Snake-Like Robots for Minimally Invasive Spine Surgery

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Abstract

Minimally invasive spine surgery (MISS) requires highly dextrous tools due to the confined spine anatomy and the proximity to vital structures. Existing tools are rigid and do not provide the manoeuvrability required to work optimally within the complex intervertebral space. Snake-like robots offer a promising solution through their extra degrees of freedom which allow for highly dextrous movement. Snake-like robotic solutions are not yet implemented in clinical setting due to limited research and lack of design methodology. This project investigates snake-like robot design for spinal surgery, to the answer the research question: How can a snake-like robot design be optimised to enable minimally invasive spine interventions?

A systematic design methodology was developed to apply and evaluate an existing design solution, the SnakeRaven Design Algorithm (SRDA), within the spine anatomical context. The SRDA, is a design algorithm that employs evolutionary optimisation techniques to develop highly dextrous robot designs. This research involved four key stages: a parameter sensitivity analysis; an optimisation performance assessment; the application of the SRDA to spine anatomy case; and the development of a dexterity fitness function capable of evaluating a design's ability to access an intervertebral surface. These stages addressed critical research gaps in the field, including: the limited understanding of the viable design space; and the lack of snake-like robot design methods for spinal environments.

The project developed a viable methodology to utilise the SRDA to produce design solutions for spine interventions. The solution space was explored to define parameter bounds containing highly dextrous robotic designs for several environment dimensions. By allowing the algorithm to search these bound parameter spaces, it was found that near optimal, dextrous design solutions could be discovered faster; with the exception of small anatomical regions (≤12 mm) where results were less consistent. These results suggest that targeted sampling from a well-understood design space could replace computationally expensive optimisation. The adapted fitness function, while clinically realistic, presented challenges including a high average runtime per evaluation. Despite these limitations, the study successfully demonstrated that the SRDA, with adaptations, can produce and evaluate designs suitable for spinal surgery.

This work contributes a foundational framework for designing snake-like robots for the purpose of minimally invasive spinal interventions. It provides novel insights into optimising for dexterity within anatomically constrained environments and opens pathways for future research to refine these tools for clinical implementation.

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1. Introduction

Surgical interventions in the spine region require high precision due to the sensitivity of the surrounding vital structures. Current common surgical tools used in minimally invasive spine surgery (MIS) are rigid and are unable to provide adequate access the intervertebral disc space without disrupting delicate structures such as the spinal cord. It is necessary to transition from rigid tools to an approach more capable of accessing and operating within this difficult space. A snake-like robot provides better access and manoeuvrability through increased degrees of freedom (DOF). As such, this project aims to answer:

How can a snake-like robot design be optimised to enable minimally invasive spine interventions?

The aim of the project is to develop a method for designing a snake-like robot suitable for the requirements of lumbar spine surgery, with proof of concept demonstrated in the context of an intervertebral fusion procedure. The proposed solution aims to develop a dextrous snake-like robot design capable of accessing the interface between the intervertebral disc and vertebrae (bone) without disrupting surrounding structures as per fusion procedure requirements.

To respond to the research question and achieve the aim of the project an existing optimisation algorithm solution was analysed in its application to the spine anatomy; that is, its ability to design a snake-like robot for the purpose of spine surgery. Through initial research limitations of the algorithm and key considerations were identified leading to the development of four primary project objectives. These are formulated as four secondary research questions:

I. Where within the snake-like robot design space do the viable and useful solutions exist for the purpose of spine interventions?
II. What is the role of optimisation techniques in enhancing the performance of a snake-like robot design?
III. Can the proposed design methodology be applied effectively to the spine anatomy to produce useful robotic solutions?
IV. How can the existing design techniques be adapted to better handle tasks specific to spine interventions?

The project adhered to an Engineering Design Process (cycle) to ensure the research aim was achieved in a reliable and valid manner. This process will be further elaborated in Section 3 Methodology. A structured set of deliverables are outlined for the project. These are used to present the project outcomes including a detailed response to the primary and secondary research questions.

1.1. Deliverables

The deliverables for the final semester of the research project include:

- A project delivery report
- Address of the proposed primary and secondary research questions (project objectives).
- An oral presentation of research findings.

The project milestones are detailed in Appendix A: Research Project Timeline & Deliverables. The project proposal detailed the scope of work for this project. This alongside a literature review informed the basis for subsequent research.

2. Literature Review & Initial Research

Minimally invasive surgery (MIS) involves making small incisions and using endoscopic instruments to perform operations. This avoids open and invasive cuts through tissue, meaning they are safer, reducing the risk of infection and complications. These methods also minimise patient recovery and rehabilitation time. As such, the advancement of these technologies is particularly important for isolated and developing areas where medical resources are scarce (Santos et al, 2024). Spine surgery requires high accuracy and precision. It involves working near vital and delicate anatomical structures and no snake-like solutions have been explored for these interventions. Current MIS approaches for spine surgery use rigid end effectors which do not achieve the high dexterity required to minimise the disruption of vital structures.

The following literature review explores snake-like robotic solutions for MIS and their potential application in spine interventions.

2.1. Existing MIS approaches for spine surgery

By investigating current MIS approaches for the spine, the requirements and constraints for surgical tools can be defined. One common spine intervention is interbody fusion surgery. The aim of interbody fusion surgery is to implant a spacer between two vertebrae that promotes bone healing to fuse the two vertebrae (Santos et al, 2018) (Refer to *Figure 1*). During an interbody fusion surgery, the surgeon removes the weakened intervertebral disc; this is referred to as a discectomy. This space can be accessed by removing the lamina (posterior interbody fusion) or through creating bone openings (transforaminal interbody fusion). It is key to protect neural structures during this manipulation (Jitpakdee et al, 2023). Current MIS operations are slowed by the discectomy which is typically the longest part of the procedure and vital as fusion depends on the proper preparation of the disc space (Qureshi, 2020). The risks associated with this procedure include non-union or a failed fusion and nerve damage (Armaghani, 2020).

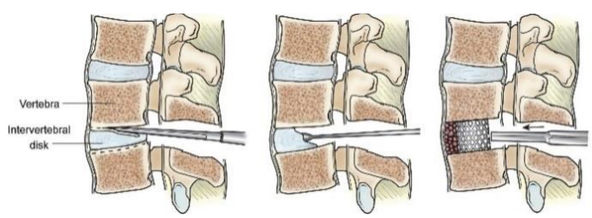


Figure 1 - Discectomy and spacer insertion for lumbar fusion procedure (Pillay, n.d.)

The incision required for MIS transforaminal interbody fusion is 2-3cm through which dilators are used to expand a surgical corridor and a tubular non-expandable retractor is inserted; this process allows the thecal sac, which contains the spinal cord, to be repositioned out of the way. Thus, instruments are constrained to the physical bounds of the retractor passage. The retractor can be of varying dimension according to the region of the spine. For example, for a lumbar discectomy a space of 15 to 20 mm in diameter is needed and so retractors are commonly 20mm (approximately between 15 and 23mm) and a length of 40 to 50 mm (Kim et al, 2007) (Phillips et al, 2019). Retractors in used in the thoracic region, however, are often up to 90mm in length. Commonly used thin-walled retractors are 0.9mm in wall thickness. Instruments are restricted by this space and are typically less than 5mm in diameter. Examples of instruments are Adson hooks (5mm), and Kerrison punches (2-5mm) (Mercian, 2023) (Figure2 (a) & (b)).

This current instrumentation for spine MIS is restricted by lack of tool tip dexterity. For example, endoscopes are commonly constrained to set viewing angles refer to Figure 2 (c) (Goldberg, 2024). Similarly, microsurgical tools such as pituitary rongeurs (Figure 2 (d)) have limited manoeuvrability inhibiting access to occluded regions of the lumbar spine. This poses a challenge for surgeons who require access to the entire intervertebral disc space during procedures.

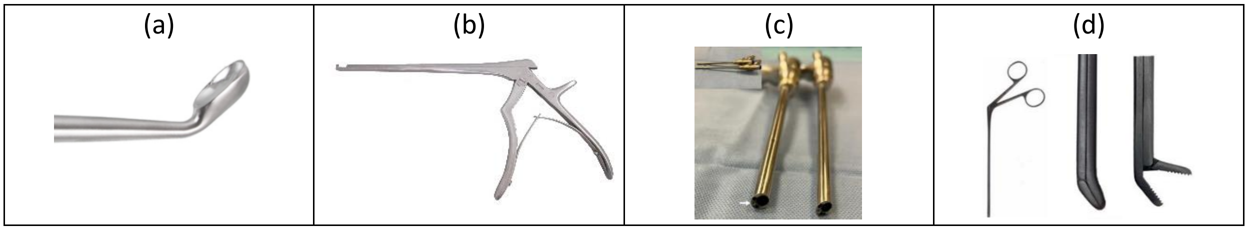


Figure 2 - Spine MIS tools. (a) 5mm Adson hook. (b) Kerrison punch. (c) Interlaminar and transforaminal surgery endoscope with 15° (left) and 30° (right) camera angles. (d) Micro Pituitary Rongeur. (Mercian, 2023), (Goldberg, 2024).

2.2. Snake-like Robots for MIS

Clinical Applications of Flexible Robotic Systems

Flexible MIS robots are characterised by their increased number of degrees of freedom (DoFs). The redundant DoFs allow for the flexible nature of snake-like robots. These robot systems allow access to confined areas of the body during MIS and better control and instrument manipulation.

This technology has been deployed in various endoscopic procedures (refer to Figure 1). For example, the Flex robotic platform (Medrorobotics, USA) performs otolaryngology and colorectal interventions. Other applications include gastrointestinal surgery which had been successfully enhanced by the i^2 Snake robot (Omnisore, 2022). Although some systems have been used to enhanced surgeons' abilities to perform safe interventions, flexible robotic solutions are not yet widespread in clinical application.

Macro Surgical Robot Platforms & Macro-Micro Teleoperation

Robotic MIS procedures typically use robot teleoperation methods. This minimises orthopaedic injuries and exposure to hazards during operations. Surgical robots assist physicians in complex procedures however proximal dexterity remains an area for improvement; in particular, tool tip dexterity and actuation. For fine manipulation, micro-robots are docked onto macro surgical robots, extending their capabilities (Omisore et al, 2022). In this way snake-like instruments can be attached to macro surgical robot.

One telerobotic platform is the Raven II, developed by Biorobotics Laboratory (University of Washington). The Raven II is a modular teleoperation solution designed to be more accessible although its clinical application is limited. The Raven II is an open-source platform for collaborative research and the platform's accessibility encourages innovation. The Raven II has 7 DoFs and attached (micro robotic) instruments are constrained about a remote centre of motion with 3 DoFs (Razjigaev, 2022).

Rolling Joint and Tendon Driven Snake-like Robots

Snake robots achieve manoeuvrability through additional or redundant DOFs. A robot could be designed to feature many segments with more DOFs to increase flexibility. The main constraint of MIS is the small workspace. This is reflected in the design approaches in the literature.

