Apports de la couleur et des modèles de réflexion pour l'extraction et le suivi de primitives.

Contributions of colour and reflection models to extract and track features

Michèle Gouiffès

Cemagref, Unité TERE, équipe PAIC, Rennes
Laboratoire SIC, Université de Poitiers
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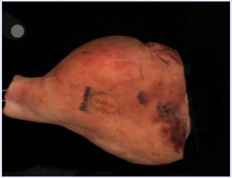
Context: robotic task

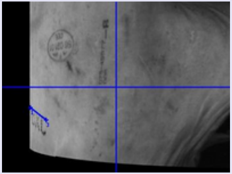
Feature extraction
an ink-jet marking

Motion of the camera in front of the window of interest: visual servoing

- selection of two points [*Collewet*02]
- selection of a window of interest [*Alhaj*04]

Final processings
characters recognition
[*Roue*04]





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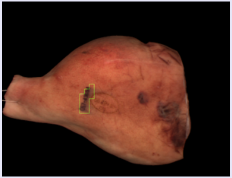

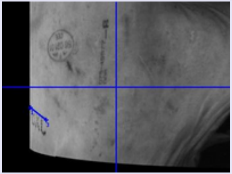

[*Collewet*02]: C. Collewet and F. Chaumette (2002). Positioning a camera with respect to planar object of unknown shape by coupling2-d visual servoing and 3-d estimations. *IEEE Trans. on Robotics and Automation* **18**(3), 322–333.

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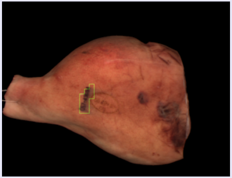

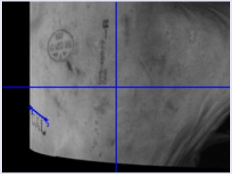

[*Alhaj*04]: Alhaj, A. (2004). *Apport de la vision dynamique en asservissement visuel, Thèse de doctorat*. Université de Rennes I, Cemagref Rennes.

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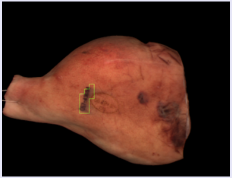

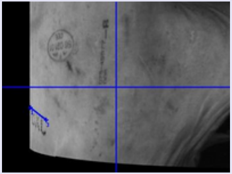

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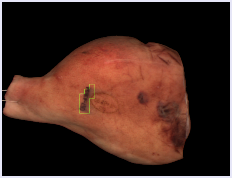

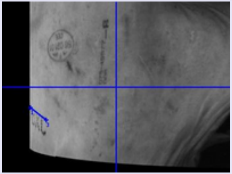

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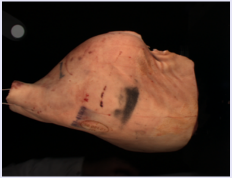
Detection of an ink-jet marking

- Variability of background colour
- Variability of marking appearence (varying ink concentration, transparency)
- Varying shape of the marking (flaw of the ink)
- Occurrence of other regions which colour $\simeq$ ink colour



Motion of the camera

Visual servoing: positionning of the camera in front of a natural and complex object.

- Natural scenes (agricultural applications): no structural features (edges, lines, corners) $\Rightarrow$
- Natural objects $\longrightarrow$ specular highlights
- Unstable lighting conditions, illumination variations

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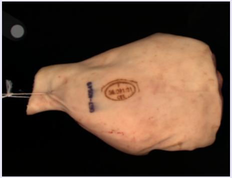

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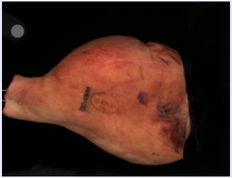

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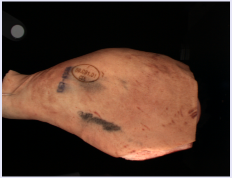

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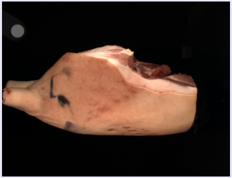

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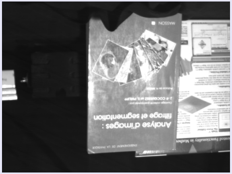

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Feature extraction

- Definition of colour attributes dedicated to ink transparency : invariant against variations of ink appearence
  - Ink concentration
  - Background colour
- Detection of an ink-jet marking by colour segmentation
- Application to the traceability control of meat products

Feature tracking (to improve camera motion)

- Modeling of illumination variations on small and large windows of interest
- Feature points tracking and textured areas robust against specular highligths and lighting changes in luminance images
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Outlines

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Transparency

Transparency

r = superimposition of a translucent filter of colour **b** on a background of colour **a** is [*Metelli*70]:

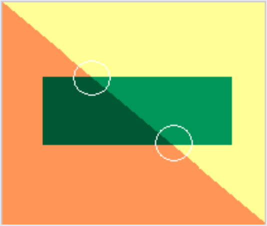
$$\mathbf{r} = \gamma\mathbf{b} + (1-\gamma)\mathbf{a} \qquad \gamma\text{: opacity}$$

Transparency in image processing

Detection of transparent filters partially covering several regions of images $\longrightarrow$ X junctions

Our context

- No X junction
- How to detect **r**:
  - whatever the ink opacity γ
  - whatever the background colour **a**



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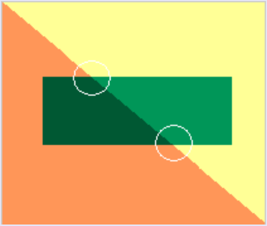

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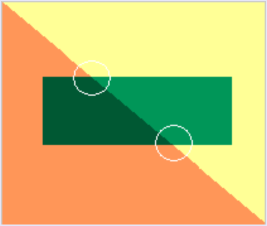

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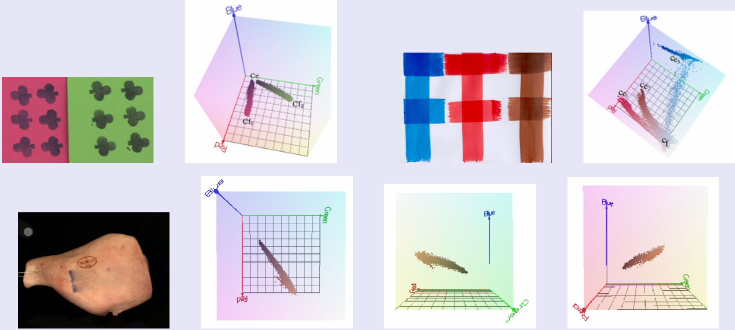
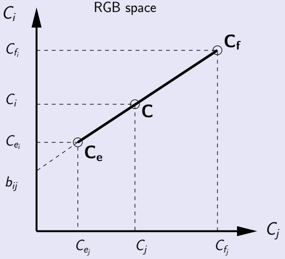
Representation of ink colours in RGB space



Example of colour distribution of ink marking in *RGB* space.

Definition of invariant attributes



Ink colour locus

$$C_i = a_{ij} C_j + b_{ij}, \quad C_i, C_j \in \{RGB\}, C_i \neq C_j \qquad (1)$$

C_{e_i}: colour of ink at maximum concentration in C_i component
C_{f_i}: colour of the background in C_i component

Distance to locus $\simeq$ membership to the region {ink-background}

Distance to ink locus in colorimetric plane $\{C_i C_j\}$

$$d_{ij} = |C_i(p) - (a_{ij} C_j(p) + b_{ij})| \qquad (2)$$

Euclidian distance d_e.

