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Subsurface Material Estimation Using Hyperspectral Imaging

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Thesis submitted in fulfilment of the requirements for the degree of

Doctor of Philosophy

under the supervision of
Dr Alen Alempijevic
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Certificate of Original Authorship

I, Jasprabhjit Mehami, declare that this thesis is submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the Faculty of Engineering and Information Technology at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

This document has not been submitted for qualifications at any other academic institution.

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Abstract

Traditional vision is focused on the perception of visible light but limits us to only detecting surface features. In the area of food analysis, features such as composition, defects and contamination cannot be typically measured using visible light. Near-infrared light can penetrate into certain materials, so to capture this light, hyperspectral cameras can be employed. However, the images from these cameras lack spatial understanding. This work centres on a multi-modal vision approach, that leverages the capabilities of modalities such as colour, depth, and computed tomography (CT) in order to improve estimation of material properties, which can be used to detect features within objects.

To remove geometric discrepancies in images and estimate camera poses relative to some world coordinate system, geometric camera calibration is required. The process generally involves an optimisation that uses images of a known planar pattern in different poses. For a hyperspectral camera this is a challenging task as they generally capture images in a line-scan manner, where there is only a single spatial dimension, which makes it difficult to find common pixel features across different images. To aid with calibration, a multi-modal camera-system is deployed by combing the hyperspectral with a traditional frame camera, and an active calibration algorithm is devised which uses observability to selectively choose images that will improve the calibration. Experiments show lower uncertainty and error when the algorithm is compared to a naive approach utilising all images.

Illumination from external light sources is an important element of image formation. Hyperspectral cameras rely on sufficient illumination within their measured spectral bands. Real light sources have an asymmetric distribution in radiant intensity but are generally modelled as being symmetric, which affects photometric estimation techniques that rely on lighting information. Therefore, the second contribution of this thesis is spatially modelling the distribution of a real light source. In order to capture the asymmetry, a data-driven model using a Gaussian process (GP) with an unique mean function is proposed. The distributions of simulated and real light sources are modelled using the proposed GP model, where it shows less error when compared to similar models whilst successfully capturing the inherit asymmetries.

Cameras measure radiance which is dependent on factors such as illumination, shape and the respective material. Reflectance, an intrinsic property of a material, is independent of these factors. The reflectance can be estimated from the radiance by assuming the interaction of light for the materials can be described using the dichromatic reflectance model (DRM). The third contribution of this thesis involved improvements to an optimisation approach for reflectance estimation, by introducing terms that exploit information from prior light source modelling and surface shape. Evaluation on rendered and real images shows improvements in estimated reflectance, whilst also having less variation across areas that contained the same material.

In order to demonstrate the advantages of the three contributions of this thesis, a case study is investigated to estimate subcutaneous fat depth on lamb carcasses using hyperspectral imaging. Ground truth fat depth was determined using a computed tomography (CT) scanner, and the previous contributions were used to estimate the reflectance of the cuts. Various regression models were fit using different reflectance estimation methods, which included the proposed method from the third contribution. It was found that fat depth was best modelled using deep learning-based regression methods with the proposed reflectance estimation method.

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List of Acronyms

AUC normalised area under the curve **xv, 131, 134, 136, 137**

BCS body condition score **120**

BRDF bidirectional reflectance distribution function **34–36, 38, 39, 76, 83, 98, 99**

cd candela **79**

CNN convolutional neural network **122, 132, 133, 139**

CRF camera response function **84, 85**

CT computed tomography **xiv, 7, 115, 117, 119, 120, 122, 127–130, 139, 144**

DEXA dual-energy X-Ray absorptiometry **120**

DLT direct linear transformation **56**

DRM dichromatic reflectance model **6, 39, 96–101, 104, 114, 122–124, 126, 139, 144, 146**

EM electromagnetic spectrum **xiii, 28**

FIM Fisher information matrix **63**

GP Gaussian process **6, 72, 77, 86–94, 98, 100, 111, 118, 123, 124, 126, 142–146**

GR girth rib **120**

IMU inertial measurement unit **44**

IR infrared **25**

LED light emitting diode **24, 25, 119**

MAE mean absolute error **xiv, xv, 131, 136, 137**

MLE maximum likelihood estimation **53, 58**

MLP multilayer perceptron **132, 136–139**

MRI magnetic resonance imaging **120**

NIR near-infrared **2, 4, 118, 119, 121**

PCA principal component analysis **121**

PCM pinhole camera model **xiii, 9, 10, 12, 14–20, 46, 47, 49, 50, 52**

PLS partial least squares regression **121**

PLS-DA partial least squares discriminant analysis **121**

PnP Perspective-n-Point **55, 60, 61**

ReLU rectified linear unit **132**

RGB red, green, and blue colour channels **1, 2, 23, 46, 78, 99, 113, 114, 119, 121–123, 125, 127, 132, 135, 142**