One prospective design solution is a monolithic compliant rolling-contact-joint (CRCJ) serial snake-like structure. An example of a CRCJ design is presented Figure 3. CRCJ designs were proposed by Zhang et al (2021), as a solution capable of a smaller bending radius. This robot structure allows for increased movement within small spaces. This structure has since been adopted for further research in its application to knee surgical interventions (Razjigaev, 2022).

Rolling joint robot designs typically employ tendon driven actuation. Extrinsic tendon-driven actuation is a commonly studied actuation method for snake-like robots for MIS. This is due to its flexibility and compact design though it is limited by its tendency to fatigue and slack. Tendon driven robots require tendon channels (Refer to Figure 3). At the small size required for MIS this may compromise the structural integrity of the robot.

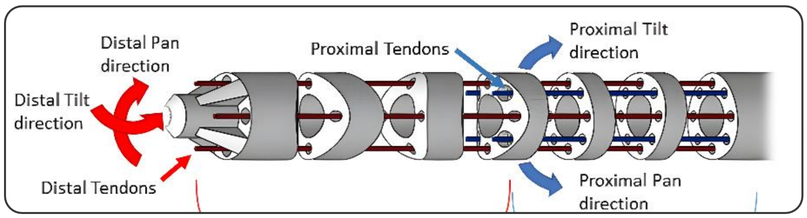


Figure 3 - Rolling joint tendon driven robot design (Razjigaev, 2022)

Robot Design and Optimisation

Snake-like robot designs can be achieved through manual or computerised methods and prototyping.

Manually selecting design characteristics or manual optimisation, rely on expertise to make decisions based on the robot's desired performance. This design method is used to explore novel approaches in snake-like robot design including robot segment shape, material, and mechanical configurations. Wu et al (2017) investigated three manually designed 6-Dof concentric tube continuum robots. The robots were composed of nested curved tubes combining concentric tube mechanisms with tendon driven actuators. The robot configurations differed in their distribution of DoFs. Results showed increasing DoFs at the proximal and distal ends increased workspace and dexterity respectively. Best overall workspace and dexterity was achieved through even distribution of DoFs.

The small workspace of the spine region imposes restrictions on aspects of the robot design including size and actuation. Due to these restrictions, robot design optimisation is crucial to ensure a highly dextrous solution can be achieved. For small environment applications, a key design approach is an optimisation algorithm. These work to optimise design parameters to achieve high capabilities such as dexterity. One of these algorithms is the SnakeRaven Design Algorithm which was developed surrounding a study of knee arthroscopy. This algorithm focuses on the optimisation of snake robots for specific tasks and task spaces in knee surgery. The designs produced by the SnakeRaven design algorithm achieved greater dexterity than state of the art rigid tools (Razjigaev, 2022). However, the implementation of this algorithm to a spinal anatomy case had not yet been investigated.

2.3. SnakeRaven Design Algorithm

The SnakeRaven design algorithm (SRDA) was selected as the platform from which potential spine surgery designs could be developed. This algorithm is coded in MATLAB. Further research was conducted to develop a comprehensive understanding of the SRDA solution, its limitations and potential pathways to overcome them; this is further explored in Section 3.1 Limitations of SRDA in its application to the Spine Anatomy.

The SRDA uses evolutionary optimisation techniques to optimise a rolling joint and tendon driven robot design. The algorithm selects the optimal design parameters to maximise dexterity. The SRDA was developed and tested on a knee arthroscopy surgery task, designing a robotic end effector which connects to a Raven II telerobotic platform for macro-micro teleoperation. The algorithm optimises using a task-based approach which optimises the robot design to reach specific targets in a patient specific task space.

The SRDA can be broken into three main components: i) The computerised mapping of the surgical workspace through voxelisation, ii) the fitness function which calculates the dexterity of a design within the constraints of the voxel model iii) the evolutionary optimisation component which optimises the robot design according to the calculated dexterity scores.

i. Task Space Voxelization: Mapping the surgical task space.

Given a 3D patient anatomy scan, the SRDA requires the segmentation of the task space into voxels to define the task space, targets, and obstacles. Voxels are labelled as goals or obstacles; the target is defined by goal voxels. Figure 4 shows the voxelisation of the knee environment and the 4 targets specified for testing.

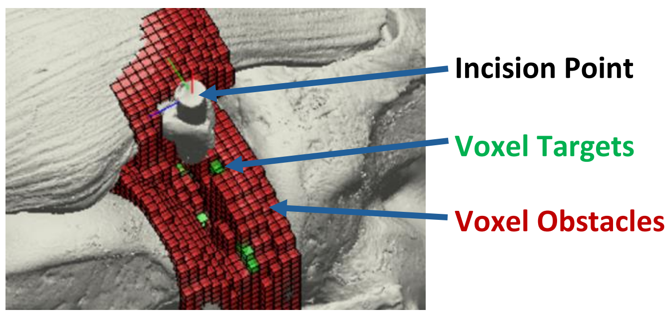


Figure 4 - SDRA voxelisation applied to knee model for task specific optimisation (Razjigaev, 2022).

ii. Dexterity Calculation Fitness Function

Dexterity describes a tools ability to reach a target from various orientations; Figure 5 (a) illustrates this concept. The SDRA fitness function performs a dexterity evaluation of one robot design within the specified environment. Each voxel is represented by a service 'sphere'. The surface area of the service sphere represents the possible orientations the end effector (robot design) could reach that voxel. Dexterity is the percentage of orientations achieved by an end effector out of all possible orientations.

The service sphere surface area can be discretised into N_θ by N_h equally sized patches; for all testing N_θ and N_h are set to 18 and 9 respectively (Refer to Section 2.3.1 for further detail on the selection of patch sizes). $N_{O,i}(v)$ represents the number of service region patches achieved by the end-effector for goal voxel; this is the number of unique 'hits'. N_{Vroi} is the total number of voxels that make up the target or region of interest (V_{roi}) i.e. the number of goal-voxels. The dexterity score, $Dex(V_{roi})$, for any given design is defined by,

$$Dex(V_{roi}) = \frac{\sum_{i=1}^{N_{Vroi}} N_{O,i}(v)}{N_\theta N_h N_{Vroi}} \in [0, 1] \qquad (Equation\ 1)$$

For every design evaluated, the algorithm determines dexterity by testing many random design configurations. Configurations are the positions one design can achieve and are determined through calculating the forward kinematics of the rolling joint design. The algorithm tracks the number of configurations which reach the target voxels. This method employs parallel computing for efficiency. This process is illustrated in Figure 5 (b).

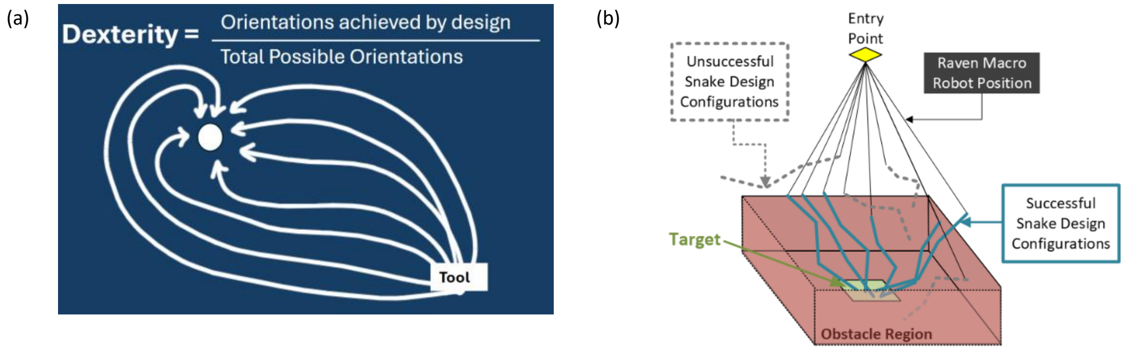


Figure 5 – (a) Dexterity and (b) Design configuration testing to determine dexterity.

iii. Evolutionary Optimisation

The SRDA employed evolutionary optimisation techniques. The algorithm evolves a population of designs over multiple generations. Each design is defined parameters which determine the shape and kinematics of the design. The initial population is randomly generated and evaluated using the fitness function. All subsequent generations are produced by retaining the best performing designs from the previous generation and generating hybrid designs. Mutations are also introduced to maintain diversity in the design population. For the purposes of this project, the evolutionary framework is used in its existing form with no modifications made to the internal structure or evolutionary variable settings.

2.3.1. Dexterity Requirements for Spine Interventions

As introduced in Section 2.3 (ii), each target voxel is split into $N_\theta \times N_h$ equally sized patches. N_θ and N_h are set to values of 18 and 9 respectively. This results in 162 potential orientations considered per voxel. This value could be reduced to consider fewer orientations (low resolution); however, this would diminish the algorithms' ability to distinguish between the dexterity scores f different designs. This limits the effectiveness of comparative analysis. The chosen quantity (162) offers a good balance between resolution and computational performance. This is important for the theoretically based testing performed in the SRDA, where the goal is to evaluate how well a design can reach a range of potential target orientations.

When determining an appropriate dexterity score requirement for spine interventions it is important to understand the relative nature of the dexterity score. Although a fixed dexterity target is not defined, an estimate can be informed by the requirements of real-world surgical procedures. In practice, tools which provide access to a target from only a few orientations increase risk due to unpredictable complications and other surgical factors which may not be accounted for in the model. A good dexterity score is one that allows for broad coverage of the possible orientations to ensure flexibility and reliability in practice. Ultimately, an appropriate level of dexterity is best validated through physical testing.

2.4. Identified Gaps and Project Contribution

Through the literature review several critical gaps were identified in the field of snake-like robotics for minimally invasive spine surgery.

Existing tools for spine MIS are rigid with limited tool tip manoeuvrability, making them poorly suited for navigating the constrained and delicate spinal anatomy. Snake-like robots are a potential tool solution to provide the required manoeuvrability. Clinical applications of snake-like robots are not yet widespread and limited research has been conducted on the application of snake-like robotics for spine interventions despite the high dexterity demands of these procedures.

There exist few computational methods for optimising robotic designs. Much of the literature investigates manually designed robots, relying heavily on expert knowledge rather than a systematic optimisation process. No design or optimisation method has been developed or validated for the spine anatomy case. One computational optimisation solution is the SnakeRaven Design Algorithm (SRDA). The SRDA was developed to optimise snake-like robot designs and has been applied to knee interventions. Its performance in spinal applications has not yet been evaluated. Additionally, the design space for snake-like robots has not been comprehensively explored, limiting the understanding of how to design useful snake-like robots for the different regions of the spine.

This project addresses these gaps by applying the SRDA to the spinal anatomy in order to evaluate its ability to design a robotic solution that meets the surgical requirements of spine interventions – such as providing dextrous access across a vertebral surface. By refining the SRDA for spinal anatomy and broader multidimensional surgical spaces, this research introduces previously unexplored insights that enhance the design process for snake-like robots in spine interventions. A tailored methodology is proposed to guide the design of effective snake-like robotic solutions for this complex and delicate environment.