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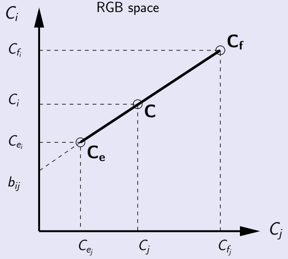

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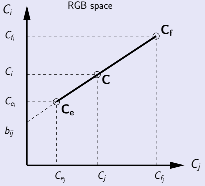

Global concentration quotient

$$Q = \frac{||\mathbf{C} - \mathbf{C_f}||}{||\mathbf{C_e} - \mathbf{C_f}||} \text{ for } \mathbf{C_e} \neq \mathbf{C_f} \tag{3}$$

Convergence model of transparency [*Metelli*70] :

$$\mathbf{C} = \gamma \mathbf{C_e} + (1 - \gamma)\mathbf{C_f}$$

From (??) $Q = \gamma \Rightarrow Q =$ opacity or concentration of ink.

Marginal concentration quotient

$$Q_{C_i} = \frac{C_i - C_{f_i}}{C_{e_i} - C_{f_i}} \text{ for } C_{e_i} \neq C_{f_i}$$

Transparency model $C_i = \lambda_i C_{e_i} + (1 - \lambda_i) C_{f_i} \Rightarrow Q_{C_i} = \gamma_i =$ opacity expressed on C_i

Theorically $\gamma_R = \gamma_G = \gamma_B = \gamma$.
Practically $\gamma_R \simeq \gamma_G \simeq \gamma_B \simeq \gamma$ because of noise, approximations of the model.

Q_{C_i} and Q almost independant of the colour background for a given ink.

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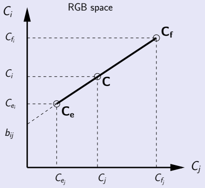

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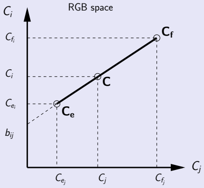

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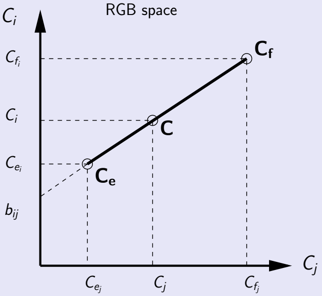

Ink concentration quotient ratios

$$\lambda^{C_i C_j} = \frac{Q_{C_i}}{Q_{C_j}} \quad \text{for } Q_{C_j} \neq 0 \qquad (4)$$

- Theorically $\gamma_R = \gamma_G = \gamma_B \Rightarrow Q_R = Q_G = Q_B$

$$\lambda^{C_i C_j} = 1 \quad \forall (C_i, C_j) \in [\mathbf{C_e}, \mathbf{C_f}]$$

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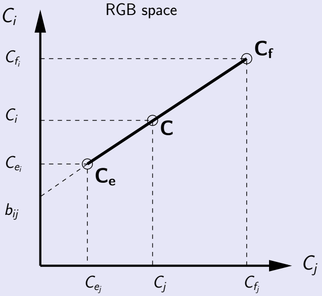

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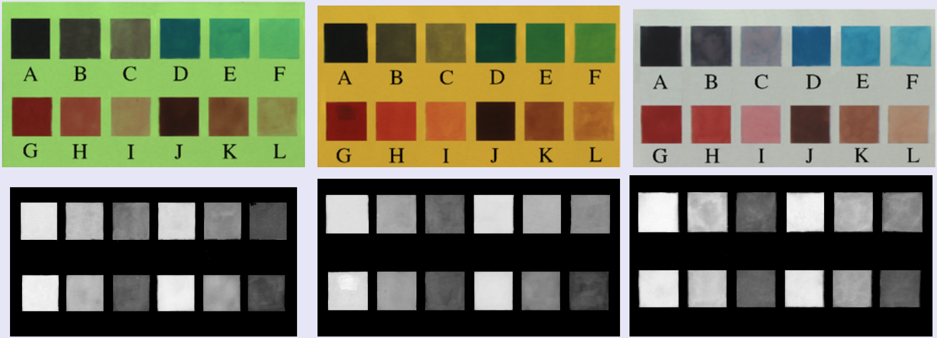
Test of invariance

Global concentration quotients

Three backgrounds: green, yellow and grey
Four food inks: black, blue, red and brown, three different concentrations



Images of the global concentration quotients

Test of invariance

Average of R, G, B and Q of three areas
on grey, yellow and green backgrounds

area C (Black ink)

background	R	G	B	Q
grey	0.4654	0.4657	0.5009	**0.4002**
yellow	0.4437	0.3891	0.1768	**0.4104**
green	0.3668	0.3811	0.2721	**0.4746**

area E (Blue ink)

background	R	G	B	Q
grey	0.1984	0.5260	0.6302	**0.7087**
yellow	0.1636	0.3858	0.1872	**0.7005**
green	0.2041	0.5624	0.3711	**0.6371**

area I (Red ink)

background	R	G	B	Q
grey	0.6888	0.4565	0.4659	**0.4006**
yellow	0.7488	0.3778	0.1684	**0.3457**
green	0.5670	0.4954	0.3068	**0.3789**

Q almost independant of the colour background.

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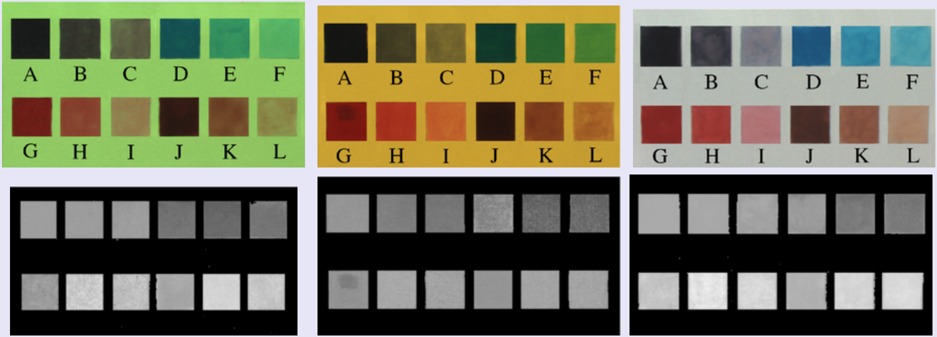
Three backgrounds: green, yellow and grey
Four food inks: black, blue, red and brown, three different concentrations



Images of the concentration quotients ratios

Test of invariance

Variability (in %) of λ and *RGB* coordinates of the ink printed on green, yellow and grey backgrounds

green background

	black	blue	brown	red
RGB	37.2	24.6	31.7	41.8
λ	**0.4**	**4.8**	**9.5**	**8.8**

yellow background

	black	blue	brown	red
RGB	38.7	25.0	32.7	38.3
λ	**8.7**	**8.9**	**7.4**	**4.2**

grey background

	black	blue	brown	red
RGB	42.1	20.8	33.0	31.8
λ	**1.8**	**10.0**	**4.6**	**7.7**

λ almost independant of the ink concentration.

