Contents

Recurring Concepts **ii**

1 C15: Microelectronics **1**
1.1 Metamaterials I . . . 1
1.2 Biomedical Image Analysis II . . . 1

2 C17: Power Electronics **2**
2.1 Power Converters I . . . 3
2.2 Power Converters II . . . 3
2.3 Electrical Machines I . . . 3
2.4 Electrical Machines II . . . 3

3 C18: Machine Vision & Robotics **4**
3.1 Machine Vision I . . . 4
3.2 Machine Vision II . . . 4

4 C19: Machine Learning **5**
4.1 Machine Learning I . . . 5
4.2 Cognitive Systems I . . . 5

5 C22: Biomedical Imaging & Informatics **6**
5.1 Biomedical Image Analysis I . . . 6
5.2 Biomedical Image Analysis II . . . 7

6 C25: Mathematical Techniques **8**
6.1 Advanced Transforms I . . . 8
6.2 Advanced Transforms II . . . 8

Recurring Concepts

Canny edge detector Explained in detail in Machine Vision I, and appears in Biomedical Image Analysis I and Advanced Transforms I. 6

local phase Explained in detail in Advanced Transforms I, and appears in Biomedical Image Analysis I. 6

monogenic signal Explained in detail in Advanced Transforms I, and appears in Biomedical Image Analysis I. 6

1 C15: Microelectronics

1.1 Metamaterials I

1.1.1 Overview

1.1.2 Summary of Lectures

1.1.3 Lecture 1

1.1.4 Lecture 2

1.1.5 Lecture 3

1.1.6 Lecture 4

1.1.7 Past Paper Examples

1.2 Biomedical Image Analysis II

1.2.1 Overview

1.2.2 Summary of Lectures

1.2.3 Lecture 1

1.2.4 Lecture 2

1.2.5 Lecture 3

1.2.6 Lecture 4

1.2.7 Past Paper Examples

2 — C17: Power Electronics

2.1 Power Converters I

2.1.1 Overview

2.1.2 Summary of Lectures

2.1.3 Lecture 1

2.1.4 Lecture 2

2.1.5 Lecture 3

2.1.6 Lecture 4

2.1.7 Past Paper Examples

2.2 Power Converters II

2.2.1 Overview

2.2.2 Summary of Lectures

2.2.3 Lecture 1

2.2.4 Lecture 2

2.2.5 Lecture 3

2.2.6 Lecture 4

2.2.7 Past Paper Examples

2.3 Electrical Machines I

2.3.1 Overview

2.3.2 Summary of Lectures

2.3.3 Lecture 1

2.3.4 Lecture 2

2.3.5 Lecture 3

2.3.6 Lecture 4

2.3.7 Past Paper Examples

3 — C18: Machine Vision & Robotics

3.1 Machine Vision I

3.1.1 Overview

3.1.2 Summary of Lectures

3.1.3 Lecture 1

3.1.4 Lecture 2

3.1.5 Lecture 3

3.1.6 Lecture 4

3.1.7 Past Paper Examples

3.2 Machine Vision II

3.2.1 Overview

3.2.2 Summary of Lectures

3.2.3 Lecture 1

3.2.4 Lecture 2

3.2.5 Lecture 3

3.2.6 Lecture 4

3.2.7 Past Paper Examples

4 — C19: Machine Learning

4.1 Machine Learning I

4.1.1 Overview

4.1.2 Summary of Lectures

4.1.3 Lecture 1

4.1.4 Lecture 2

4.1.5 Lecture 3

4.1.6 Lecture 4

4.1.7 Past Paper Examples

4.2 Cognitive Systems I

4.2.1 Overview

4.2.2 Summary of Lectures

4.2.3 Lecture 1

4.2.4 Lecture 2

4.2.5 Lecture 3

4.2.6 Lecture 4

4.2.7 Past Paper Examples

5 — C22: Biomedical Imaging & Informatics

5.1 Biomedical Image Analysis I

5.1.1 Overview

5.1.2 Summary of Lectures

5.1.3 Lecture 1

Contains:

- Finding Edges (derivative based operators, Canny edge detector)
- Finding Other Features (local energy and local phase, the monogenic signal)

General chat as an overview:

Medical images are rarely RGC color (exceptions exist e.g photos of wounds), instead commonly discretised into greyscale. Medical images can be 2D, 2D+T, 3D, 3D+T. Important to understand although examples use 2D, this is not the main implementation.

