

UNIVERSITY OF TECHNOLOGY, SYDNEY

**Autonomous exploration and mapping of
complex 3D environments by means of a
6DOF manipulator**

by

Gavin David Paul

A thesis submitted in partial fulfillment for the
degree of Doctor of Philosophy

in the
Faculty of Engineering and IT
Intelligent Mechatronic Systems Group

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I, Gavin David Paul , declare that this thesis titled, ‘Autonomous exploration and mapping of complex 3D environments by means of a 6DOF manipulator’ and the work presented in it are my own. I confirm that:

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Abstract

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Intelligent Mechatronic Systems Group

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The futuristic vision of industrial robotic systems that operate in complex, unstructured and diverse environments is beginning to become a reality due to the advances in computing, sensing and control. Automatically acquiring the structure and the properties of an environment in a timely manner is one of the key tasks that need to be accomplished in many field robotics applications. This thesis presents a novel and efficient approach to the exploration of three-dimensional (3D) environments using an industrial robot manipulator. The approach presented combines the objectives of 3D map building and surface material-type identification. The manipulator is manoeuvred through a sequence of viewpoints that are selected to maximise the quality of the map generated, minimise the time taken for the exploration, as well as minimise the uncertainty of the surface material type estimation, all whilst avoiding potential collisions between the manipulator and the environment.

The thesis first focuses on acquiring the geometry of surfaces in the environment while exploring the industrial robot manipulator's collision-free configuration space. Ellipsoidal virtual bounding fields are positioned around the manipulator's links so that distance queries can be performed and collisions with obstacles in the environment or unexplored space are avoided. Information theory is used to measure the information remaining on the geometric map and the manipulator's configuration space. A sampling strategy is used to select candidate viewpoints which are predicted to reduce the information remaining to measure. Each viewpoint enables the manipulator to position and orientate a sensor so that environment data can be gathered. The candidate viewpoint solutions can then be ranked based upon the exploration objectives. The collected sensor data is fused into a map. The map is then segmented into groups of Scale-Like Discs (SLDs), which are generated via principal component analysis.

Once the surface geometry becomes available, a strategy is required to maximise the accuracy of the surface material-type identification. Surface material-type identification is made possible through intensity measurements, which indicate the reflectivity of the surface when illuminated by an infra-red laser. Thus, identification is significantly influenced by the relative geometry between the sensor and the surface to be identified. Information theory is used again to determine surfaces which have not had their surface material-type identified. Appropriate viewpoints facilitating accurate identification are selected by solving an optimisation problem using the Levenberg-Marquardt algorithm.

This two-stage exploration approach is shown to successfully determine viewpoints enabling an accurate environmental map to be generated. The proposed algorithms and approaches are integrated into the system, Autonomous eXploration to Build A Map (AXBAM). Extensive experimental studies have been conducted on a complex steel bridge structure using a Denso industrial robot that has been equipped with a laser range finding sensor. These experimental studies demonstrate the efficacy of the AXBAM system.

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Abbreviations

ARC	Australian Research Council
AXBAM	Autonomous eXploration to Build A Map, system
CAS	ARC Center of Excellence for Autonomous Systems
CAM	Computer Aided Manufacturing
C-space	Configuration Space of manipulator
DOF	Degrees of Freedom
EM	Expectation Maximisation algorithm
FOV	Field Of View
GA	Genetic algorithm
GUI	Graphical User Interface
HRI	Human-Robot Interaction
LRC	Laser Range Classifier [5]
MER	Maximum Entropy Reduction
MLE	Maximum Likelihood Estimate
MSE	Mean-Squared Error
NSW	New South Wales (Australia)
OG	Occupancy Grid
PCA	Principal Component Analysis
RTA	Roads and Traffic Authority of New South Wales
SLD	Scale-Like Disc
UTS	University of Technology, Sydney