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Outlines

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Colour segmentation

Definition

- Partition of the image in regions of spatially connected pixels
- Homogeneity of the regions colour
- Disconnection of each region

Our application

- Detection of one region, not colourimetrically homogeneous
- Pixels are not all connected
- Varying shape

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Colour segmentation methods

Edges

- Marginal approaches, derivatives on each plane
- Vectoriel Approaches, Hue gradient
- Snakes, active contours

Regions

- Region-growing
- Split and merge

Classification

- Clustering (k-means, ISODATA, fuzzy c-means)
- Histogram analysis (1D, 2D, 3D)
- Spatio-colorimetric approaches: connexity pyramid, homogram

Mixed approaches

- Region + edges
- Classification + region

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Proposed segmentation method

1. Computation of colour invariant attributes Q_{C_i}, λ, d_e
   - Background colour $\mathbf{C}_f$ obtained by histogram analysis
   - Ink colour by calibration
2. Classification: selection of candidate pixels, according to their invariant attributes (d, λ, Q_{C_i}).
3. Computation of a membership score according to the neighbouring pixels of the candidate pixels
4. Selection of a seed pixel (highest membership score) and selection of the marking region by region-growing

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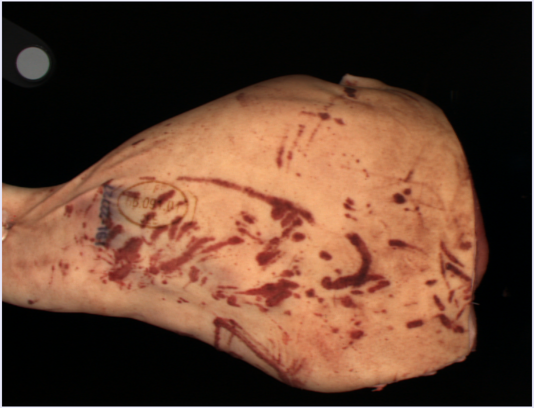
Initial image