3. Methodology

To answer the research question, a systematic methodology was developed. This approach is informed from the initial research and literature review and involves multiple stages including:

1. an initial investigation into the limitations of the SRDA in its application to the Spine anatomy,
2. the refinement of four guiding secondary research questions (SRQs)
3. a parameter sensitivity analysis (Addressing SRQ I.)
4. an evolutionary optimisation performance assessment (Addressing to SRQ II.)
5. the application of the informed SRDA to the spine anatomy (Addressing to SRQ III.) and
6. the introduction of a modified fitness function to process surface-targets (Addressing to SRQ IV.).

Each stage builds upon the outcomes of the previous stage, to systematically evaluate the performance of the SRDA and to establish a framework for applying the SRDA to the case of the spine anatomy. This methodology structure also allows for reiteration and further refinement of the design process as the project progresses.

In addition to addressing the primary research questions, this methodology section will also extend to cover several challenges and foundational considerations. These include the development of appropriate testing environment, the selection of a suitable sample size for the fitness function, and the management of algorithm limitations relevant to the analyses conducted.

3.1. Limitations of SRDA in its application to the Spine Anatomy

In reviewing the application of the SRDA to the knee anatomy and the requirements of spine interventions, three key limitations and considerations for the SRDA were identified.

1. Tool entry port characteristics

The entry port characteristics for lumbar spine MIS must be considered. This will involve correctly positioning the start point of the robot when modelling the workspace; this is defined by the Remote Centre of Motion (RCM) variable in MATLAB. The retractor port, which restricts the robot's entry, can be simulated by correctly restricting the Raven Joint positions (limits). This will constrain the position of the snake-robot design to be within the appropriate retractor bounds.

2. Task and Patient Specific Designs

The SRDA optimises tools for task and patient specific applications. That is one tool is used to reach only one target in a patient unique anatomy. The task space of the spine is more correctly defined as a target surface; not a set of separate points as SRDA implementation. As such a surface processing approach is more appropriate. Additionally, it may be possible to develop designs specific to the workspace/environment dimension rather than the patient specific approach. This introduces opportunity to develop a single design or fixed set of designs that works for the various spine applications. This avoids complexities of introducing patient specific instruments in clinical settings. This is particularly relevant to the sustainability considerations further explained in the Ethics & Sustainability section of this report.

3. Algorithm Inefficiencies

The fitness function of the design algorithm is not efficient due to its use of a random configuration testing framework that requires a large sample size of design configurations to be tested. Additionally, the algorithm searches a large design space and optimises over many generations. As such, an important investigation is to find the sub-space within the larger design space, where the best solutions for spinal interventions exist.

3.2. Development of Secondary Research Questions

Secondary research questions, first introduced in Section 1, were further refined after the identification of the limitations of the SRDA. These questions contribute to the resolution of the primary research question and aim to address the limitations of the SRDA identified in Section 3.1. These revised questions now reflect the more detailed project context.

I. Where within the design space do the viable and useful design solutions exist for the spine anatomy?
II. What is the role of evolutionary optimisation in enhancing the dexterity outcomes? What are the associated computational costs, and can this cost be justified by any improvements achieved?
III. Can the algorithm be applied effectively to the spine anatomy to produce useful design solutions?
IV. How can the algorithm be adapted to handle surface target cases?

Each question is addressed throughout the subsequent methodology. Namely SRQ: (I) is addressed in Section 3.3. Parameter Sensitivity Analysis; (II) is addressed in Section 3.4. Optimisation Algorithm Performance Analysis; (III) is addressed in in Section 3.5. Algorithm Application to Spine Anatomy; and (IV) is addressed in Section 3.6. Adapting the Fitness Function to Process Surface .

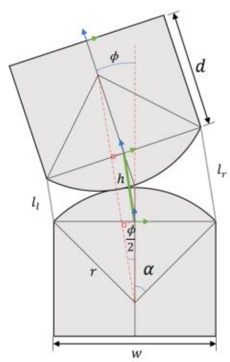
3.3. Parameter Sensitivity Analysis

A parameter sensitivity analysis was conducted to investigate the relationship between each design parameter, environment dimension and dexterity. This analysis investigates the dexterity output of the algorithm's fitness function; at this stage, no evolutionary optimisation was performed. This analysis aims to answer secondary research question (I) and determine where within the design space useful configurations exist for spine interventions.

The main outcome of the PSA is the ability to create 'bound' design spaces. A bound design space is a subset of the design space tailored to capture the best performing parameter values for each environment dimension.

3.3.1. SnakeRaven Design Parameters

The SnakeRaven design is defined by 4 parameters; visualised in Figure 6. These are: the width or diameter of the SnakeRaven (w), the distance between the rolling surfaces (d), the total number of joints in a module (n) and half the angle of curvature of the rolling joints (α). The SRDA works to optimise only parameters α, n and d. All other variables are selected by the user and remain at fixed values. The width is chosen during the voxelisation stage. An additional variable is the tool tip length. This length protrudes from the tip of the SnakeRaven design; this value is also fixed and not optimised.



Design Parameter Ranges

α [0.01, π/2] rad
d [1, 10] mm
n [1, 5]
w [1, 5] mm

Figure 6 - Diagram defining design parameters, α, d, n and w, on rolling joint robot model. (Andrew Razjigaev, 2022)

3.3.2. Parameter Ranges and Real-World Constraints

Many variables can affect the dexterity score outputted by the fitness function. These include the environment dimensions, the 4 primary design parameters (α, w, d, n), tool tip length and target position. Parameters α and d increase in increments of 0.01 while n and w are varied in steps of 1. Given the broad parameter ranges the resulting design space expands in many dimensions and is complex to evaluate exhaustively. It was critical to make informed and strategic engineering decisions to focus the analysis on the parameter paths that were most likely to yield meaningful insights. This involved considering real-world constraints on size and structural feasibility. Additionally, as the investigation progressed, better performing variables we selected to be held constant within the design to further test the behaviour of other parameters. Tested parameters ranges were all noted in a testing log (Refer to Section 3.7).

One primary constraint is the width of robot. The robot design must accommodate various tendon channels as well as an internal housing for tool attachments. As such, a 1mm diameter robot is not considered a viable design option. The number of segments is also restricted. A high number of segments amplifies positional error due real-world construction inaccuracies. This parameter value is therefore limited to a maximum of 5 segments.

3.3.3. Environment for purposes of PSA testing

'Box' environments were used for parameter sensitivity analysis (PSA). A box environment is defined as a square prism of varying internal dimensions (Refer to Figure 7). This form was selected for its regular scalable shape which minimises variability. This ensures a consistent framework for the comparison required in the PSA which includes the definition of identical targets. Additionally, a box effectively mimics the intervertebral environment by constraining the robot's movement between walls. The box has only one opening located at one square face of the prism. The internal dimensions used for the PSA, range from 8mm to 30mm (at varying intervals: 8, 10, 12, 14, 18, 22, 26 and 30 millimetres) and the depth of the box is 40mm. The outside dimensions of the box remain equal for all testing at 40mmx40mmx45mm.

The defined target is a 1mm extrusion located on an internal wall; after voxelisation the target spans a 5mmx5mm area across the face of the wall. The side wall target position best represents the placement of targets along the inner vertebral surface. Two target depths were defined as 10mm and 20mm below the box opening.

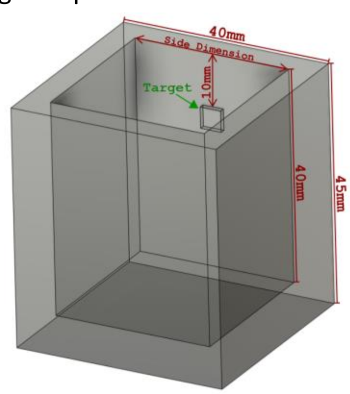


Figure 7 - Box Environment and target set up diagram

3.3.4. Dexterity Calculation Adjustments for Width Testing

A limitation of the SDRA was noted when testing the effect of the width parameter on dexterity. Width largely affects the voxel model of the environment. The voxelisation stage dilates the obstacle voxels in the model according to the width. This results in reduction of target voxels; this process is illustrated in Figure 8 for a 3mm width example. As such, when analysing the influence of width on dexterity, scores are scaled to reflect the true number of target voxel selected. As all other comparisons used the same width, and dexterity is a relative value, dexterity was left unadjusted for all other analysis testing. This adjustment ensures the parameter sensitivity analysis yields fair and valid results.

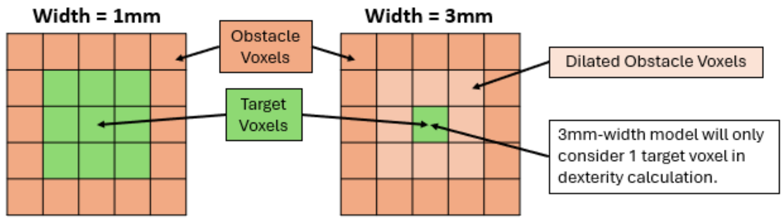


Figure 8 - Example of Reduction of Target Voxels in Dexterity Calculation

3.3.5. Determining an appropriate Sample Size

The sample size corresponds directly to the number of configurations tested. In theory a large enough sample size captures all possible robot configurations; this is an important consideration to ensure the reliability of all subsequent testing. As such, as the sample size increases the dexterity score should converge to some maximum measure; That is the true measure of dexterity for the robot design. Four sample-size tests were conducted to determine an appropriate sample size for subsequent parameter relationship tests; The detailed results are contained in Section 13.1 Appendix B. A sample size of $5 \times 1e^{8}$ was selected as it was determined that new successful configurations are less likely to be found beyond this value. This value is large enough to capture most of the viable configurations but is also chosen to minimise computational resources use for practical testing.

3.4. Optimisation Algorithm Performance Analysis

Once an understanding of the design space was established, the performance of the evolutionary optimisation component of the algorithm was evaluated; this analysis aims to respond to the secondary research question (II). The SDRA was tested under two conditions: 1- using the full unedited parameter ranges (unbound algorithm) and 2- using the bound parameter ranges informed by the PSA (bound algorithm). The comparison of the bound and unbound algorithms evaluates the validity of the PSA results as well as the potential benefits of searching a smaller more informed design space.

Additionally, this analysis assesses the contribution of the optimisation component toward progressing the robot design to an optimal tool for spine interventions. To ensure consistency and fairness in comparison, this phase of the project uses the same box environments as the PSA for testing. Note that only 4 environment dimensions were tested (12mm, 14mm, 18mm and 26mm). These dimensions were chosen to best represent a broad range of potential spine dimensions. Multiple trials were conducted to ensure reliability of results.

3.5. Algorithm Application to Spine Anatomy

After testing the algorithm on the box environment, the algorithm was applied to the anatomical spine model. This phase responds to secondary research question (III) and aims to assess whether the insights identified in the PSA and optimisation analysis, translate effectively to the organic spine structure.

