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# Introduction to Computer Vision

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Jean Ponce, Mathieu Aubry, Gül Varol, Karteek Alahari

Class notes by Antoine Groudiev



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# Contents

<b>1</b>	<b>Introduction to Computer Vision</b>	<b>2</b>
<b>2</b>	<b>Camera Geometry</b>	<b>2</b>
<b>3</b>	<b>Camera Calibration</b>	<b>2</b>
3.1	Affine models: weak perspective projection . . . . .	2
<b>4</b>	<b>Image processing using filters and convolutions</b>	<b>2</b>
4.1	Filters and convolution . . . . .	2
4.1.1	Basic filters . . . . .	2
4.1.2	Convolutions . . . . .	2
4.2	Computing derivatives . . . . .	3
4.3	Edge detection . . . . .	3
4.4	The Canny edge detector . . . . .	3
4.5	Denoising, sparsity and dictionary learning . . . . .	3
<b>5</b>	<b>Edge detection</b>	<b>3</b>
<b>6</b>	<b>Radiometry and Color</b>	<b>3</b>
<b>7</b>	<b>Color perception and Two-view geometry</b>	<b>3</b>
<b>8</b>	<b>Epipolar Geometry and Binocular Stereopsis</b>	<b>3</b>
<b>9</b>	<b>Markov random fields</b>	<b>3</b>
<b>10</b>	<b>Recovering structure from motion</b>	<b>3</b>
<b>11</b>	<b>Mean-shift algorithm for segmentation</b>	<b>3</b>
<b>12</b>	<b>Multi-view object models</b>	<b>3</b>
<b>13</b>	<b>Neural Networks for Visual recognition</b>	<b>3</b>
<b>14</b>	<b>Learning methods</b>	<b>3</b>

## Abstract

This document is Antoine Groudiev's class notes while following the class *Introduction to Computer Vision* (Introduction à la vision artificielle) at the Computer Science Department of ENS Ulm. It is freely inspired by the class notes written by Jean Ponce.

# 1 Introduction to Computer Vision

## 2 Camera Geometry

## 3 Camera Calibration

### 3.1 Affine models: weak perspective projection

## 4 Image processing using filters and convolutions

An image can be interpreted either as a continuous function  $f(x, y)$  or as a discrete array  $F_{u,v}$ .

### 4.1 Filters and convolution

#### 4.1.1 Basic filters

An image can be blurred using a filter, by replacing a point by the average of its neighbors. Blurring an image gives a smoother image, making it easier to compute derivatives.

#### 4.1.2 Convolutions

Given two integrable functions  $f, g : \mathbb{R} \rightarrow \mathbb{R}$ , we can define their convolution as:

$$\begin{aligned} f * g : \mathbb{R} &\longrightarrow \mathbb{R} \\ x &\longmapsto \int_{-\infty}^{+\infty} f(x-t)g(t)dt \end{aligned}$$

Note that  $f * g = g * f$  using a change of variable.

This is the definition of the convolution from a continuous perspective. When dealing with images, we want to apply the convolution to a discrete array.

$$R_{i,j} = (F * G)_{i,j} = \sum_{u,v} F_{i-u,j-v} G_{u,v}$$

Convolution follow basic properties:

**Commutativity**  $f * g = g * f$

**Associativity**  $(f * g) * h = f * (g * h)$

**Linearity**  $(af + bg) * h = af * h + bg * h$

**Shift invariance**  $f_{\dagger} * h = (f * h)_{\dagger}$

Note that is the only operator that is both linear and shift-invariant.

The convolution can be differentiated:

$$\frac{\partial}{\partial x}(f * g) = \frac{\partial f}{\partial x} * g$$

Gaussian filters are used to blur images.

4.2 Computing derivatives

4.3 Edge detection

4.4 The Canny edge detector

4.5 Denoising, sparsity and dictionary learning

5 Edge detection

6 Radiometry and Color

7 Color perception and Two-view geometry

8 Epipolar Geometry and Binocular Stereopsis

9 Markov random fields

10 Recovering structure from motion

11 Mean-shift algorithm for segmentation

12 Multi-view object models

13 Neural Networks for Visual recognition

14 Learning methods