RGB image

Computation
of invariant attributes

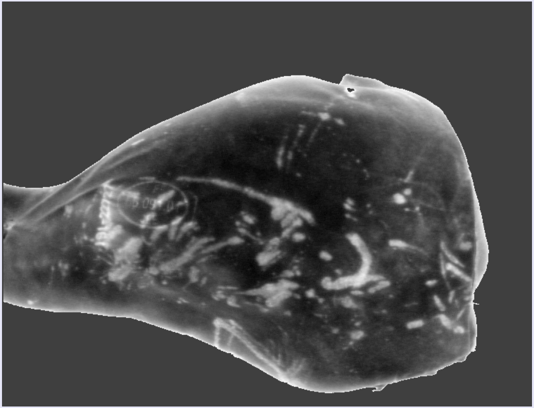
Selection
of candidate pixels

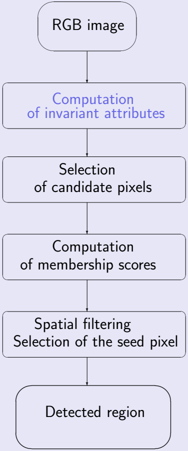
Computation
of membership scores

Spatial filtering
Selection of the seed pixel

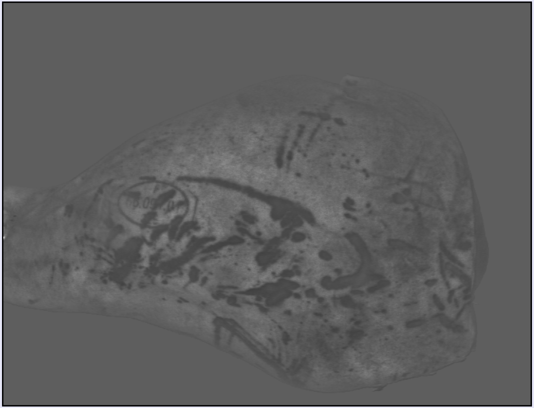
Detected region

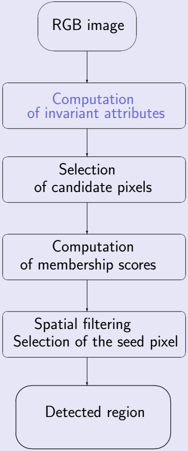
Concentration quotient on R



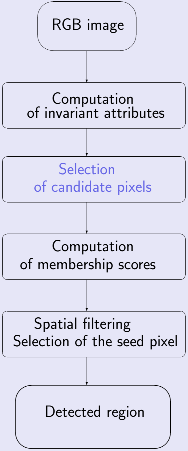


Concentration quotient ratios λ

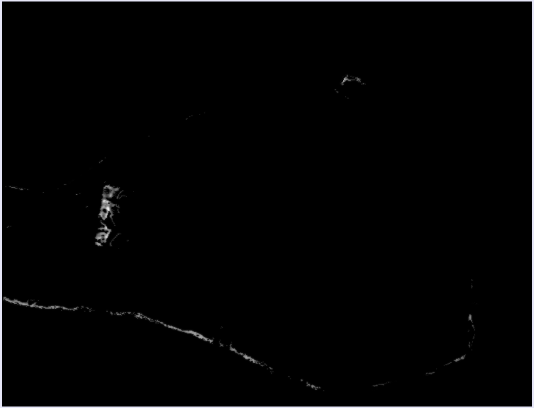


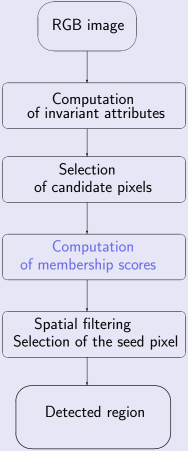


Selection of candidate pixels

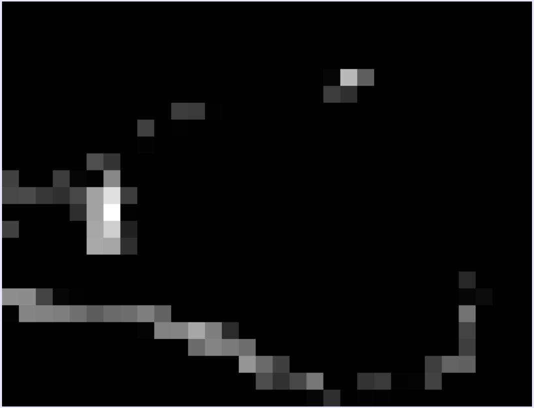


Computation of a membership score $I_{\mathcal{A}}$





Region growing



RGB image

Computation of invariant attributes

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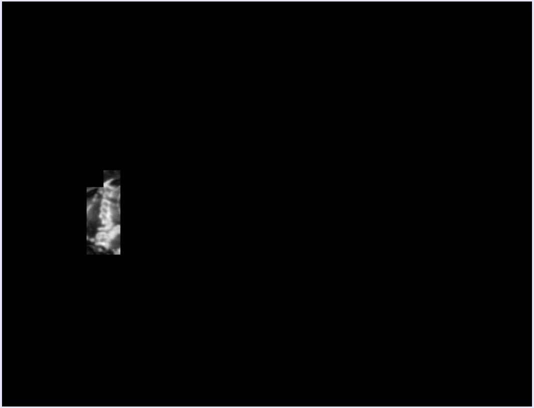
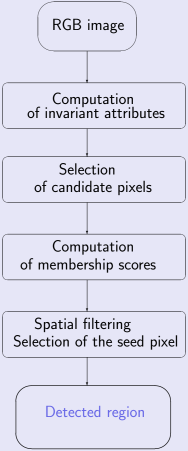
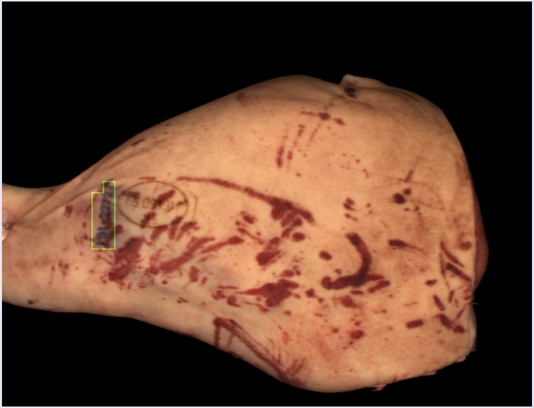
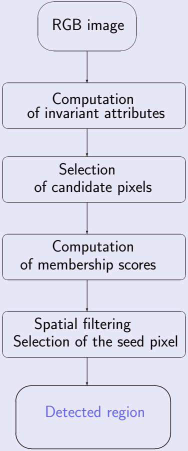




Result

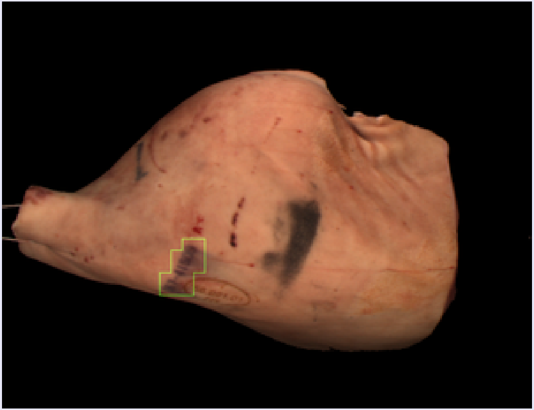



RGB image
Computation of invariant attributes
Selection of candidate pixels
Computation of membership scores
Spatial filtering
Selection of the seed pixel
Detected region

Outlines

Outlines

Examples of results



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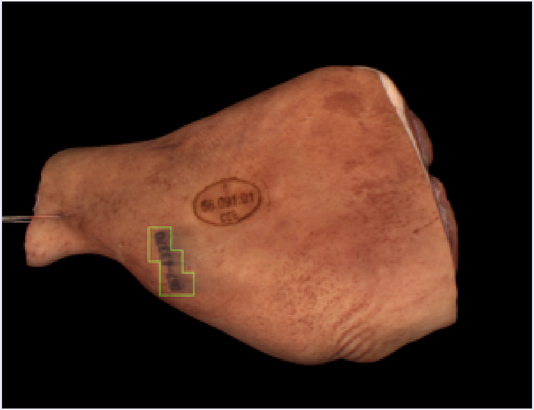

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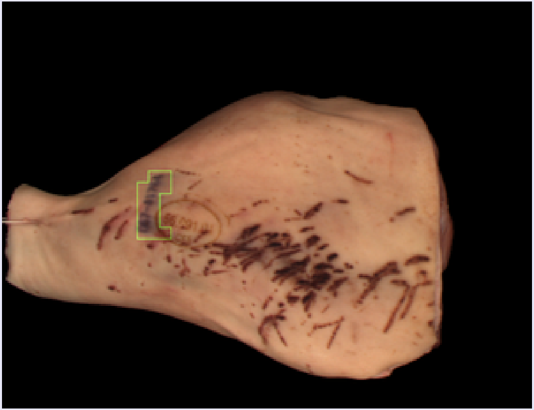

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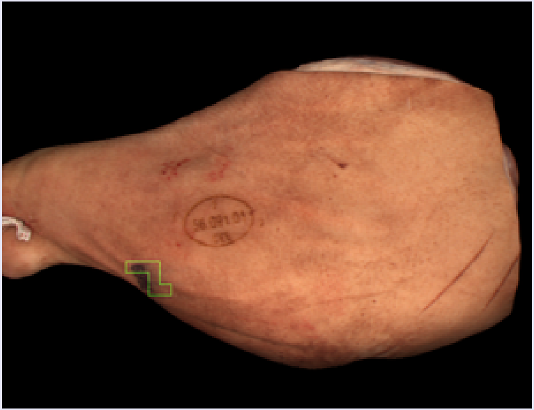

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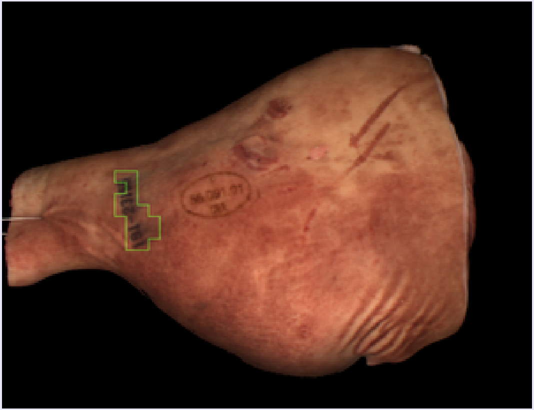

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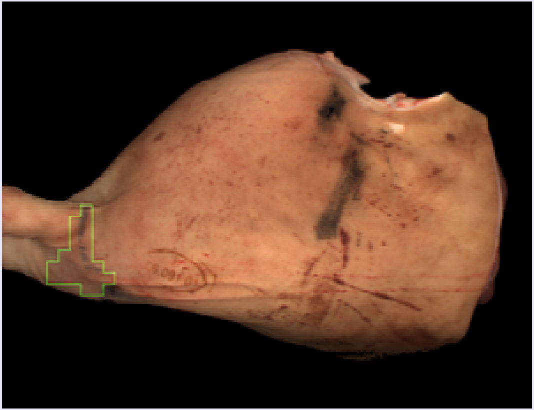

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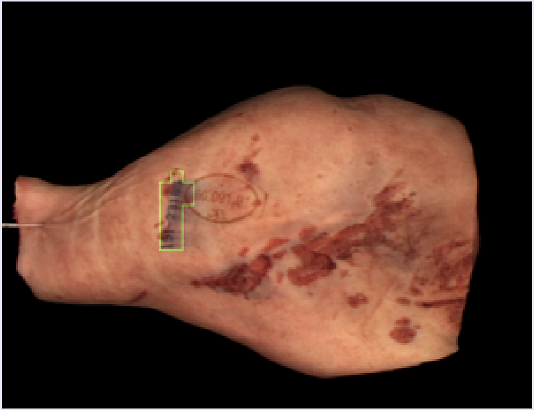

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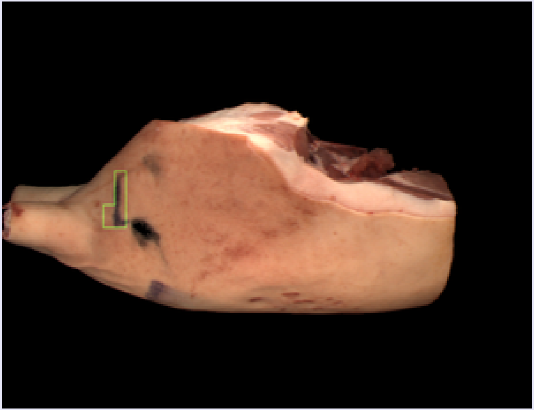

Quantitative results

Comparison of the proposed method with:

- the same technique without neighbourhood analysis
- a technique based on the connexity triangle in HSV [*RFIA*04]

Defect	**Nb. of images**	**No neighbourhood analysis**	HSV space [*RFIA*04]	**Proposed approach**
no defect	40	5	0	0
scratches and burns	132	5	7	0
veterinary mark	10	0	0	0
hematoma	23	0	2	1
erythema	16	0	1	0
hair	4	0	0	0
fat stains	19	0	0	0
second marking	7	1	1	3
occlusion	2	1	2	1
	253	12	13	**5**

[*RFIA*04] M. Gouiffès, P. Marty-Mahé, C. Fernandez-Maloigne and A. Trémeau. Comparaison de deux méthodes de segmentation couleur appliquées à la traçabilité de produits carnés. RFIA2004.

