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Robust Image Registration using Improved Local Descriptors and Support Vector Machines

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Abstract

This thesis presents a detailed study and improvement to local descriptor processes for registering images for the purpose of three-dimensional reconstruction, using four Māori artefacts as case studies. The motivation for the research came from the issues which still exist in image registration when dealing with large magnitudes of image transformations.

Four major pieces of work were carried out in the course of this research. First, an evaluation was carried out to study the performance of local descriptor processes and based on the results, the local descriptor process was divided into three stages, of which two were closely analysed. Second, the local descriptor formation stage was studied, and two methods, colour and hybrid local descriptor methods, were developed using colour images instead of greyscale images to improve the uniqueness of local descriptors. Third, the local descriptor matching stage was studied, and a new method based on support vector machines was developed. Fourth, an assisted image registration programme was developed and is a semi-automatic approach for registering images.

Extensive amount of experiments were carried out to validate these work. It was found that the colour and hybrid local descriptor methods had gains in matching accuracy of up to 10% over existing methods, and the support vector machine maching method had increased matching performance of up to 20%. When the two methods were combined, it was found that performance gains of up to 25% could be achieved. For the assisted image registration programme, up to 50% improvement was achieved, and the advantage was more significant as the magnitude of image transformation increased, highlighting the need for such programme.

These results show that the proposed work in this research are significant contributions to literature. In addition, these results show that the proposed methods can be used successfully for registering images for three-dimensional reconstruction, where the image transformation between images are often large. As there is currently a need to reconstruct Māori artefacts, this research has provided a new approach for registering images of these artefacts, which could then be used to construct three-dimensional models of the artefacts.

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List of Abbreviations

1D One-dimensional
 2D Two-dimensional
 3D Three-dimensional

ALH Adaptive Local Hyperplane
CLD Colour Local Descriptors

CSIFT Colour Scale Invariant Feature Transform

CT Computed Tomography
DoG Difference of Gaussian
DoH Difference of Hessian

EPICS Engineering Projects In Community Services
GLOH Gradient Location Orientation Histogram

HLD Hybrid Local Descriptors

ISDA Iterative Single Data Algorithm

KHNN *k*-local Hyperplane Nearest Neighbour LESH Local Energy-Based Shape Histogram

LoG Laplacian of Gaussian

LOOCV Leave-One-Out Cross-Validation

MATLAB MATrix LABoratory

MRI Magnetic Resonance Imaging

NN Nearest Neighbour

NNR Nearest Neighbour Ratio
PC Principal Component

PCA Principal Component Analysis RANSAC RANdom SAmple Consensus

RFE-SVMs Recursive Feature Elimination with Support Vector Machines

SIFT Scale Invariant Feature Transform

SVM Support Vector Machines



List of Symbols

Due to the vast number of symbols present in this thesis, the symbols are listed in the chapter they first appear.

List of symbols from Chapter 2: Literature Review.

	y 1
c_x, c_y	Principal point
f_x , f_y	Focal length
O(n)	Big O notation
\mathbf{H}^{12}	Homography matrix
K	Camera/intrinsic matrix
$(\mathbf{R}^1, \mathbf{T}^1),$	Extrinsic parameters consisting of the rotation and translation matrices for
$(\mathbf{R}^2, \mathbf{T}^2)$	the reference and sensed images, respectively
S	Distortion factor
T_n	Triangular number
(x^1,y^1)	Location of a single pixel in the reference image
$\hat{x^1}, \hat{y^1}, \hat{l^1}$	Components of \mathbf{x}^1
$\mathbf{x}^1, \mathbf{x}^2$	Location of pixels in the reference and sensed images, respectively
X	Location of 3D points which correspond to x

List of symbols from Chapter 3: Performance Evaluation of Local Descriptor Methods.

	T. T
C_o^1, C_o^2	Camera centre of the reference and sensed images, respectively
d^1, d^2	Distance from the reference and sensed image planes to the object,
	respectively
h_O^1, h_O^2 I^1, I^2	Height of the object in the reference image and sensed images, respectively
I^1, I^2	Reference and sensed image planes, respectively
0	Object
S	Scale
x	Location of a pixel along the x-axis
x_c	Radial distortion centre along the x-axis
\hat{x}	Corrected pixel location along the x-axis taking into account radial
	distortion
ŷ	Corrected pixel location along the y-axis taking into account radial
	distortion
ΔT	Translation change from C_o^1 to C_o^2
θ	Angle of change when the camera is moved from C_o^1 to C_o^2

List of symbols from Chapter 4: Colour and Hybrid Local Descriptors Methods.