Unlike the box environments the spine environments are irregular and introduce a more complex obstacle environment for the robot designs to perform within. To choose an appropriate bound design space a representative dimension measurement was taken between the widest point on the vertebrae. An appropriate bound design space was then chosen based on this measurement. For this testing, it is important to take into consideration the surgical constraints. As such, the spine models used were prepared to be align with realistic surgical practice.

3.5.1. Spine Environment Model Preparation

For the spine optimisation analyses an anatomical 3D human spine model is required (see Section 8. Resources) . Two vertebral models were selected and modelled to capture the variation in anatomical constraints between the different spine regions. These are, L2-L3 representing the wider lumbar spine region and T9-T10, representing the narrower thoracic spine. Each pair was extracted from the complete spine model to create the isolated spine environments for testing. These models required further preparation prior to testing including, vertebrae distraction, facetectomy as well as accurate retractor positioning. This preparation process is informed by a Minimally Invasive Spine Surgery medical textbook (Phillips et al. 2019) which details the medical protocols for minimally invasive spine interventions.

Vertebrae distraction is the controlled separation of the vertebrae typically performed to facilitate the placement of an implant such as an interbody space during fusion procedures. A facetectomy involves the partial or complete removal of the facet joint; this is also commonly performed before fusion operations. A facetectomy allows for a greater surgical access. Both procedures were replicated in Fusion360 for the lumbar and thoracic spine models.

A tubular retractor was modelled to inform the position of the spine relatively to the raven entrance point during the preparation stage and is not included in the voxelised model. The retractor was correctly positioned parallel to the vertebrae and sitting on the facet joints. Robot joint limits were set to account for the retractor. A bounding structure is placed around the vertebrae to ensure robot configurations are only able to enter the spine space from the correct opening. An effort was made to ensure targets were similar sizes and spread apart reasonable, so a better understanding of the dexterities achieved in different locations. The prepared models accurately represent their anatomical and procedural contexts; The diagram in Figure 9 shows the prepared lumbar spine model.

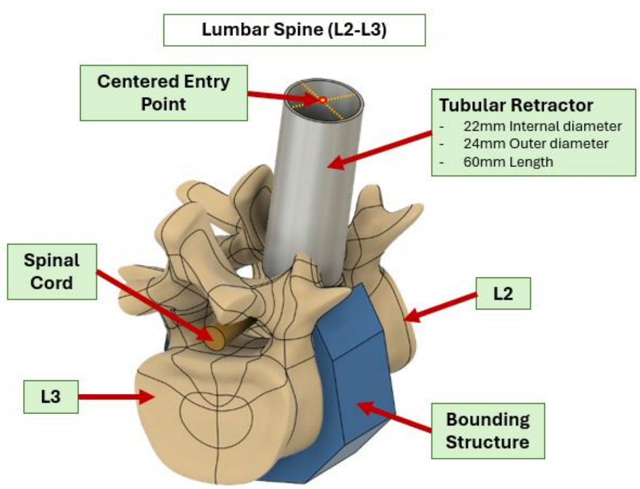


Figure 9 - Diagram of Lumbar Spine Model Prepared for Optimisation Testing

3.6. Adapting the Fitness Function to Process Surface Targets

In real-world applications, it is more useful for tools to be able to service entire spinal surfaces rather than target points. The SRDA was limited by its inability to optimise robot designs for surface targets. To extend the capabilities of the SRDA to handle surface targets an adapted fitness function was developed. This function was not tested within the full optimisation framework but is a standalone fitness function which may be used to map the dexterity achieved at individual voxels making up a surface area. The adapted function is distinct from the regular fitness function in two primary ways:

1. It does not allow a design to traverse goal voxels except at the tip of the tool. This ensures no configurations which traverse the vertebral surface to reach a target voxel (i.e. traverse the bone) are considered successful.
2. A dexterity map is created to keep track of dexterity scores for the individual voxels which comprise the full surface target.

The function outputs a dexterity map which visualises a tools ability to reach different areas on a surface. This approach is better suited to determine a design's ability to be dextrous in the spine environment.

3.7. Data collection & Interpretation

3.7.1. Data Collection and Management

Due to the large number of variables and outputs considered throughout the various analyses it was important to ensure good data management.

To streamline the analysis process and to ensure data was correctly classified, various data management methods were implemented. These include consistent file naming conventions, time-stamped files, automated data logging and custom scripts to generate visualisations of raw data. Data extraction scripts were created to automatically generate visual and tabulated summaries of the key metrics recorded in each test. A log of all tests completed was kept; this log tracks all changed variables for both the SRDA and computational resource HPC set up. All coded resources produced were managed using data version control and cloud storage platforms including GitHub and MATLAB Drive.

3.7.2. Data interpretation

The PSA data was largely analysed using graphical data representation which allowed trends to be visually identified. The PSA analysis does not quantify these trends but rather qualitative behaviours of the parameter relationships. This is due to the application of the bound spaces of the design.

While a box environment allows for reliable parameter-dexterity relationships to be identified, in practice the findings of the PSA are applied to organic spine cases. These practical cases yield different dexterity scores making direct quantitative extrapolation ineffective. Identifying trends qualitatively is a more appropriate approach as qualitative insights into the parameter interactions are more transferrable to the real-world organic spine context. The qualitative analysis of the results identifies: trend directions, plateaus and inflection points in the data. These results are organised to define parameter behaviour profiles for various environment dimensions.

Optimisation results which include measures of dexterity, time and computational resources were organised into tables for further comparison. Generational data such as the increase of dexterity over various generations is more appropriately interpreted graphically.

4. Results, Analysis and Discussion

4.1. Parameter Sensitivity Analysis Results

The detailed PSA, including graphs showing the parameter-dexterity relationships, are contained in Appendix C. The following PSA summary contains both the general finding for all environments dimensions (e-dims) as well as dimension profiles which detail parameter behaviours for the selected environment dimensions.

General Findings

The following general observations are true for all environment dimensions.

- $\alpha -$ As the rolling joint increases, dexterity increases.
- $w -$ As width decreases dexterity increases significantly.
- $d -$ Smaller lengths d, provide better dexterity. A 1mm length consistently achieves the highest score.
- $n -$ A design with only one rolling joint, n, achieves only a low dexterity score.
- Increasing the depth of the target from 10mm to 20mm below the box opening had no significant impact on the dexterity scores achieved.
- Larger environments consistently produce higher dexterity scores for the same robot designs compared to smaller environments.
- Designs featuring shorter tool tip lengths achieved higher dexterity scores.

Environment Dimension Specific Findings

The following observations capture the parameter effects on dexterity within different environment dimensions: Large (26mm), medium (18mm) and small (14mm). For simplicity these results reflect behaviours for a robot width of 3mm; the effect of changing the robot width is further detailed in the *Additional Observations* Section below. These dimension profiles are capture the general behaviours for all environments within an 8mm to 30mm range. In conjunction with the general observations an appropriate bound design space can be defined for each environment dimension.

26mm dimension Environment (Large dimension)

For a large environment of 26mm, dexterity peaks with a design using 4 rolling joints (n); however, there is no significant difference between using of 3 and 4 joints. As the distance parameter d is reduced, dexterity increases consistently in an approximately linear manner. A consistent increase in dexterity is observed as the half angle of curvature value, α, increases from 0 to 90°.

18mm (medium dimension)

For an 18mm environment dimension, increasing n from 2 to 4 improves dexterity, but a sudden drop in performance occurs at 5 rolling joints. Dexterity remains consistently low for distance, d, values above 4mm. There is a negligible decrease in dexterity when increasing d beyond this threshold. Below the threshold, dexterity increases rapidly as d decreases with significant variation only observed within this range (1-4mm). A consistent increase in dexterity is observed as parameter α increases from 0 to 70°. Beyond 70° the dexterity score converges quickly and does not increase.

14mm (small dimension)

A moderate linear decrease in dexterity is observed as the number of rolling joint increases from 2 to 5. Similarly to the 18mm environment, parameter d stabilises at a low dexterity value above a 3mm threshold. Greater variation is observed within the 1mm-3mm range with 1mm producing the highest dexterity as per the general findings. This smaller environment also sees diminishing returns from increasing parameter α with no improvement in dexterity beyond a $35°$ value.

Additional Observations

The width parameter had a noticeable impact on best performing values for parameter n. Reducing w from the initially examined 3mm to 2mm, caused a shift in the n-dexterity relationship, such that an additional rolling joint (n) now provided the highest dexterity within small e-dims (<14mm). Reducing w also noticeably affects the α-dexterity relationship for medium e-dims where increasing α now consistently increases dexterity.

Bound Design Spaces

The final bound spaces used for further testing are recorded in *Table 1*. The final width value selected is 2mm; this value allows for more dextrous designs while remaining a viable option for real-world practical application. To maximise dexterity, a 1-2mm range is selected for d, for all environment dimensions. However, it can be noted that the larger dimensions may allow longer segment designs to achieve comparable dexterity scores to short-segment designs within smaller environments. Longer segments may offer increased physical sturdiness; this aspect is not explored in this project. A tool tip length of 3mm was set constant for all designs.

Table 1 - Bound Design Spaces

Environment Dimension [mm]	Bound Design Space			
	α [^{0}]	n	d [mm]	w [mm]
12	[30, 70]	[2, 3]	[1, 2]	2
14	[30, 70]	[3, 4]	[1, 2]	2
18	[50, 90]	[3, 4]	[1, 2]	2
26	[50, 90]	[3, 4]	[1, 2]	2

4.2. Optimisation Algorithm Performance Results

The following results describe the performance of the bound and unbound algorithm cases tested. The bound algorithm is configured to search the bound design spaces presented in the PSA. While, multiple trials were conducted, averaging results is not appropriate due the variation of measured computational metrics. This variation is due to the randomised testing employed by the SRDA. Similar trends were observed across several trials, and a representative trial is presented.

Computational cost can be described by the time taken to optimise designs; Table 2 records these metrics. The bound design space contains 14,342 unique designs while the unbound space contains 707,285 unique designs. So, it was expected the bound algorithm would converge to the optimal design much faster searching the reduced design space. It can be noted that the bound algorithm achieved very similar dexterity scores to unbound algorithm. Initial observations of the data in Table 2 shows there is great variation in the time to achieve these dexterity scores which suggest no consistent computational efficiency is gained from the bound algorithm. However, in exploring the full data sets a more complex result is observed. For example, for the 26mm e-dim, the bound algorithm achieves the highest of dexterity (0.454) in the 22nd generation but reaches a rounded down value of 0.45 within the first generation; that is, 21 additional generations are used to increase the dexterity score by only 0.004. Although, the unbound algorithm achieves its highest score (0.458) faster, in the 12th generation, it takes 7 generations to achieve the 0.45 score; this is 6 generations slower than the bound algorithm.