Outlines

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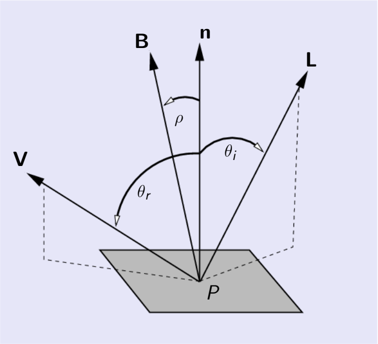
Outlines

Geometry of the scene

f and g: images acquired at two different instants k and k'.
Point P of the scene: projected on p (x_p, y_p) in f and on p' $({x'}_p, {y'}_p)$ in g .

n	normal vector in P
V	viewing direction
L	lighting direction
B	bissecting line between **V** and **L**
θ_r	angle between **V** and **n**
θ_i	angle between **L** and **n**
ρ	angle between **B** and **n**.



Model of luminance

Luminance f can be modeled by the sum of 3 terms:

$$f(p) = K_d(p)a(p)\cos\theta_i(P) + K_s(p)h_f(P) + K_a(p) \tag{5}$$

Diffuse reflection

- $K_d(p)$ depends on the gain of the camera and lighting intensity
- a depends on the reflectance of the surface.

Specular reflection

- K_s depends on the gain and direct light intensity
- h_f depends on the scene geometry and roughness:
  - Phong specular model [*Phong*75]: $h_f(P) = \cos^n(\rho(P))$. n: inversely proportional to roughness of the material.
  - Torrance-Sparrow model [*Torr*67]: $h_f(P) = \dfrac{e^{\frac{-\rho^2(P)}{2\varsigma^2}}}{\cos(\theta_r(P))}$ ς proportional to the roughness of the material.

Ambient lighting

- K_a: depends on the gain and intensity of ambient lighting.

[*Phong*75]: B-T Phong. Illumination for computer generated images. *Communications of the ACM 1975* **18**(6), 311–317.
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Specular highlights occurrence in luminance images

Unchanged parameters

- Lighting source and scene motionless: $\theta_i{}'(P) = \theta_i(P)$.
- Lighting intensity constant: K_a, K_d and K_s constant during the time.
- Reflectance constant by definition $a'(p') = a(p)$

$\Rightarrow K_d(p)a(p)\cos\theta_i(P)$ (diffuse reflection) does not vary.

Changed parameters

- Motion of the camera $\Rightarrow \theta_r$ and ρ not constant
- Specular highlights : $g(p') = K_d(p)a(p)\cos\theta_i(P) + K_s(p)h_g(P) + K_a(p)$

Modeling of the specular highlights occurrence

$$g(p') = f(p) + \psi(p) \quad (6)$$

with $\psi(p) = K_s(p)[h_g(P) - h_f(P)]$

Model of lighting changes in luminance images

Changed parameters

1. Ambient lighting (or gain) change t_a: $K_a'(p') = K_a(p) + t_a(p)$
2. Direct lighting t_d : $K_d'(p') = K_d(p) + t_d(p)$, t_s : $K_s'(p') = K_s(p) + t_s(p)$
3. Light source and/or scene motion $t_i(P)$, $t_r(P)$ and $t_\rho(P)$:

$$\theta_i'(P) = \theta_i(P) + t_i(P)$$
$$\theta_r'(P) = \theta_r(P) + t_r(P)$$
$$\rho'(P) = \rho(P) + t_\rho(P)$$

Model of luminance after lighting change

$$g(p') = K_d{}'(p')a(p)\cos\theta_i{}'(P) + K_s'(p')h_g(P) + K_a{}'(p') \tag{7}$$

Modeling of lighting changes in luminance images

First model of lighting changes G_1

$$g(p') = f(p) + \phi(p) \qquad (8)$$

$$\phi(p) = t_a(p) + t_d(p)a(p)[\cos\theta_i(P)\cos t_i(P) - \sin\theta_i(P)\sin t_i(P)] + t_s(p)h_g(P) + \psi(p)$$

Second model of lighting changes G_2

$$g(p') = \lambda(p)f(p) + \eta(p) \qquad (9)$$

$$\begin{aligned}\lambda(p) &= \frac{(K_d(p) + t_d(p))\cos(\theta_i(P) + t_i(P))}{K_d(p)\cos\theta_i(P)} \\ \eta(p) &= (K_s(p) + t_s(p))h_g(P) + K_a(p) + t_a(p) - (K_s(p)h_f(P) + K_a(p))\lambda(p)\end{aligned}$$

Modeling of lighting changes in colour images

First model of lighting changes

$$\mathbf{g}(p') = \mathbf{f}(p) + \phi(p) \qquad (10)$$

$$\phi(p) = \mathbf{t}_a(p) + \mathbf{t}_d(p) \cdot \mathbf{a}(p)[\cos\theta_i(P)\cos t_i(P) - \sin\theta_i(P)\sin t_i(P)] + \mathbf{t}_s(p)h_g(P) + \psi(p)$$

Second model of lighting changes

$$\mathbf{g}(p') = \boldsymbol{\lambda}(p)\mathbf{f}(p) + \boldsymbol{\eta}(p) \qquad (11)$$

$$\begin{aligned} \boldsymbol{\lambda}(p) &= \frac{(\mathbf{C}_d(p) + \mathbf{t}_d(p))\cos(\theta_i(P) + t_i(P))}{\mathbf{C}_d(p)\cos\theta_i(P)} \\ \boldsymbol{\eta}(p) &= (\mathbf{C}_s(p) + \mathbf{t}_s(p))h_g(P) + \mathbf{C}_a(p) + \mathbf{t}_a(p) - (\mathbf{C}_s(p)h_f(P) + \mathbf{C}_a(p))\boldsymbol{\lambda}(p) \end{aligned}$$

Modeling of lighting changes in luminance images

First model of lighting changes: G_1

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Second model of lighting changes: G_2

$$g(p') = \lambda(p)f(p) + \eta(p) \qquad (9)$$

$$\begin{aligned} \lambda(p) &= \frac{(K_d(p) + t_d(p))\cos(\theta_i(P) + t_i(P))}{K_d(p)\cos\theta_i(P)} \\ \eta(p) &= (K_s(p) + t_s(p))h_g(P) + K_a(p) + t_a(p) - (K_s(p)h_f(P) + K_a(p))\lambda(p) \end{aligned}$$

Local photometric models

Second model of lighting changes G_2

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\end{aligned}$$

Local photometric model

- Approximation of the photometric model
- Valid locally in each point m (projection of a point M of the scene) of a small area of the image $\mathcal{W}$ centered on p

Conservation of luminance

Constant luminance [*Horn*81]:

$$g(m') = f(m) \qquad \forall m \in \mathcal{W} \tag{12}$$

Assumptions

$\lambda(m) = 1$ and $\eta(m) = 0$ $\forall m \in \mathcal{W}$.