RGB-D colour depth channels **122, 128, 142**

RID radiant intensity distribution **xiv, 6, 74–76, 79–81, 85–87, 94, 142, 143**

RMS root mean square **110, 112, 113**

RP rough plastic **110, 112, 113**

SAM spectral angle mapper **102, 111, 112, 114**

SE squared exponential **77, 86**

SGD stochastic gradient descent **136**

SI International System of Units **32**

SLAM simultaneous localisation and mapping **41, 45**

SSE sum of squared error **111, 112**

STD standard deviation **63, 64, 66–68, 104, 106, 108**

SVM support vector machine **121**

UT unscented transform **59–62**

UV ultraviolet **25**

List of Symbols

Spaces, Geometry, Algebra

$\mathbb{R}$	The set of Real numbers
$\mathbb{P}^n$	The n-dimensional projective space
$\mathbb{E}^n$	The n-dimensional Euclidean space
$\boldsymbol{x}$	A vector
$\mathbf{X}$	A matrix
$\mathcal{A}$	A coordinate system
$\mathcal{W}$	The world coordinate system
P	A point in the world coordinate system
$\boldsymbol{P}$	The vector of P in the world coordinate system
${}^{\mathcal{F}}\boldsymbol{P}$	The vector $\boldsymbol{P}$ defined in the coordinate system $\mathcal{F}$
$\boldsymbol{x}$	A measurement vector, where the components of one or many Euclidean points are stacked together
$\boldsymbol{x}^\top, \mathbf{X}^\top$	The transpose of $\boldsymbol{x}$ and $\mathbf{X}$
$\mathbf{X}^{-1}$	The inverse of $\mathbf{X}$

${}^{\mathcal{F}}\mathbf{T}_{\mathcal{G}}$	The homogeneous transformation of $\mathcal{G}$ with respect to $\mathcal{F}$
$\mathbf{T}_{\mathcal{G}}$	The homogeneous transformation of $\mathcal{G}$ with respect to world coordinate system
$\mathbf{R}$	A rotation matrix
$\boldsymbol{t}$	A translation vector
r_x, r_y, r_z	Euler angles measured in radians
$f(x)$	A function defined in terms of x
$\mathbf{J}_f, \mathbf{J}_f(\boldsymbol{x})$	The Jacobian matrix of a function $f(\boldsymbol{x})$ with respect to $\boldsymbol{x}$

Vision

u, v	Image coordinates in pixels
x, y	2D normalised image coordinates.
X, Y, Z	3D Cartesian coordinates in the world coordinate system.
$\tilde{p}, \tilde{\boldsymbol{p}}$	Homogeneous coordinates of p and $\boldsymbol{p}$
$\tilde{w}$	The appended dimension to create a homogeneous coordinate
$\mathbf{E}$	The extrinsic matrix
$\mathbf{K}$	The intrinsic matrix
$\mathcal{I}$	The pixel image coordinate system
$\mathcal{F}$	The frame camera optical coordinate system
$\mathcal{S}$	The 2D Cartestian imaging sensor coordinate system
$\mathcal{H}$	The hyperspectral camera coordinate system
$\mathcal{P}$	The pattern coordinate system
F	Focal length of a pinhole camera measured in world units

u_0, v_0 Principal point of the image plane in pixels

α Skew angle of a pixel

s_α Skew parameter of the pinhole camera model

f_x, f_y Focal lengths in the x and y directions of a pinhole camera image measured in pixels

$\mathbf{M}$ Camera projection matrix of a pinhole camera

K_n Radial distortion parameter n of an optical lens

T_n Tangential distortion parameter n of an optical lens

l_x, l_y Length of pixels in the x and y directions measured in world units

$\boldsymbol{\vartheta}$ A vector of camera parameters

$\boldsymbol{u}$ Measurement vector of pixel features where the u and v are stacked together

f_{crf} The camera response function

Statistics, Probability and Optimisation

μ_x The mean of a random variable x

σ_x The standard deviation (STD) of a random variable x

σ_x^2 The variance (VAR) of a random variable x

$\boldsymbol{\Sigma_x}$ The covariance matrix of a random vector $\boldsymbol{x}$

$\mathcal{N}(\mu, \sigma^2)$ A normal or Gaussian distribution with mean μ and variance σ^2

$\widehat{x}$ The optimised parameter solution of x

Radiometry and Light

$\mathcal{L}$ The light source coordinate system

ν	The wavelength of light from the electromagnetic spectrum in world units
λ	The frequency of light from the electromagnetic spectrum in hertz
c	The speed of light in a vacuum
ω	A solid angle measured in steradians
$\hat{\boldsymbol{\omega}}$	The solid angle direction vector of a light ray
Q	The radiant energy of given radiation measured in joules
Φ	The radiant flux of given radiation measured in watts
E	The irradiance of given radiation measured in watts per square meter
s	The radiant intensity of given radiation measured in watts per steradian
L	The radiance of given radiation measured in watts per square meter per steradian
f_{brdf}	A BRDF function of a surface for material
$\hat{\boldsymbol{n}}$	The direction vector surface normal
(r, θ, φ)	The 3D spherical coordinate system defined using the euclidean distance and the zenith and azimuth angles
δ	The Dirac delta function
ρ	The diffuse reflectance of a surface
ρ_k	The specular reflectance of a surface
k	The specular coefficient of a surface
g	The shading factor of a surface due to lighting and surfae shape