Table 2 - Optimisation Test Results

Test	Design Space Size	E-Dim (mm)	Highest Dexterity	Time to achieve highest dexterity	
				Generation	Runtime (hr)
Unbound	707285	26	0.458	12	19.06
		18	0.43	10	15.7
		14	0.363	16	24.7
		12	0.308	9	15.14
Bound	14342	26	0.454	22	34.47
		18	0.433	8	14.49
		14	0.363	7	13.1
		12	0.275	8	11.04

Further insights which demonstrate the effectiveness of the bound algorithm are more clearly interpreted in the dexterity over generational (gen) time graph in Figure 10 for the four chosen environment dimensions (e-dims). It can be noted that for the 14, 18 & 26mm e-dims, the bound algorithm achieved a similar dexterity score to the unbound algorithm with a maximum difference of 0.004 which equates to 9.72 orientations per target. Recalling that each target voxel allows up to 162 orientations and targets comprise of 15 voxels after width dilation; at most there is a loss of 9.72 orientation out of a total 2,430 possible orientations.

Notably, the bound algorithm dexterity scores quickly increase, surpassing the unbound algorithm scores within the initial generations. The bound algorithm did not perform as well for the smallest e-dim of 12mm. This may be due to over-constraining the solution space and suggests the smaller environments are more sensitive to parameter tuning.

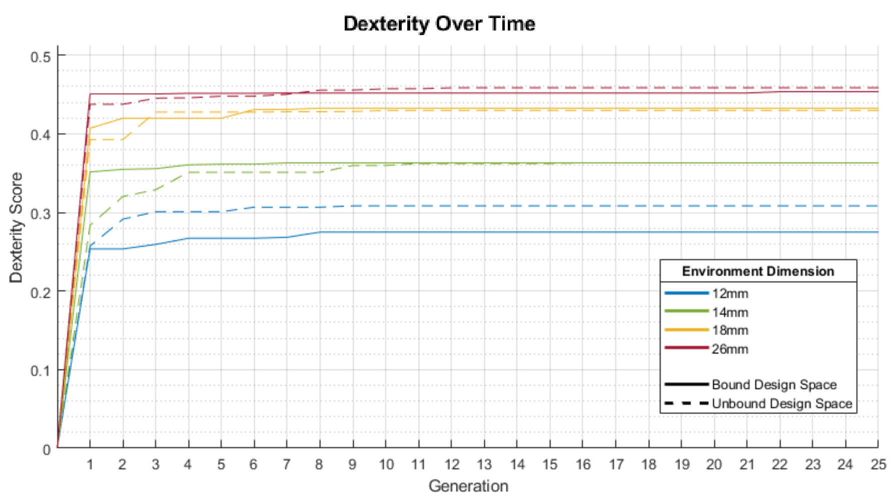


Figure 10 - Dexterity Over Generational Time (Bound vs Unbound Design Space)

These results reveal that much of the computational cost is due to pursuing a marginal dexterity increase. In particular, the data suggest evolutionary optimisation provides minimal added benefit in achieving a high dexterity score for 14-26mm e-dim designs.

4.3.

4.3. Spine Anatomy Model Testing

Spine anatomy was tested on both a thoracic and lumbar spine environment. The bound and unbound algorithms were tested in their performance to optimise robot designs for 5 targets. Representative environment dimensions of 10mm and 17mm were selected for the thoracic and lumbar environments respectively. Figure 11 depicts one lumbar spine vertebrae with the selected targets labelled.

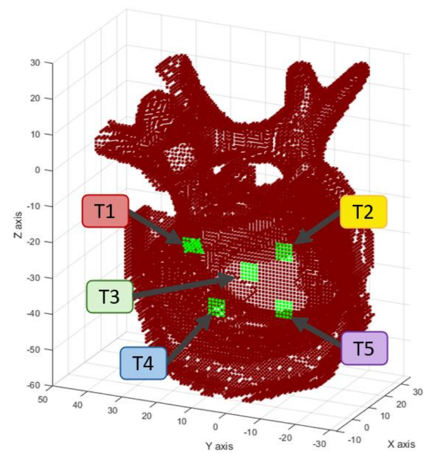


Figure 11- Diagram of selected targets on Lumbar Spine (Indicative for Thoracic Spine model, Notation: T denotes target)

The development of dexterity over generational time for the bound and unbound algorithms are presented in Figure 12. It can be generally observed that the bound algorithm designs achieved higher dexterity scores faster than the unbound algorithm for targets 2, 3, 4 and 5.

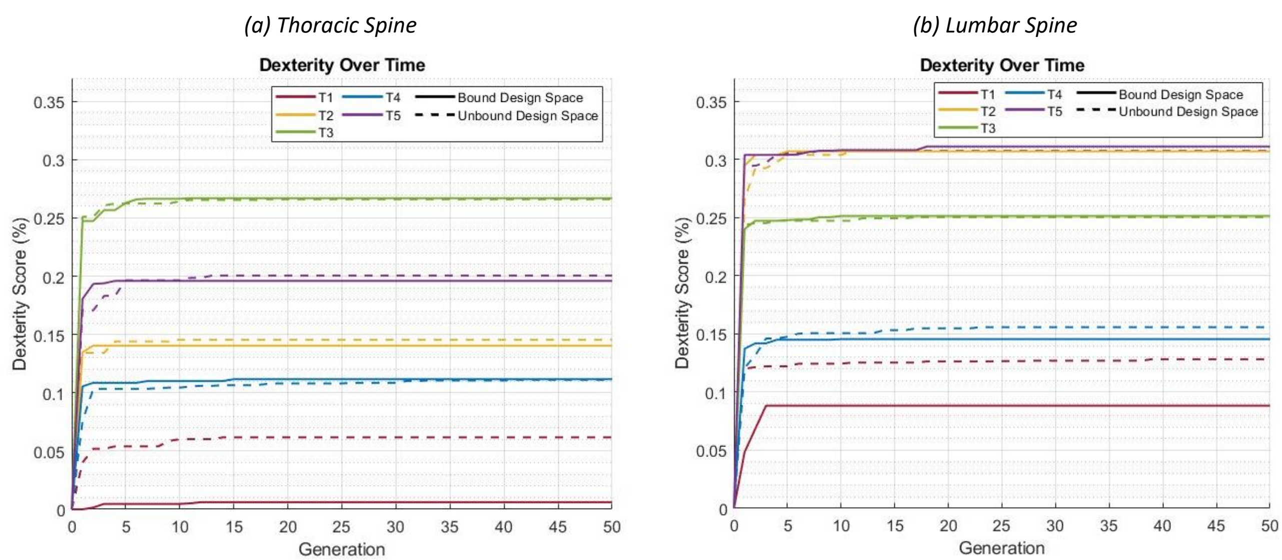


Figure 12 - Dexterity over time results for Spine tests

Table 3 records the recorded metrics for the lumbar spine tests. Similarly to results presented in Section 4.2 (*Optimisation Algorithm Performance Results*) it can be noted that overall runtime is largely increased in pursuit of a marginal dexterity increase for most target cases. It is also observed that targets further from the midline of the entry portal are more difficult to reach, yielding much lower dexterity scores.

The total number of unique evaluated designs is also recorded. While value is largely dependent on the algorithms randomised testing process, searching the unbounded design space increases the likelihood of encountering more unique designs, thereby increasing the time to evaluate a generation of designs. The bound algorithm runtimes are not consistently faster for the lumbar environment. However, for the smaller dimension thoracic spine anatomy, the best performing design is consistently achieved in a shorter runtime by the bound algorithm (refer to Appendix D for results table).

Table 3 - Spine Anatomy Testing Results - Lumbar Spine

Design Space	Design Space Size	Target	Highest Dexterity	Time to achieve highest dexterity		No. Unique designs tested
				Gen	Runtime (hr)	
Unbound	707285	1	0.128	39	33.93	1036
		2	0.307	11	11.36	571
		3	0.251	17	9.66	337
		4	0.156	23	22.28	921
		5	0.308	8	8.22	428
Bound	28542	1	0.088	3	3.01	198
		2	0.307	5	5.43	315
		3	0.252	10	10.48	416
		4	0.146	10	6.55	243
		5	0.311	18	15.89	874

From these results it can be determined that although bound design spaces provide a theoretical advantage, a shorter runtime is not consistently observed due to the algorithms dependency on randomised testing processes. However, a high dexterity solution is often found within the bound design spaces.

4.4. Adapted Fitness Function for Surface Targets

To evaluate the capabilities of the adapted fitness function, the best performing design from the bound-algorithm lumbar spine tests (Targets 2) was selected for further analysis. A visualisation of the selected surface target is shown in Figure 13(a). Five trials were conducted with all trials using the same sample size to ensure reliability of results.

Due to the organic structure of the vertebral space, the algorithm produced several design solutions during the Spine Anatomy Model Testing (Section 4.3). The adapted fitness functions provides a good method to test capability of a single design in reaching the several target location.

The dexterity map produced by the adapted fitness function is shown in Figure 13(b). The map displays the dexterity score achieved for individual target voxels. High dexterity areas achieve a dexterity score of up to 0.48; that is 48% of the 162 possible orientations were achieved at those voxels. These high-scoring locations correspond to the high-scoring targets in Section 4.3 testing; this was observed in every trial. However, it is important to note that while some individual voxels correspond to a high dexterity score, other areas of the surface performed poorly which reduces the overall or total surface dexterity score. The resulting map suggests dexterity tends to decrease as the target moves further from the midline of the entry port.

The dexterity map effectively records and visualises the dexterity performance of a design across a surface. Although the current fitness function output relies on a qualitative visualisation of the raw dexterity map data, this data could be further processed to quantify the overall dexterity performance – This refinement shall be discussed further in Section 7 Future Works.

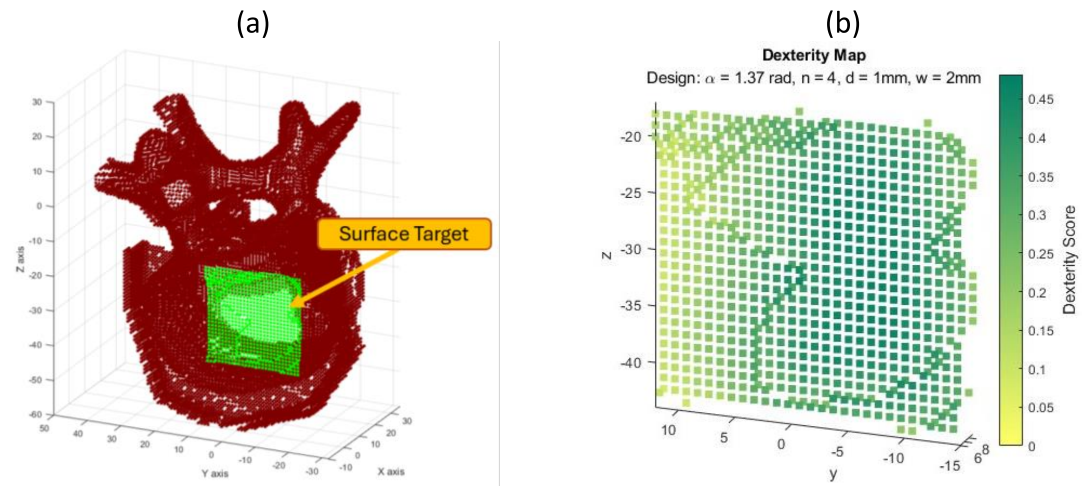


Figure 13 – Lumbar Spine Test (a) Surface Target Selection, (b) Adapted Fitness Function Dexterity Map Output (Target 2 Design)

4.5. Discussion of Findings and Limitations

Overall, highly dextrous solutions were frequently found within the bound design spaces. Although searching a bound design space does not guarantee improvements in efficiency metrics (runtime), it enables an alternative approach. Rather than relying on the computationally costly evolutionary optimisation methods to design a good solution for the spinal space, a diverse set of designs could be sampled across the bounded space and evaluated directly; this approach is validated from the fast and high dexterity performance of the bound algorithm, as observed across the optimisation tests. The best performing design could then be selected based on the known dexterity trends. This approach, however, is not reliable for the smallest environments (~$\leq 12mm$) which produced more inconsistent results throughout testing.