- $t_d(m) = 0$ and $t_i(M) = 0$ $\forall m \in \mathcal{W} \Rightarrow$ no lighting change
- $t_a(p) = 0 \Rightarrow$ no ambient lighting change
- $h_f(M) = h_g(M)$ $\forall m \in \mathcal{W}$.

Correct assumptions $\forall m$ if the material is lambertian and the scene geometry is motionless.

Model widely used in computer vision.

[*Horn*81] K.P. Horn and B. G. Schunck. Determinig optical flow. *Artificial Intelligence 1981* **7**, 185–203.

Affine model

$$g(m') = \lambda f(m) + \eta \qquad \forall m \in \mathcal{W} \tag{13}$$

Assumptions

λ and η are constant in each point of $\mathcal{W}$:

- K_d, K_a, K_s constant $\Rightarrow$ lighting intensity constant in each point m in $\mathcal{W}$
- t_d, t_a, t_s constant $\Rightarrow$ lighting changes constant
- θ_i, t_i constant $\Rightarrow$ lighting angle constant in $\mathcal{W}$
- h_f, h_g constant $\Rightarrow$ specular highlights constant in each point m in $\mathcal{W}$.

Photometric models for small interest windows

First model of lighting changes G_1

$$g(p') = f(p) + \phi(p) \qquad (8)$$

$$\phi(p) = t_a(p) + t_d(p)a(p)[\cos\theta_i(P)\cos t_i(P) - \sin\theta_i(P)\sin t_i(P)] + t_s(p)h_g(P) + \psi(p)$$

ϕ is variable on $\mathcal{W}$. It depends on:

- the viewing and lighting angles $\longrightarrow$ on the normal $\mathbf{n}$ in each point of $\mathcal{W}$.
- the roughness of the material (n or ς).

In case of lighting changes or a motion light/object, ϕ is expressed according to the reflectance of the surface (*via* $a(p)$).

Photometric models for small interest windows

ϕ can be approximated on $\mathcal{W}$ by a continuous and derivable function ϕ_{mod}.
Expansion of ϕ_{mod} in Taylor series at first order in m of coordinates $(x, y) \in \mathcal{W}$ centered on p:

$$\phi(m) \simeq \alpha(x - x_p) + \beta(y - y_p) + \gamma. \tag{14}$$

$$\alpha = \left.\frac{\partial \phi_{mod}}{\partial x}\right|_p \quad \beta = \left.\frac{\partial \phi_{mod}}{\partial y}\right|_p \quad \gamma = \phi_{mod}(p).$$

By substituing ϕ in (11) by (14):

$$g(m') \simeq f(m) + \alpha(x - x_p) + \beta(y - y_p) + \gamma \tag{15}$$

Photometric models for small interest windows

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$$\alpha = \left.\frac{\partial \phi_{mod}}{\partial x}\right|_p \quad \beta = \left.\frac{\partial \phi_{mod}}{\partial y}\right|_p \quad \gamma = \phi_{mod}(p).$$

Colour images:

$$\mathbf{g}(m') \simeq \mathbf{f}(m) + \boldsymbol{\alpha}(x - x_p) + \boldsymbol{\beta}(y - y_p) + \boldsymbol{\gamma} \tag{17}$$

Photometric models for large interest windows

Second model of lighting changes G_2

$$g(p') = \lambda(p) f(p) + \eta(p)$$

$$\begin{aligned}
\lambda(p) &= \frac{(K_d(p) + t_d(p)) \cos(\theta_i(P) + t_i(P))}{K_d(p) \cos\theta_i(P)} \\
\eta(p) &= (K_s(p) + t_s(p)) h_g(P) + K_a(p) + t_a(p) - (K_s(p) h_f(P) + K_a(p)) \lambda(p)
\end{aligned}$$

- λ depends on θ_i: can vary on $\mathcal{W}$ (specially on large windows or when the surface is not planar).
- η depends on specular highlights changes, intensity and angles: can vary on $\mathcal{W}$

Continuous surface and continuous roughness on $\mathcal{W} \Rightarrow \lambda$ and η continuous.

Photometric models for large interest windows

λ and η can be approximated on $\mathcal{W}$ by a Taylor series.

$$\begin{aligned} \lambda(m) &\simeq \lambda_1(x-x_p)+\lambda_2(y-y_p)+\lambda_3 \\ \eta(m) &\simeq \eta_1(x-x_p)+\eta_2(y-y_p)+\eta_3 \end{aligned}$$

with:

$$\lambda_1 = \left.\frac{\partial \lambda_{mod}}{\partial x}\right|_p,\ \lambda_2 = \left.\frac{\partial \lambda_{mod}}{\partial y}\right|_p,\ \lambda_3 = \lambda_{mod}(p)$$
$$\eta_1 = \left.\frac{\partial \eta_{mod}}{\partial x}\right|_p,\ \eta_2 = \left.\frac{\partial \eta_{mod}}{\partial y}\right|_p,\ \eta_3 = \eta_{mod}(p)$$

Luminance images:

$$g(m') \simeq [\lambda_1(x-x_p)+\lambda_2(y-y_p)+\lambda_3]f(m)+\eta_1(x-x_p)+\eta_2(y-y_p)+\eta_3 \quad (18)$$

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Colour images:

$$\mathbf{g}(m')\simeq[\boldsymbol{\lambda}_1(x-x_p)+\boldsymbol{\lambda}_2(y-y_p)+\boldsymbol{\lambda}_3]\mathbf{f}(m)+\boldsymbol{\eta}_1(x-x_p)+\boldsymbol{\eta}_2(y-y_p)+\boldsymbol{\eta}_3 \quad (19)$$

Validity of the model

Validity of the approximation of λ

- Small orientation between the tangent plane and the sensor plane
- Small curvatures (continuity) of the surface
- Lighting direction $\mathbf{L}$ concurrent with the normal $\mathbf{n}$
- The light is far from the surface and the camera is near the surface

Validity of the approximation of η, when $\lambda = 1$

- Small curvatures (continuity) of the surface
- Small orientation of the sensor plane /tangent plane of the surface in P
- Roughness of the surface
- Camera near the surface

Outlines

Outlines

Classical method

Principle

Deformation of f due to the motion of the camera /scene modeled in m by a function δ, such that $m' = \delta(m, \mathbf{A})$:

$$f(m) = g(\delta(m, \mathbf{A})) \tag{20}$$

Computation of $\mathbf{A}$ between 2 images f and g.
Because of noise and approximation of the model: minimization of the following criterion [*Lucas*81] [*Tomasi*91] :

$$\epsilon_1(\mathbf{A}) = \sum_{m \in \mathcal{W}} (f(m) - g(\delta(m, \mathbf{A})))^2 \tag{21}$$

[*Lucas*81] B.D. Lucas and T. Kanade. An iterative image registration technique. Dans: *International Joint Conference on Artificial Intelligence 1981*. pp. 674–679.