List of syı	mbols from Chapter 4: Colour and Hybrid Local Descriptors Methods.
a,b,c,d	Real numbers of quaternions
ang^{O_1} , ang^{O_2}	Opponent angles
ang^{S_1} , ang^{S_2}	Spherical angles
c_1, c_2, c_3	Channels of the $c_1c_2c_3$ colour model
C	Covariance matrix
d_{m_1}	Difference of two neighbouring pixels in a given orientation for the m_1
	colour channel
d_x , d_y	Wavelet responses along the horizontal and vertical axes
D	Diagonal matrix of eigenvalues
H(R,G,B)	Hue image
i, j, k	Imaginary components of quaternions
I(R,G,B)	Intensity image
l_1, l_2, l_3	Channels of the $l_1l_2l_3$ colour model
L^2	Euclidean distance measure
m	Number of local descriptor pairs
m_1, m_2, m_3	Channels of the $m_1m_2m_3$ colour model
M	Maximum value for R , G and B
MNCC	Normalised cross-correlation
p	Number of pixels along the horizontal or vertical axis in an interest region
p^1, p^2	Number of pixels along the horizontal or vertical axis in an interest region
	for the reference and sensed images, respectively
q	Quaternion
r	Number of interest regions
r(R,G,B),	Normalised R , G and B
g(R,G,B),	
b(R,G,B)	
\mathbf{r}^1 , \mathbf{r}^2	Interest regions of the reference and sensed images, respectively
$\overline{\mathbf{r}^1}, \overline{\mathbf{r}^2}$	Mean of the interest regions of the reference and sensed images,
	respectively
$\widehat{\mathbf{r}^2}$	Mean subtracted region from the sensed image
R, G, B	Red, green and blue pixels
S(R,G,B)	Saturation image
v	Size of the local descriptor concerned
$v_{m_1}, v_{m_2}, v_{m_3}$	Number of vectors for each of the three colour channels of the $m_1m_2m_3$
	colour model
\mathbf{V}	Eigenvectors

w_{L^2}, w_{MNCC}	Weights for the Euclidean distance measure and modified normalised
	cross-correlation values, respectively
$w_{m_1}, w_{m_2}, w_{m_3}$	Weights for the three colour channels of the $m_1m_2m_3$ colour model
(x,y),(u,v)	Indices for the pixels in an image
x_i^1, x_i^2	$i^{\rm th}$ vector of local descriptors from the reference image and sensed image,
	respectively
$\tilde{x}(m_1), \ \tilde{x}(m_2),$	Median for the three colour channels of the $m_1m_2m_3$ colour model
$\tilde{x}(m_3)$	
$\mathbf{x}_1, \mathbf{x}_2$	Image locations of two neighbouring pixels
X	Input data matrix
Y	Greyscale pixel
δang^O	Opponent angle with error analysis
δang^S	Spherical angle with error analysis
λ_i	i th eigenvalue
$ au_{ m HLD}$	Threshold for the hybrid local descriptor method
$ au_{L^2}$	Threshold for the threshold matching method using the Euclidean distance
	measure

List of symbols from Chapter 5: Local Descriptor Matching with Support Vector Machines.

b	Bias term for SVM
<i>C</i> , σ	Penalty and threshold for SVM with a Gaussian kernel
c_i	Square of the weights for RFE-SVMs
d	Order of polynomial for SVM with a polynomial kernel
$G(\mathbf{x}, c_i)$	Gaussian kernel
k	Number of iterations for cross-validation
L^1	Rectilinear distance measure
L^p	<i>p</i> -norm distance measure
n	Number of available classes for SVM
$n(LD^1),$	Number of local descriptors in the reference and sensed images,
$n(LD^2)$	respectively
$n(LD_{correct}),$	Number of correctly and incorrectly matched local descriptor pairs,
$n(LD_{incorrect})$	respectively
$n(\mathrm{LD}_{\mathrm{total}})$	Total number of local descriptors
p	Number of features to be removed at each iteration by RFE-SVMs
r	Ranking vector for RFE-SVMs
s	Indices of vectors of local descriptors to be emptied and ranked in ${f r}$

 w_i Weight of the i^{th} value in the difference vector for SVM with a Gaussian

kernel

 w_i Weights of each input vector for RFE-SVMs **x**, **x**_i Input matrix for SVM and the ith input vector

X⁰ Input matrix for RFE-SVMs

 \mathbf{y} y_i Output vector for SVM and the i^{th} output value

 \mathfrak{R}^n *n*-dimension real number

 $\begin{array}{ll} \tau_T & & \text{Threshold for the threshold matching method} \\ \tau_{NN} & & \text{Threshold for the nearest neighbour method} \end{array}$

 au_{NNR} Threshold for the nearest neighbour ratio method au_{SVM} Threshold for SVM output in the range of [-1, 1]