This methodology is viable given the established understanding of the dexterity score achievable across different environment dimensions (informed by the PSA). Knowing the level of dexterity that can be expected in a particular space as well as the design parameter characteristics allows for a more targeted and cost-effective process which effectively reduces the optimisation task to a single-generation search. This calls into question the necessity of the full optimisation process, although further testing is advised before dismissing this approach.

Furthermore, dexterity can now be evaluated across a target surface rather than select points. This allows for a more realistic analysis of how robot designs perform spatially.

A limitation of the overall project is the algorithms reliance on randomised testing. Although overall trends were observed, increasing the number of trials and calculating the observed variance in the results would increase the statistical confidence in the findings. However, this is constrained by the high computational cost of running the SDRA, limiting the feasibility of extensive repeated testing.

Another limitation is the manual tuning of the bound spaces which relied on engineering judgement. Not all design pathways were explored. While design choices were informed by both the PSA results and real-world constraints, bias and error are not eliminated.

Finally, the adapted surface-target fitness function possesses some limitations. It was only tested as a static evaluation tool and not within the optimisation framework. As such potential benefits of the optimisation process remain unverified. Additionally, the runtime of this fitness function is exceptionally high at an average of 27 hours per design evaluation. This is due to the sequential nature of dexterity mapping. Unlike the original fitness function the adapted function cannot take advantage of parallel computing as the tracking of individual voxel dexterity scores requires evaluations to be performed sequentially.

5. Project Risks

Due to the computer based and theoretical nature of this research project, no pertinent health and safety risks were expected to be encountered. However, various risks to the success of the project were identified. Risks were mitigated through consistent management throughout the project timeline. Two major encountered risks are detailed in this section.

1. Acquiring a lumbar spine model for algorithm testing posed an unexpected challenge and risk to the success of the project. Initially I intended to use real patient scans from publicly available databases including the Visible Human Project and the Zenodo MRI dataset. However, patient scans required cleaning and sectioning.

A general CAD model was used as a substitute for the patient MRIs. This introduced limitations in the validity and accuracy of the model due to it being sourced from a public CAD repository in contrast to a verified medical database. Despite this limitation the model is deemed suitable for this theoretical testing based project. The CAD geometry used, offered a practical alternative to the more complex process of converting an MRI scan to a 3D model which requires the acquisition of medical imaging processing skills and is deemed beyond the scope of this project. To further mitigate this risk, the spinal geometry was reviewed and verified to ensure alignment with realistic human anatomical dimensions.

2. Computational limits were identified as primary risk affecting research progress. The SRDA relies heavily on the use of a High-Performance Computing unit (HPC) due to the large sample size required for the fitness function. Without access to a high-performance computer (HPC) testing the SRDA is significant slower and inefficient. As such, access to the university's HPC system was organised in Semester 1. Continuous and proactive monitoring of computational requirements and HPC availability (including maintenance periods and outages) was essential to minimising interruption of project progress.

All testing involving the SDRA was scheduled early enough to allow for multiple trials, methodology refinement and iterations. This mitigated the risk of prolonged timelines and delays in project milestones. Additionally, to further minimise computational inefficiencies, unnecessary visualisations were avoided as these processes require a large amount of computational resources power and can greatly increase the total runtime of each trial. For example, after an initial environment were configured, full model voxelisations were not plotted as generating these visualisations could take up to 1 hour. Instead, model verification was performed by checking key numerical outputs including the total number of target and obstacle voxels, and by visualising only the target region. This approach allowed for accuracy while reducing computational costs.

Several additional project risks were identified including scope creep, mismanagement of results data and loss of written or coded resources. Section 13.4 Appendix E contains a table summarising the identified risks, consequences, and mitigation strategies. The risk classification is determined by the consequence severity and likelihood matrix.

6. Ethics and Sustainability Considerations

Ethics

In decision making and conduct, it was a priority to stay in aligned with the *Engineers Australia Code of Ethics and Guidelines on Professional Conduct* (EA-CEGPC). I uphold professional integrity and transparency (EA-CEGPC Guidelines 1.1, 1.2) by always representing findings accurately and acknowledging the limitations of the project. This has been implemented in all project documentation.

I have engaged responsibly with my stakeholders (EA-CEGPC Guidelines 4.1) through frequent project updates. I have ensured my supervisors are up to date and have submitted draft project documentation so they could provide feedback, contributing to the refinement of my project's development. This also better ensures the alignment of my project with stakeholder expectations.

Clear communication of potential risks and limitations of my project has been consistent. Additionally, I have adhered to a well-structured engineering design process to ensure I can act on the basis of adequate knowledge (EA-CEGPC Guideline 2.2). Following these guidelines has been essential in the development of ethical research with intended medical applications.

Sustainability Considerations

Sustainability is also a key focus. Following the guide of *the Engineers Australia Implementing Sustainability: principles and practice guidelines*, (EA-ISppg), this project aims to contribute to the development of environmentally conscious technologies within the clinical field.

This project follows these sustainability guidelines by considering the life-cycle and span of the snake-like robot (practice C6.1, Stewardship, Product end of life). The prevalence of waste in the clinical setting was made apparent during a hospital visit. I was invited to view two surgery procedures performed by stakeholder Dr. Ross Crawford. Plastic is a common material for disposable clinical tools. During the surgery viewings it was clear that plastic was utilised at all stages of surgery from the surgeons' garments to the surgical sutures. It is a common material used for instrument construction due to its low cost, flexibility, biocompatibility, and disposability.

Based on this observation it was decided that efforts should be made towards reducing the environmental impact of this project. Whilst previous approaches have focused on single use, patient and task-specific disposable instrument design, this project explored solutions that are potentially multipurpose; namely in developing a method to design tools to work in differently sized environments as well as developing techniques to evaluate the performance of single instrument over larger task-spaces . The successful design of a standardised device or set of devices supports the case for reusable, sterilisable tools which avoid the resultant waste of single use tools. The use of an optimisation algorithm also addresses sustainable practice C3.5 (Design. Process optimisation). This alongside efforts to create a multipurpose reusable robotic tool enables better use of materials fulfilling practice C3.4 (Design. Resource efficiency).

Finally, one main objective of my project is to evaluate and improve the efficiency of the SRDA. Improvements in efficiency results is faster and cheaper robot design which increases the accessibility to robotic medical solutions. This aligns with the United Nation's Global Sustainable Development Goals (SDG). Namely SDG 3 which aims to improve access to good health and well-being (UNDP, n.d.).

7. Future Works

A continuation of the project could explore the integration of adapted surface fitness function into full optimisation framework. Since this function uses a dexterity map rather than a single aggregated dexterity score, there are nuances in quantifying the general dexterity capabilities of a robot design when accessing a broader target surface. Additional limitations listed in Section 4.5 can also be addressed to further improve the algorithm's capabilities.
This project explores a single-module robot design requiring the optimisation of only one set of design parameters. Future research could investigate a two-module design to assess potential improvement in dexterity. The suitability of the developed bound-algorithm approach for designing this more complex robotic solution should be evaluated.
Finally, the real-world validation of the analyses results, through prototyping and testing, is a crucial step toward developing a solution for practical medical implementation.

8. Resources

My research relied heavily on literature resources referenced throughout this report. The most important resource used in my project was the SnakeRaven design algorithm. This is the code resource I worked with throughout the entire project. Andrew Razjigaev, the author of the SnakeRaven algorithm published this algorithm on GitHub. Other published (online) documentation includes his thesis, research papers and presentation and experiment videos. I have interacted with these resources to better understand the SnakeRaven design algorithm. An overall project resource table, refer to

Appendix F: Resources, was developed to document all published materials and software which contributed to the completion of this project.

9. Stakeholders and other acknowledgments

I would like to acknowledge the support and guidance of my project supervisors Prof. Cameron Brown and Prof. Will Browne. Their expertise greatly influenced the focus of my research. Through regular feedback and constructive discourse I was able to refine my project scope, outcomes, design choices and the engineering design process employed to complete my project. They provided great insight into the current technological opportunities and limitations relevant to my project objectives.

Both supervisors played a crucial role in ensuring my proposed methodology was technically sound. Prof. Cameron Brown guided the project towards a focus on the snake-like robot design space (parameter sensitivity analysis). This initial direction provided the framework key to the development of a meaningful response to the core research question. As an artificial cognitive systems expert, Prof. Will Browne provided great insights into the evolutionary optimisation techniques used within the algorithm. This was invaluable to the analyses of the SRDA. I am also very grateful to Andrew Razjigaev, the creator of the SnakeRaven Design Algorithm (SRDA), who generously supported my project by offering many insights into the SRDA logic and processes. His contributions were vital to the implementation and understanding of the SRDA and to the success of the project.

My project stakeholder Dr. Ross Crawford provided many insights into real surgery operations. Being invited to view two of his surgeries (in person) in Semester 1, I witnessed first-hand the extensive use of plastic in surgical procedures. It was also evident sanitation and patient safety were the ultimate priorities. This had a significant impact in setting a goal to align my project with environmental sustainability while maintaining patient safety and sanitation standards.

10. Conclusion

This research project aimed to develop a method to design a snake-like robot that enables minimally invasive spine interventions. Project outcomes were achieved through following a structured engineering design process in the systematic evaluation of the SnakeRaven Design Algorithm. The algorithm's application within the context of minimally invasive spine surgery was explored to identify key limitations and considerations.

To address the primary research question,

How can a snake-like robot design be optimised to enable minimally invasive spine interventions?

the project developed and refined a set of guiding secondary guiding questions. These were designed to improve the understanding of the snake-like robot design space and to assess the contribution of optimisation in achieving highly dextrous design solutions. These targets outcomes were resolved through a parameter sensitivity analysis and the evaluation of the employed evolutionary optimisation technique. The results provided insight into viable design spaces and demonstrated that highly dextrous solutions can be achieved through a more targeted and informed design approach.