Nomenclature

General Formatting Style

$f(\dots)$	A scalar valued function
$\mathbf{f}(\dots)$	A vector valued function
$[\dots]^T$	Transpose
$ \cdot $	Absolute value
$\ \cdot\ $	Vector length and normalised vector
C	Covariance matrix
D	A diagonalised matrix
$H(Y)$	Entropy of a random variable Y
$\{n, m\}$	Independent variables signifying the last index of a set or to refer to a count
$P(x_i)$	Probability of discrete state x_i
$P(x z)$	Conditional probability of x , given evidence z
$[\cdot]/[\cdot]$	Piecewise division i.e. i th vector element divided by i th element of another vector

Specific Symbol Usage

A_i	The i th geometric region of interest
c_{wi}	Weighting co-efficient of the i th region of interest
$dist(\vec{Q})$	The minimum algebraic distance to all unsafe points in an environment for all of a manipulator's encompassing ellipsoids, as a function of the manipulator pose, \vec{Q}
$j_{\mathbf{c}}$	C-space node set interfered with by voxel j

$f_i(\vec{Q})$	i th Stage One objective function
$g_i(\vec{Q})$	i th Stage Two cost function, optimal value, $\hat{g}_i = 0$
$\mathbf{g}(\vec{Q})$	Sum of squared cost functions
$\mathbf{H}_1(\mathbf{X})$	Geometric information remaining (i.e. uncertainty) of state of geometric environment \mathbf{X}
$\mathbf{H}_2(\mathbf{C})$	C-space information remaining in all voxels (in Euclidean space) because of uncertainty in C-space \mathbf{C}
$\mathbf{H}_3(\mathbf{M})$	Material-type information remaining about state of voxels containing surfaces in an environment \mathbf{M}
j	Voxel's index
k	Sensing viewpoints iterator during exploration
$L(c_i)$	Likelihood of traversing a C-space node, c_i , (i.e. a manipulator pose) during a random trajectory
n_p	Number of points in a point cloud or vertices in a mesh map
n_Q	Feasible poses (i.e. nodes) sampled from C-space solution space \mathbf{Q}
${}^j n_Q$	Count of C-space nodes interfered with by voxel j
n_m	Number of surface voxels requiring material-type identification
n_s	Number of map segments the environment is divided up into
n_{ss}	Number of small SLDs
n_t	Number of surface material-type states
n_u	Number of unknown voxels in an environment
n_v	Number of voxels in an environment
\mathbf{p}	A vector position variable (point or vertex) $[x, y, z]^T$
\mathbf{P}	A vector (or set) of 3D points or vertices
\mathbf{p}_a	Point where end-effector tool (sensor or maintenance) is directed
$P({}^j X = {}^j x_o)$	Probability that the j th voxel's occupancy state variable ${}^j X$, is in a possible occupancy state
$P({}^j M = {}^j x_m)$	Probability of j th voxel state variable, ${}^j M$ being a possible material-type

$P(jx_c)$	Probability of j th geometric voxel interfering with a path through C-space while taking into consideration the relative likelihood of traversing each C-space node
q_i	Individual manipulator joint for 6DOF case $i \in \{1, \dots, 6\}$
\vec{Q}	Industrial manipulator's joint vector, $[q_1 \dots q_6]$, also a sensing viewpoint
\mathbf{Q}	Viewpoint solution space for manipulator pose joint vectors
$R_{\theta, \alpha}$	Matrix of distance range values from viewpoint, when tilting scanner through angle, α , where elements are scalar range values $r_{i,j}$
s_i	i th SLD
${}^0T_f(\vec{Q})$	Homogenous end-effector robotic transformation matrix at pose \vec{Q} in base coordinate frame
${}^{i-1}T_i(q_i)$	Homogenous transformation matrix from link $i - 1$ to i based on the joint, q_i
${}^fT_s(\vec{Q})$	Homogenous transformation matrix between the end-effector and sensor. Combined with ${}^0T_f(\vec{Q})$ to describe viewpoint transforms
$V_r(\vec{Q})$	Approximate volume that the robot currently occupies at pose \vec{Q}
$V_{new}(\vec{Q})$	New volume of geometric space sensed from the latest viewpoint
jx_o	Occupancy states of j th voxel (i.e. freespace, unknown, occupied)
jx_c	C-space interference states for the j th geometric voxel
jx_m	Material-type states of the j th voxel (estimated as \hat{x}_m)
α	Tilting the planar laser sensor through α results in a 3D FOV
ϕ_{max}	Sensing angular constraint for LRC to identify material-type
ρ_{min}	Sensing accuracy constraint for LRC

