Potato inspection

Paper evaluation

The good

- ✓ The authors provided background and previous work
- ✓ Setup and process mostly described
- ✓ Numerous methods for classifications are presented

The bad

- × Portions of the paper are badly written
- × Lacking a section of future directions
- × References to entire books instead of a specific chapter or method

The ugly

Figure: Defective potato

Example: Beef quality from color and texture

Background

Prediction of beef eating quality from colour, marbling and wavelet texture features - Jackman, P. et al. (2008)

- Prediction of platability is required for meat products
- The quality of beef can be determined in several methods:
  1. Trained experts can be costly and subjective
  2. Using a meat sample for predicting a whole carcass or batch
  3. Consumer panel
- A fast, non-invasive cheap method for evaluating will be beneficial.
  - Computer vision is a possibility.

Example: Beef quality from color and texture

Analysis methods

Methods of evaluation

- Coloring of samples
- Marbling histogram and other statistics
- Proposed method: Feature extraction of textures on beef using Wavelets
  - Wavelets have been used for feature extraction in other fields

Figure: Steak

Example: Beef quality from color and texture

Materials

Sample preparation

- Numerous steaks were cut from 32 heifers (female calfs).
  - Two steaks for computer vision
  - One for sensory panel at 14 days
  - One for texture profile analysis
  - Four for WBS analysis at 2, 7, 14 and 21 days
  - The above set was repeated for each carcass

Example: Beef quality from color and texture

Materials

- After respective ageing, images were acquired
  - Special care in order to decrease chance of reflection and increase color detection
- HSI space was used for texture extraction

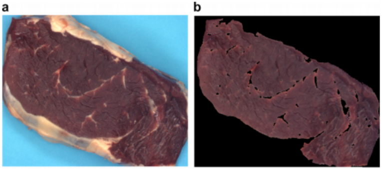


Figure: Steak acquisition

Example: Beef quality from color and texture

Data processing

Initial data consisted of:

- RGB components were calculated for color features
- Histograms of fat portions for marbling
- Texture features calculated via 6 wavelet types
    - Biorthogonal, Coiflet, Daubechies, Symlets and more
    - Values extracted and normalized by standard deviation

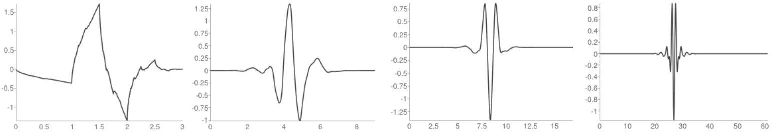


Figure: Wavelet functions ψ

Example: Beef quality from color and texture

Data processing

Prediction method performed via a regression model

- Several tests were evaluated - hardness, tenderness, acceptibility, juiciness and flavour.

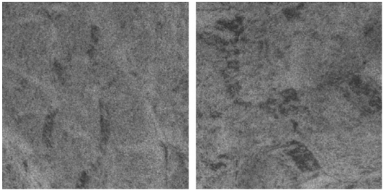


Figure: Steak texture

Example: Beef quality from color and texture

Results

- Only few wavelets produced satisfactory results
- Squared terms were added to improve the regression model

Preliminary results of $r^2 = 0.72$ for Symlet.
Manual improvements were implemented:

- Model order reduction
- Resulted in a simpler and more stable model

Example: Beef quality from color and texture

Results

After introducing above modifications, improvement was apparent.

- A very high $r^2 = 0.88$ for the overall acceptance test, similar to the other benchmarks.
- A result of $r^2 = 0.71$ for tenderness was not very high, but shown improvement relative to previous works yielding r^2 of 0.62 and 0.58.

	Accept	Tender	Classic tender	Hard	Juice	Flav
r^2	0.88	0.78	0.71	0.48	0.60	0.65
RMSEP	1.693	4.575	4.933	31.73	4.934	2.048
stdev	4.86	9.12	9.12	40.70	7.46	3.41
RRR	0.35	0.50	0.54	0.78	0.66	0.60
components	18	20	11	8	14	7

Figure: Regression results

Example: Beef quality from color and texture

Results

Table shows importance of wavelet in regression

Accept	Tender	Classic Tender	Hard	Juice	Flav
d7-2	h5-2	Correlation2	d5-2	v2-2	h2-2
v5-3	h6-2	1st IM3	h5-3	d8-2	d5-2
v9-3	h7-2	Contrast4	d9-4	h4-3	d6-2
d5-3	d7-2	SumSq4	v9-5	h7-3	ap3-2
d8-3	h7-3	2nd IM10	d6-6	h7-4	d8-3
v8-5	d8-3	MaxProb10	d8-6	h9-5	d9-3
h7-6	d9-3	IQR Run2	h6-7	v9-5	d6-4
h5-7	v8-4	Kurt Run4	h8-7	d9-5	h6-5
h9-7	v9-4	Kurt Run5	v9-7	h3-7	d6-5
v9-7	d6-5	IQR Run5	d7-7	d2-7	v9-6
d5-7	h4-6	Kurt Run7	ap9-7	Std red	h7-7
d7-7	h8-6	Kurt Run9	v6-8	Std green	Skew red
d8-7	h5-7	IQR Run9	d5-8	Std blue	Kurt red
h5-8	h7-7	Mean red	Std blue	Skew blue	Kurt green
v9-8	v6-7	Mean green	Skew red	Kurt red	IQR red
d6-8	d7-7	Mean blue	Kurt red	Kurt blue	IQR green
d8-8	h5-8	Std fat	Kurt green	IQR red	IQR blue
d9-8	v6-8			IQR blue	
Mean red	v8-8			Mean fat	
Skew green	Std blue			Std fat	
Skew blue	Skew green			Skew fat	
Mean fat	Skew blue			#dens	
	IQR green				
	Std Fat				
	Areadens				

Figure: Regression parameters

Example: Beef quality from color and texture

Paper evaluation

The good

- ✓ A new method for beef quality
- ✓ Improvement w.r.t previous methods
- ✓ Clear explanations
- ✓ Background and future directions are mentioned
- ✓ The results are presented objectively

The bad

- × The model lacks automation
- × No suggestions as to why only one wavelet works
- × Data not presented in a meaningful way

The ugly

- The fate of the 32 heifers is not mentioned

Summary

- Computer Vision is an emerging subject in precision farming and food inspection.
- The use of computers allows for increased efficiency with less manpower.
- Inspite of recent progress, the work is cut out for agricultural engineers.
- Many of the works are naïve.
- A good idea would be to get advice from experienced EE and CS in this area.

Summary

Thank you.

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