A significant advancement was the adaptation of the SRDA's fitness function to handle surface targets. This approach better suits the complex anatomical constraints and requirements of spine interventions and moves the design methodology closer to realistic clinical applications.

Overall, this work contributes a foundational framework for future development of snake-like robots for spine interventions. By addressing key gaps in the literature, a pathway towards enhanced surgical outcomes is establish. Additionally, multiple avenues for future research and refinement have been identified.

This project was made possible through stakeholder support and has considered engineering ethics and sustainability principle throughout its development.

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12. Appendix A: Research Project Timeline & Deliverables

Table 4 - Project Timeline and Deliverables (Note, Semester 2 denotes the second semester of the research project and is equivalent to Semester 1 2025.

No.	Focus	Deliverable	Dependency	Milestone Achieved (Date/time-period)
1	Literature Review	Literature Review Report (Included in project proposal report)		24th April
2	Project Proposal	Project Proposal Report	1	24th April
3	Initial Project Research	Project context: Identification of existing MIS approaches and limitations.	1, 2	Semester 1, Week 9
4	Application of current technologies to lumbar spine case.	Project context: Selection of optimisation technique/approach to respond to research question. Development of secondary research questions.	3	Semester 1, week 10
5	Progress Report	Progress report detailing findings and method of the project.	3, 4	Semester 1, week 13
6	Oral Presentation	A presentation of the research achieved up to this stage.	4, 5	Semester 1, week 13
7	Second Stage: Modifying current tools and algorithms.	Development of testing environments and testing methodology for parameter sensitivity analysis.	3	Semester 2, week 2
8	Parameter Sensitivity Analysis	Parameter sensitivity analysis responding to research question (I).	7	Semester 2, weeks 3 & 6
9	Optimisation Analysis	Optimisation analysis responding to research question (II).	8	Semester 2, weeks 7 & 8
10	Application of developed methodology to spine anatomy context	Application of developed methodology to spine anatomy context. Responding to research question (III).	7, 8	Semester 2, week 9
11	Development of Surface Handling Fitness Function	Development of modified fitness function to process surface targets within the spine anatomy. Responding to research question (IV).	10	Semester 2, weeks 10 & 11
12	Final modified algorithm	Final coded solution.	7	End of Semester 2
13	Final Report	Report presenting the final projects methodology and findings.	11, 12	28/5/25
14	Project Delivery Oral presentation	Presentation of the final outcomes/achievements.	11, 12	30/5/25

13. Other Appendices

13.1. Appendix B: Sample Size Testing & Results

Figure 2 contains the plots for the 4 cases tested to determine an appropriate sample size. Cases a), b) and c) use the SBSE10 environment, and test case d) uses SBSE20 environment. Various values of n were tested; 3, 4, and 10 for tests a), b) and c) respectively. The width is set to 1mm to minimise collisions and expand the range of successful configurations.

The number of successful configurations for each design (within each environment) steeply increases up to approximately $2 \times 1e^8$ configurations. This behaviour slows down and begins to stabilise around $4 \times 1e^8$ configurations. From the results it was determined that new successful configurations are less likely to be found beyond of $5 \times 1e^8$ samples. A sample size of $5 \times 1e^8$ is chosen for the all subsequent tests. This value is large enough to capture most of the viable configurations but is also chosen to minimise computational resources use for practical testing.

Successful Configurations vs Total Configurations Tested

a) 30mm SBSE10, Robot design: n = 3, d = 3mm, w = 1mm

b) 30mm SBSE10, Robot design: n = 4, d = 3mm, w = 1mm

c) 30mm SBSE10, Robot design: n = 10, d = 3mm, w = 1mm

d) 30mm SBSE20, Robot design: n = 3, d = 3mm, w = 1mm

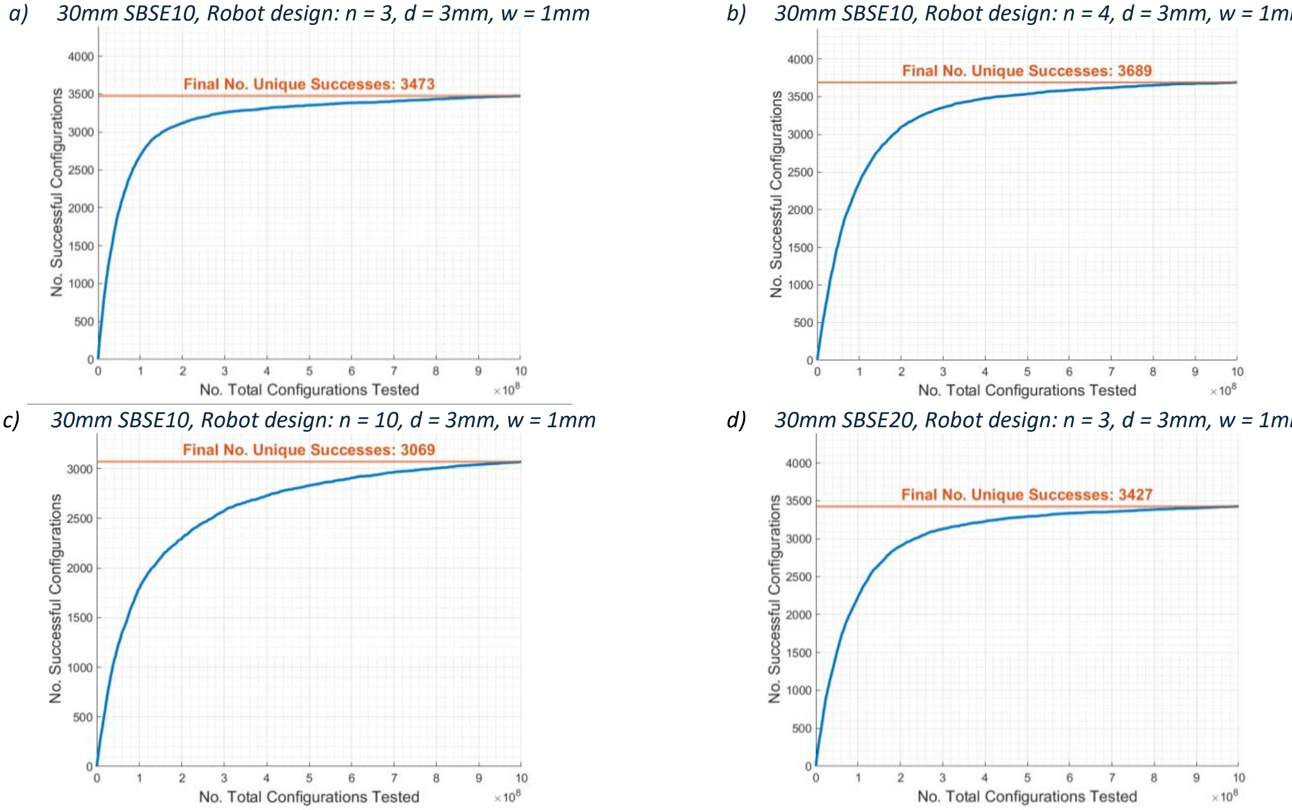

*Figure 14: Sample Size Testing Results for sample size of 6*1e8 configurations (alpha = 90 deg).*

13.2. Appendix C: Comprehensive Parameter Sensitivity Analysis

13.2.1. Relationship between half angle of curvature ($\alpha, alpha$) and environment dimension

The half-angle of curvature parameters determines the angle the robot module can curve. It is expected that a larger rolling angle will result in higher dexterity as it allows for greater range of motion; a larger rolling angle allows for a larger range of position configurations.

The maximum bending angle of a robot (one module) is given by,

$$\pm\,\theta_{max} = \pm\frac{n\alpha}{2} \qquad \text{(Equation 2) (Cheng et al, 2014).}$$

As such the maximum bending angle of a robot allowing a $90°$ half angle of curvature and 3 rolling joints (n) is between $\pm\ 135°$. To determine the relationship between the rolling angle and each environment dimension, the baseline design (with and w = 1) was tested for the SBSE10 environment with dimensions ranging from 14mm to 30mm. The successful configurations are sorted by the configured angles corresponding to each alpha value through Equation 2. This allows us to group the configurations by alpha value ($1 - 90°$), determining how many configurations are successful as the half-angle of curvature increases. A second test increased the robot width from 1mm to 3mm; the results (Refer to Figure 15) showed similar trends.

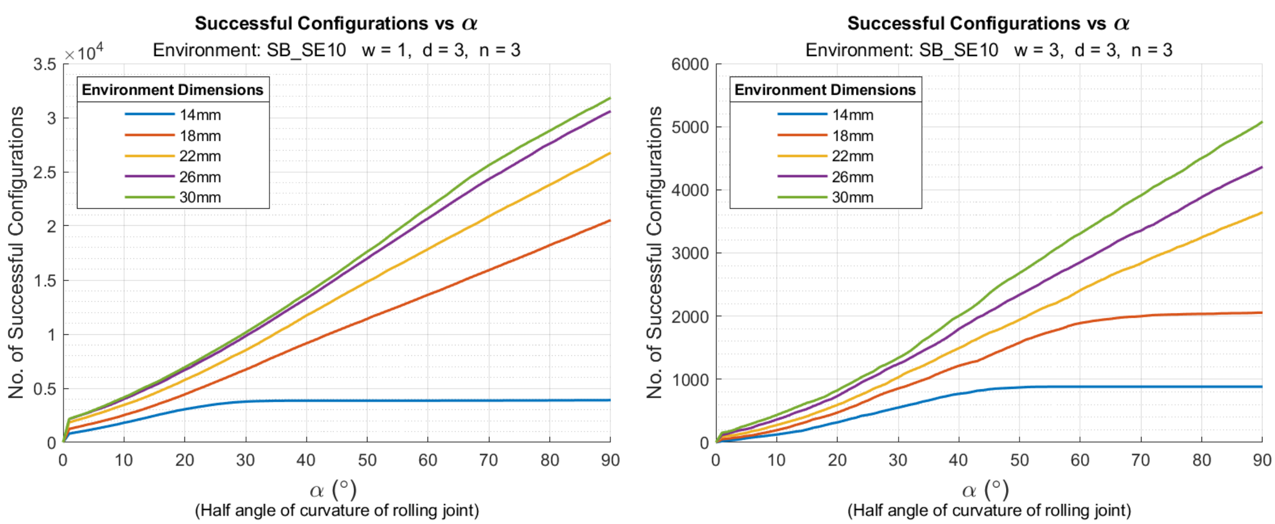

Figure 15: Successful Configurations vs α (Design: d = 3, n = 3, w = 1, 3)

In general, larger α values allow for more successful configurations. However, this sees diminishing returns as the environment dimension decreases; the total number of hits (successful configurations) begins to converge to a maximum where greater α values provide no additional hits.

When alpha is set to $90°$, as the environment dimension increases dexterity increases. Following the results from above it can be estimated the subsequent value (when alpha is set to $90°$) is the highest dexterity value possible for any value of α. Two additional tests repeated the above testing with α set to $45°$. Following the above results, it was expected that the final dexterity scores would be reduced greatly for the larger environments. The final dexterity values are shown below in Figure 16.