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Tracking method using an affine photometric model

$$g(m') = \lambda f(m) + \eta \qquad \forall m \in \mathcal{W}$$

Computation of the affine model [*Jin and Soatto* 01]

$$\epsilon_2(\mathbf{A}, \lambda, \eta) = \sum_{m \in W} (\lambda f(m) - g(\delta(m, \mathbf{A})) + \eta)^2 \tag{22}$$

Parameters λ and η are computed in each frame at the same time as the motion model.
Conditionning of the matrix used to solve the minimization depends on the luminance in $\mathcal{W}$.

Photometric normalization [*Tommasini*99]

$$\epsilon_3(\mathbf{A}) = \sum_{m \in W} \left(\frac{f(m) - \mu_f}{\sigma_f} - \frac{g(\delta(m, \mathbf{A})) - \mu_g}{\sigma_g} \right)^2 \tag{23}$$

μ_f and μ_g: averages, σ_f and σ_g: standard deviations on $\mathcal{W}$.
Unstable when σ_f and $\sigma_g \simeq 0$.

[*Jin and Soatto* 01] H. Jin, P. Favaro and S. Soatto. Real-time feature tracking and outlier rejection with changes in illumination. *IEEE ICCV 2001* pp. 684–689.
[*Tommasini*99] T. Tommasini, A. Fusiello, E. Trucco and V. Roberto. Improving feature tracking with robust statistics. *Pattern Analysis & Applications 1999* 2(4), 312–320.

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Tracking methods adapted for specular highlights and lighting changes

Feature points tracking

Photometric model $g(m') = f(m) + \alpha(x - x_p) + \beta(y - y_p) + \gamma$

$$\epsilon_4(\mathbf{A}, \mathbf{C}) = \sum_{m \in \mathcal{W}} \left(f(m) - g(\delta(m, \mathbf{A})) - \mathbf{U}^T \mathbf{C} \right)^2 \quad (24)$$

$\mathbf{U} = (x - x_p, y - y_p, 1)^T$, $\mathbf{C} = (\alpha, \beta, \gamma)^T$.

Tracking of large windows

$g(m') = [\lambda_1(x - x_p) + \lambda_2(y - y_p) + \lambda_3] f(m) + \eta_1(x - x_p) + \eta_2(y - y_p) + \eta_3$

$$\epsilon_5(\mathbf{A}, \boldsymbol{\lambda}, \boldsymbol{\eta}) = \sum_{m \in W} \left(\mathbf{U}^T \boldsymbol{\eta} f(m) - g(\delta(m, \mathbf{A})) - \mathbf{U}^T \boldsymbol{\lambda} \right)^2 \quad (25)$$

$\boldsymbol{\lambda} = (\lambda_1, \lambda_2, \lambda_3)^T$ and $\boldsymbol{\eta} = (\eta_1, \eta_2, \eta_3)^T$

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$\boldsymbol{\lambda} = (\lambda_1, \lambda_2, \lambda_3)^T$ and $\boldsymbol{\eta} = (\eta_1, \eta_2, \eta_3)^T$

Experiments

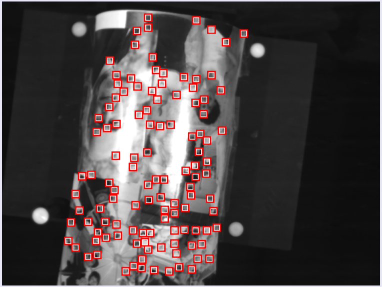
- Detection of points of interest [*Harris*88]
- The same points of interest for each technique
- Computation of an affine motion between the first image of the sequence and the current one:

$$m' = \mathbf{D}m + \mathbf{T} \tag{26}$$

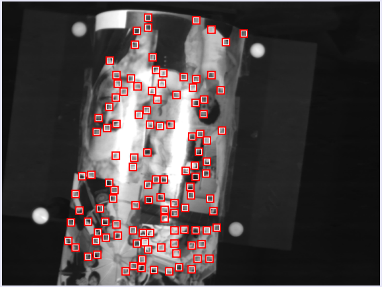
- A point is rejected of the tracking process if its residuals $\epsilon > \mathcal{S}_{conv} = \mathcal{N}^2 E^2_{moy}$

Experiments: specular highlights occurrence

$\mathcal{N}$=9, $E_{moy} = 15$



[*Jin and Soatto* 01] (ϵ_2)
15 points lost



Proposed approach (ϵ_4)
2 points lost

Experiments: specular highlights occurrence

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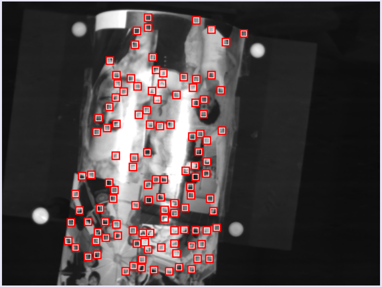

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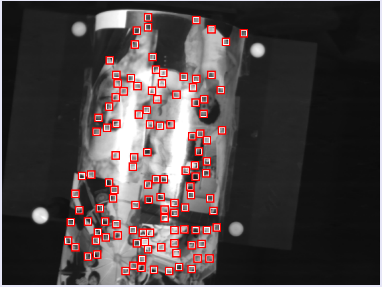


Proposed approach (ϵ_4)
2 points lost

Experiments: lighting changes

$\mathcal{N}=9,\ E_{moy} = 15$

[*Jin and Soatto* 01] (ϵ_2)
6 points tracked

Proposed approach (ϵ_4)
19 points tracked

Experiments: lighting changes

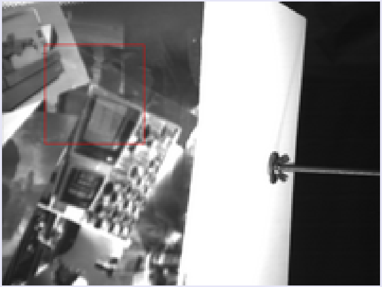
$\mathcal{N}$=9, $E_{moy} = 15$

[*Jin and Soatto* 01] (ϵ_2)
6 points tracked

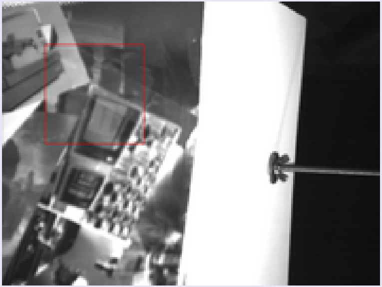
Proposed approach (ϵ_4)
19 points tracked

Experiments: tracking of large areas

$\mathcal{N}$=151, $E_{moy} = 35$



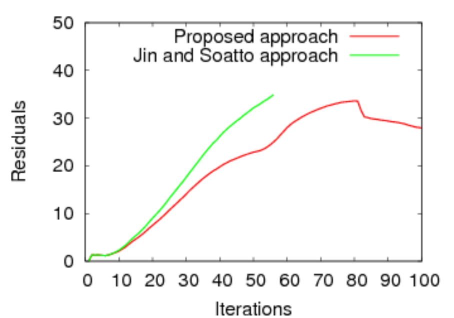
[*Jin and Soatto* 01] (ϵ_2)