Combinations of Variables

$\{d_{min}, d_{max}\}$	Sensing range constraints where d must be for the LRC
$\{\hat{P}_i, \vec{n}_i, \mu\}$	i th SLD centre 'home point', \hat{P}_i , normal vector \vec{n}_i and radius μ

$\mathbf{p}_{c,i}$	Manipulator's collision avoidance i th ellipsoid centre vector, $\mathbf{p}_{c,i} = [x_{c,i}, y_{c,i}, z_{c,i}]^T$
$\mathbf{a}_{e,i}, \mathbf{b}_{e,i}, \mathbf{c}_{e,i}$	The ellipsoid parameters for equatorial radii $[\mathbf{a}_{e,i}, \mathbf{b}_{e,i}]$ and polar radius, $\mathbf{c}_{e,i}$, that encase the i th manipulator joint for collision avoidance
$\{q_{i,max}, q_{i,min}\}$	Set of maximum and minimum physical angular limits on each joint. $q_{t,max}$ related to the tilting joint for 3D sensing
$\{v_i, \lambda_i\}$	i th eigenvector and corresponding eigenvalue of sub-point cloud
$\{\delta\theta_{ij}, \delta d_{ij}, \delta p_{ij}, \delta q_{ij}\}$	For surfaces \mathbf{s}_i and \mathbf{s}_j : the angular difference, distance between the centres and the planes, pose joint difference

Glossary of Terms

Blasting	Grit blasting maintenance operations on certain surfaces.
Environment	A complex 3D unstructured place in which a manipulator is positioned. Assumed to have some structural characteristics such as planar surfaces.
Freespace	Areas in the environmental model or map that are known to be free of objects, obstacles and surfaces.
Grid	A type of representation based on OGs used to divide a space into discrete grid cells. For 3D geometry this becomes voxels, and for C-space this becomes nodes.
Iteration	A single step or viewpoint which is determined by optimisation, or in the case of Levenberg-Marquardt optimisation, one iteration of the least squared optimiser.
Manipulator	In this thesis, this is a six-degree of freedom Denso industrial robotic manipulator, with either a laser range scanner or a grit-blasting tool mounted on the end-effector.
Map	Model of the geometry and material-type of surfaces in the surrounding environment.
Node	Manipulator pose in 6D C-space.
Obstacle	An object within the manipulator's workspace which a manipulator can collide with.
Occlusion	Not visible from a viewpoint due to an obstruction.
Obstruction	A surface within sensing range which causes an occlusion.
Platform	The movable platform on which the robot manipulator is fixed.

Planning	The act of generating a path (and motion) course which the robot can then follow to get between two poses.
Scaffolding	Temporary structure built under and around the bridge to allow maintenance by humans or robots.
Sensor	Generally refers to a laser range finder which returns range values to objects in an environment.
Scale-Like Disc	Small disc-shaped targets arranged in a scale-like overlapping pattern to form a representation of surfaces.
Solution Space	All possible solutions to an optimisation problem. In this case, it is within the physical bounds of the industrial robot manipulator's movements
Structural	Mainly consisting of planar surfaces in a man-made fixture such as a bridge. This type of environment can be unstructured with regards to a robot if it is not set up specifically for the robot.
Surface	This is the face of an object in the environment. The geometric and material-type properties must be determined.
Surface Normal	A 3D vector perpendicular to a surface.
Material-type	The type of material on an object's surface. Includes painted steel, rusted steel, timber, plastic and concrete
Unstructured	A Real-world environment that cannot be set up to facilitate ease of actuator movements. There are no limitations on the geometry of the environment, although it is generally assumed to consist of relatively smooth or planar surfaces.
Viewpoint	A position in space and an orientation of a sensor that a corresponding manipulator pose can achieve, can be expressed by the homogeneous transformation matrix, ${}^0T_s(\vec{Q})$, or manipulator joint vector, \vec{Q} .
Voxel	Volumetric Pixel which represents a 3D cube-like volume in Euclidean space.