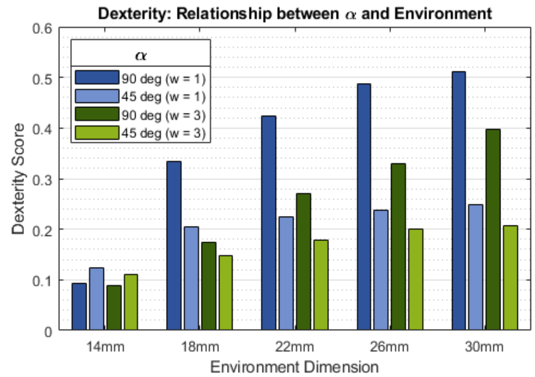

Figure 16: Dexterity - Environment Relationship when $\alpha = 90°$ and $45°$ for $w = 1$ (blue) and $w = 2$ (green)

As expected, the larger environments are most affected by the decrease in alpha. For both the width of 1mm and 3mm cases, the largest environment (30mm) score is approximately halved when alpha is halved. The smallest environment of 14mm however stays relatively the same for both cases at a score of around 0.1; Note the slight increase in dexterity for the $45°$ case in the 14mm environment may result from an increased number of configurations tested in a reduced configuration space.

Relationship between distance between rolling joints (d) and environment dimension

Figure 17 contains a bar graph showing the dexterity scores for varying d values across different environment dimensions. The best performing d-value is consistently 1mm for all environment dimensions. It can be observed that the dexterity tends to increase as d decreases for all environments. However, dexterity is most positively affected at different inflection points for each environment. The parameter ranges that offer greater variation in dexterity are indicated in the graph by trend lines. For example, for the 14mm dimension, increasing d reduces the dexterity score significantly until (approximately) $d = 3mm$, where the score settles at 0.07 for the remaining values up to $d = 10mm$. However, for the larger environment dimensions of 26mm and 30mm, increasing d always reduces the dexterity score.

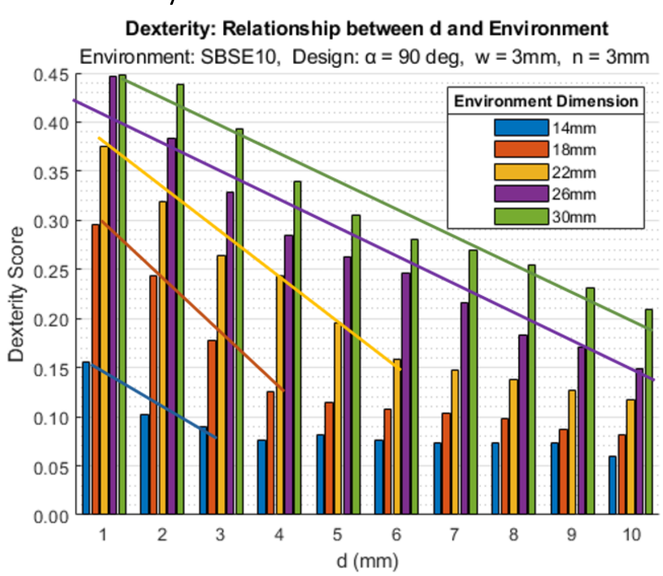

Figure 17: Dexterity - Relationship between d and Environment Dimension

Relationship between width of robot (w) and environment dimension

The relationship between the robot width and the environment dimensions can be observed in Figure 18. Two environments were tested: SBSE10 and SBSE20. Note results from the SBSE20 environment tests have been omitted as target depth had a negligible impact on dexterity. Also note, the presented scores are scaled to reflect the true number of target voxels considered; refer to Section 3.3.4 Dexterity Calculation Adjustments for Width Testing). Scaling is note require for comparisons between designs using the same width parameter value.

It is evident that width significantly affects dexterity scores. Dexterity quickly decreases as width increase. Designs of widths above 3mm yield zero and near-zero dexterity scores across the environments tested (14, 18 and 26mm). In the practical implementation of a robot design, it is important to consider the size constraints of the design, in particular accounting for a tendon driven system that requires tendon channels in each robot segment as well as an internal channel to accommodate a medical tool. While a 1mm robot width yields the highest dexterity, it is also more complex to produce.

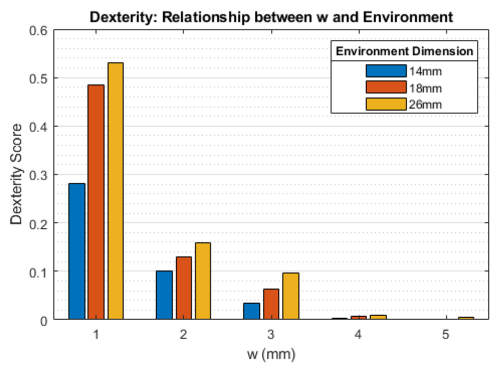

Figure 18: Dexterity - Relationship between w and Environment Dimension (SBSE10) (Design $\alpha = 90°, n = 3, d = 1mm$)

Relationship between number of rolling joints (n) and environment dimension

For the SBSE10 environment, the number of rolling joints that produced a highest dexterity is around 3 or 4 and there is a notable drop at $n = 1$ for all dimensions (see Figure 19). Smaller environments are more greatly impacted by changes in n. For these environments there is also an increase in dexterity around $n = 6$ & 9 . Due to the inconsistency of this trend a specific inflection points or range is difficult to define for smaller environment.

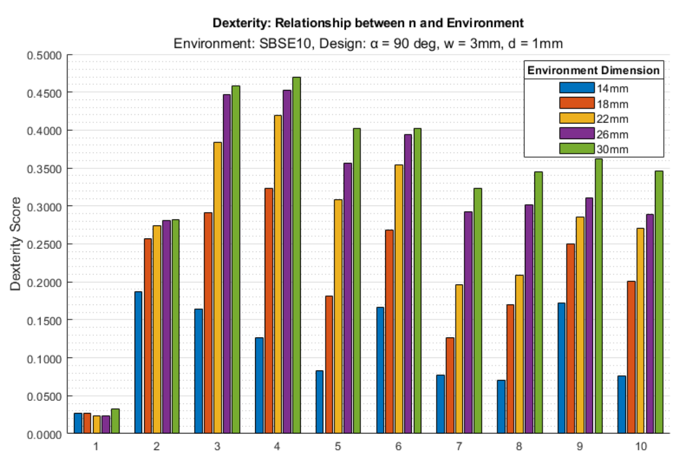

Figure 19 – Dexterity – Relationship between n and Environment

13.3. Appendix D: Spine Anatomy Testing Results

Table 5 - Spine Anatomy Testing Results - Thoracic Spine

Design Space	Design Space Size	Target	Best Dexterity	Time to achieve Best		No. Unique designs tested
				Gen	Runtime (hr)	
Unbound	707285	1	0.062	14	12.96	460
		2	0.146	10	10.00	400
		3	0.266	18	11.83	391
		4	0.111	41	33.70	1033
		5	0.201	13	10.99	340
Bound	42612	1	0.006	12	9.72	336
		2	0.140	2	2.01	199
		3	0.267	11	9.55	294
		4	0.112	15	12.14	828
		5	0.196	4	3.97	217

Table 6 - Spine Anatomy testing results -Lumbar Spine

Design Space	Design Space Size	Target	Highest Dexterity	Time to achieve highest dexterity		No. Unique designs tested
				Gen	Runtime (hr)	
Unbound	707285	1	0.128	39	33.93	1036
		2	0.307	11	11.36	571
		3	0.251	17	9.66	337
		4	0.156	23	22.28	921
		5	0.308	8	8.22	428
Bound	28542	1	0.088	3	3.01	198
		2	0.307	5	5.43	315
		3	0.252	10	10.48	416
		4	0.146	10	6.55	243
		5	0.311	18	15.89	874

13.4. Appendix E: Risk Identification and Management

Table 7 - Project Risk Summary

Risk	Consequence (Severity, Likelihood)	Risk category	Mitigation
Scope Creep Risk for project scope to expand beyond capability.	Overload of milestones and tasks preventing progress toward overall project outcomes. **(Major, Possible)**	High	Careful definition of research question and scope. Continual referral to project proposal guidelines.
High computational requirements	Time wasted in running intensive algorithm and inefficiency. **(Major, Likely)**	High	Improving code efficiency and acquiring access to more powerful computing resources.
Unable to use MRI lumbar spine model	Unable to test algorithm and halt to project process. **(Major, Minor->Likely)**	High	Use more general CAD models available online. (This risk has been controlled).
Extended project timeline due to setbacks.	Prevents successful completion of project. **(Moderate, Possible)**	Moderate	Good project management through task tracking, regular revision of project plan and proactive action to correct setbacks.
Lost algorithm code or alterations to code beyond repair.	Lack of code traceability or loss of code. This impacts productivity in having to redo tasks. **(Major, Possible)**	High	Code management will be implemented through use of GitHub software for version control.
No access to necessary resources e.g. Raven II	May delay or terminate project progress. **(Major, possible)**	High	Access to resources will be organised far in advance. Alternative simulation testing methods are planned to avoid dependency.
Lab Hazards during testing – including damage to equipment and safety hazards.	Testing equipment maybe behave unexpectedly causing collisions during testing. **(Minor, Possible)**	Low	Conducting risk assessments before testing and correct use of test equipment: Consulting product instructions, guidelines, experienced user, lab protocols and wearing PPE.

Table 8 - Consequence severity & Likelihood Matrix

Likelihood	Consequence Severity				
	Insignificant	Minor	Moderate	Major	Catastrophic
Almost Certain	Moderate	High	High	Critical	Critical
Likely	Moderate	Moderate	High	High	Critical
Possible	Low	Moderate	Moderate	High	High
Unlikely	Low	Low	Moderate	Moderate	Moderate
Rare	Low	Low	Low	Moderate	Moderate

13.5. Appendix F: Resources

Table 9 - Project Resources

Resource	Purpose	Access
SnakeRaven design algorithm code	The design algorithm platform that will be modified.	Access Acquired – Published on GitHub platform. Under permissive licence. Permissions include modification and distribution.
GitHub – developer platform	To manage coded solutions: version control.	Access acquired through free student access.
MATLAB & MATLAB Drive	Programming language and platform used for development of algorithm.	Software-access acquired through free student access.
Fusion 360 3D modelling Software	Used to develop environment models for SRDA testing.	Access acquired through free student access.
High Performance Computing Unit (HPC) & file store.	Employed to run SRDA optimisation scripts.	Access to the QUT HPC system (Aqua) granted through 'QUT Access' (research student resource).
3-Dimensional Anatomical Spine Model	Used to create task space model for testing of the SRDA.	Resource acquired – publicly available CAD repository (GRABCAD Community). 'Human Spine' model published by Negar An : https://grabcad.com/library/human-spine-1.
Microsoft Office Suite	Applications to be used for project documentation including reports and presentation visuals.	Software-access acquired through free student access.