Proposed approach (ϵ_5)

Experiments: tracking of large windows

Evolution of the residuals (previous sequence)



Outlines

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1. Part I: Detection of an ink marking
    1. Definition of invariant attributes
    2. Colour segmentation
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    1. Luminance and colour variations
    2. Feature tracking in luminance images
    3. **Feature tracking in colour images**
3. Conclusion and prospects

Tracking points in colour images

Classical tracking in vectorial images [*Heigl*99]

$$\epsilon_1(\mathbf{A}) = \frac{1}{2} \sum_{m \in \mathcal{W}} \| \mathbf{f}(m) - \mathbf{g}(\delta(m, \mathbf{A})) \|^2 \quad (27)$$

Proposed tracking approach

Photometric model: $\mathbf{g}(m') \simeq \mathbf{f}(m) + \alpha(x - x_p) + \beta(y - y_p) + \gamma$

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[*Heigl*99]: B. Heigl, D. Paulus and H. Niemann. Tracking points in sequences of color images. *German-Russian workshop Pattern Recognition and Image Understanding*. 1999, pp. 70–77.

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Comparison of the two approaches

Tolerated variation between **f** and **g** : 5%.

RGB (ϵ_1)

0 points tracked

RGB + model (ϵ_2)

2 points tracked

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Colour Invariants

Dichromatic model [*Shaf* 85]

$$\mathbf{C}(p) = m_b(p)\mathbf{C_b}(p) + m_s(p)\mathbf{C_s}(p) \quad (29)$$

$\mathbf{C_b}(p)$ and $\mathbf{C_s}(p)$: colour of body and specular reflection
$m_b(p)$ and $m_s(p)$: depend on the scene geometry and material properties.

Lambertian surfaces, white illuminant

No specular reflection $\Rightarrow m_s(p)\mathbf{C_s}(p) = 0$
White illuminant $\Rightarrow \mathbf{C_b}(p) = I(p)\mathbf{D}(p)$
$I(p)$: lighting intensity
$\mathbf{D}(p)$: camera sensibility and material reflectance.

$$\mathbf{C}(p) = I(p)m_b(p)\mathbf{D}(p)$$

Ratio of color components (L_1 and L_2 norms, $C_1C_2C_3$ attributes [Gevers97]) $\Rightarrow$ invariance to the scene geometry $m_b(p)$ and lighting intensity:

$$L_1 \text{ norm: } r = \frac{R}{R+G+B} = \frac{I(p)m_b(p)D_R(p)}{I(p)m_b(p)(D_R(p)+D_G(p)+D_B(p))} = \frac{D_R(p)}{D_R(p)+D_G(p)+D_B(p)}$$

[*Shaf* 85] S.A. Shafer. Using color to separate reflection components. *Color Research and Applications 1985* **10(4)**, 210–218.
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Colour Invariants

Dichromatic model [Shaf85]

$$\mathbf{C}(p) = m_b(p)\mathbf{C_b}(p) + m_s(p)\mathbf{C_s}(p) \tag{30}$$

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$m_b(p)$ and $m_s(p)$: depend on the scene geometry and material properties.

Specular surfaces, white illuminant

$$\mathbf{C}(p) = I(p)m_b(p)\mathbf{D}(p) + I(p)m_s(p)Q \tag{31}$$

Q only depends on the camera sensibility (white balance)
Example: $l_1 l_2 l_3$ attributes [Gevers98]:

$$l_1 = \frac{(R-G)^2}{(R-G)^2+(R-B)^2+(G-B)^2} = \frac{(D_R-D_G)^2}{(D_R-D_G)^2+(D_R-D_B)^2+(D_G-D_B)^2}$$

[Gevers98] T. Gevers, A. W. M. Smeulders and H. M. G. Stokman. Photometric invariant region detection. *9th BMVC 1998.*

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Use of colour invariants

L_2 (ϵ_1)
0 points tracked

$l_1 l_2 l_3$ (ϵ_1)
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Colour invariants compensate well for lighting variations
Less adequate when specular highlights occur

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Colour invariants compensate well for lighting variations
Less adequate when specular highlights occur

Joint use of colour invariants and a specular highlights model

- Modeling of the part of the illumination changes d_{spec} that is not compensated by the colour invariants defined for lambertian surfaces.
- Example of norm L_1:

$$d_{spec}(p) = \frac{K_2(p)(D_G(p) + D_B(p) - 2D_R(p))}{K_1(p)(D_R(p) + D_G(p) + D_B(p))^2 + 3K_2(p)(D_R(p) + D_G(p) + D_B(p))}$$

with $K_1(p) = I(p)m_b(p)$ and $K_2 = I(p)m_s(p)Q$.

- Approximation of $d_{spec}(p)$ by a Taylor series:

$$\mathbf{g}(m') = \mathbf{f}(m) + \alpha(x - x_p) + \beta(y - y_p) + \gamma$$

Idem for L_2 norm, $C_1C_2C_3$ attributes.

Joint use of colour invariants and photometric model

L_2 + model (ϵ_2)

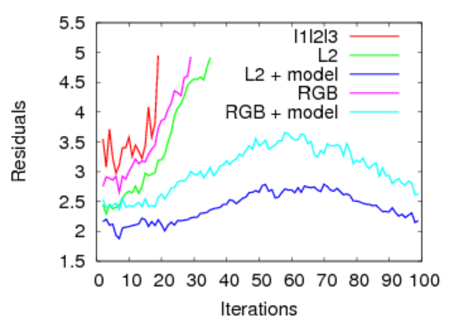
12 points tracked

Joint use of colour invariants and photometric model

L_2 + model (ϵ_2)
12 points tracked

Comparison of the residuals

Evolution of the residuals (%)



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Improvment of high level tasks (visual servoing, object tracking, pattern recognition) by the improvment of low level processes:

- features extraction
- features tracking

Use of colour to extract feature

- Study of the ink transparency: definition of invariant features /colour background and /ink concentration
- Robust segmentation with respect to the transparency effect, the colour of the background, the shape of the marking
- Well adapted to the traceability control: adapted to different ink colours

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Use of reflection models to track feature

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Future works

Colour segmentation

- Colour segmentation in ideal conditions (diffuse lighting)
- Industrial conditions $\Rightarrow$ use of direct lighting $\Rightarrow$ specular highlights
- Solutions:
  - Use of colour invariants
  - Removing of specular highlights

Future works

Feature tracking (short term)

- Large area: selection of the pixels which fit as well as possible to the photometric and motion models (M-estimates)
- Selection of points adapted to the method (use the same matrix as the tracking)
- Updating of the reference interest window [*Matthews*04]
- Improving the use of colour invariants
  - Noisy when unsaturated colours
  - But very pertinent when saturated colours

$\Rightarrow$ joint use of colour invariants and luminance during the image sequence

Possible applications (long term)

- Active vision: avoid the camera locations where specular highlights occur

[*Matthews*04]: Matthews, I., T. Ishikawa et S. Baker (2004). The template update problem. *IEEE Transactions on PAMI* **26**(6), 810–815.

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Possible applications (long term)

- Active vision: avoid the camera locations where specular highlights occur

[*Matthews*04]: Matthews, I., T. Ishikawa et S. Baker (2004). The template update problem. *IEEE Transactions on PAMI* **26**(6), 810–815.

Thank you for your attention