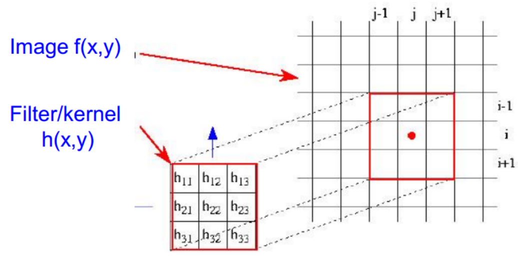


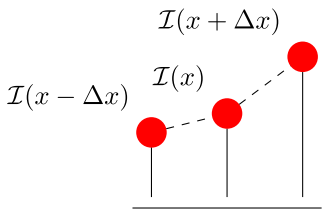
Figure 5.1: A 2D filter mask $\bar{h}(x, y)$

$$g(x) = h(x) * f(x) = f(x) * h(x)$$
$$= \int f(\tau)h(x-\tau)d\tau$$
let $\tau = x + \tau'$, thus $x - \tau = -\tau'$ and $d\tau = d\tau'$
$$= \int f(x+\tau')h(-\tau')d\tau'$$
$$g(x) = \sum_i \sum_j \mathcal{I}(x+i, y+j)\bar{h}(i,j) \tag{5.1}$$

Principles of filter kernels are explained as per B14, and Machine Vision I. A quick recap is shown above in fig. 5.1 and eq. (5.1). NB: eq. (5.1) explains the relationship between convolution with the filter function $h(x, y)$, and correlation with the filter mask $\bar{h}(x, y)$. This is for your own benefit, in this paper all you need say is *"$h(x)$ is often symmetric (even) making the two operations equivalent"*.

It then goes on to show the effect of a Gaussian (LOW PASS) filter and how increasing σ results in wider blurring / narrower bandwidth. Trivial stuff.

Next, derivative based operators are discussed using an identical discussion to Machine Vision I. Again, a quick recap is shown in **??**–5.2



! !

$$\mathcal{I}_x(x,y) = \frac{\partial \mathcal{I}(x)(x,y)}{\partial x} \approx \left\langle \hat{\mathcal{I}}_x \big|_{y=i} \right\rangle$$

$$\begin{aligned} \mathcal{I}_x = \frac{\partial \mathcal{I}}{\partial x} &\approx \frac{\mathcal{I}(x) - \mathcal{I}(x-\Delta x)}{\Delta x} \\ &\approx \frac{\mathcal{I}(x+\Delta x) - \mathcal{I}(x)}{\Delta x} \end{aligned}$$

$$\hat{\mathcal{I}}_x = \frac{\mathcal{I}(x+\Delta x) - \mathcal{I}(x-\Delta x)}{2\Delta x} \qquad (5.2)$$

Note that the Prewitt turns out to be the least squares optimal planar approximation to the continuous image. Essentially it reduces the variance of the simple gradient estimate ($\begin{bmatrix} 1 & 0 & -1 \end{bmatrix}$ mask) arising due to noise, by taking a statistical average in the orthogonal variable y. Exactly the same principle of Bartlett smoothing of periodograms. The Sobel is just a weighted average that gives greater influence to more relevant pixels.[1]

5.1.4 Lecture 2

5.1.5 Lecture 3

5.1.6 Lecture 4

5.1.7 Past Paper Examples

5.2 Biomedical Image Analysis II

5.2.1 Overview

5.2.2 Summary of Lectures

5.2.3 Lecture 1

5.2.4 Lecture 2

5.2.5 Lecture 3

5.2.6 Lecture 4

5.2.7 Past Paper Examples

[1] I suppose the appropriateness of each is determined by the noise, white noise encourages simple mean (as it is equally likely to occur for all pixels, so none are to be trusted more than any other!)

6 — C25: Mathematical Techniques

6.1 Advanced Transforms I

6.1.1 Overview

6.1.2 Summary of Lectures

6.1.3 Lecture 1

6.1.4 Lecture 2

6.1.5 Lecture 3

6.1.6 Lecture 4

6.1.7 Past Paper Examples

6.2 Advanced Transforms II

6.2.1 Overview

6.2.2 Summary of Lectures

6.2.3 Lecture 1

6.2.4 Lecture 2

6.2.5 Lecture 3

6.2.6 Lecture 4

6.2.7 Past Paper Examples