REDEFINING INTERACTIVE SPACE THROUGH PHYSICAL COMPUTING AND MACHINE LEARNING

by

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ABSTRACT

SEYEDEHSAN ABOUTORABI. Redefining Interactive Space Through Physical Computing and Machine Learning. (Under the direction of PROF. ERIC SAUDA)

Making of physical systems that integrate software and hardware to sense their surroundings and respond to have gone through a lot of transformations with development in Artificial intelligence. These systems can blend digital and physical processes to form interactive experiences that seem more intuitive and predictive .This form of interactions between people and built-environment would enable space to be more responsive and adaptable. Such qualities would accommodate the environment for us to thrive, and help us have more meaningful connections. This thesis proposes a form of physical system that help us design an environment which uses machine learning to learn from us and to explore different possible interaction in order to provide appropriate physical responses by changing its shape through flexible move-able parts. The question as to what form of physicality would provide enough solution space is explored through physical computing. Different fabrication technologies have been explored in order to find the proper materials and assembly methods. As a result an interactive system which uses the proximity sensors as an input data is proposed. Then the data would be processed through a set of machine learning modules to provide feedback data for actuators. This system is responsible for developing a human-device relation that would learn and evolve through time. These characteristics of the system would create a unique user experience for each individual based on their interactions with built-environment.

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LIST OF ABBREVIATIONS

ANN An acronym for Artificial neural network.

COR An acronym for Center of Rotation.

DOF An acronym for Degree of Freedom.

IOT An acronym for Internet of Things.

LSTM An acronym for Long Short Term Memory.

ML An acronym for Machine Learning.

PLA An acronym for Polylactic Acid.

RNN An acronym for Recurrent Neural Network.

RPI An acronym for Raspberry Pi.

SMA An acronym for Shape Memory Alloy.

CHAPTER 1: INTRODUCTION

This thesis investigates the form of physical system that help us design an environment which uses machine learning to learn from us adapt to our needs and to provide appropriate physical responses by changing its shape through flexible move-able parts. in order to study such a physicality we need to better understand the origins of such a technologies and also to see where design and architecture position is in respect to that. In the era of digital transformation which is based on the integration of information and communication technologies and industrial technology [1] more complex and automated processes, high-level competitiveness and emerging technologies, have paved the way for a new generation of goods, products and services [2]. some of these technological implementations in some specific built environments have been implemented by architects, but the absence of emerging technologies in architecture is more frequently felt as each day other fields of study are being revolutionized. one can argue that architecture is mostly trying to use these technological products more as a consumer. There are different technological advancements that if realized, can shift this consumer approach. Among those, the most related to this research are fabrication technologies, physical computing, biology, and last but not least Artificial intelligence.

Fabrication technologies have created unprecedented opportunities in all fields of industry and have revolutionized with the introduction of additive manufacturing, the ability to control the position of material in different scales, from Nano to Macro. This process would enable the user to have control over the geometry of the materials and as a result we can expect to have multifunctional materials, in any given state or position. this is would make development of repetitive non-standardized building systems through digitally controlled variation and serial differentiation, i.e. mass-customization possible [3].

With the rising computational power of microcontrollers it has made possible to look beyond screens and to give this ability to our physical and built environment. New computation development in edge computing,in which computing and storage nodes are placed at the Internet's edge in close proximity to mobile devices or sensors[4], has made the use of sensors and actuators more accessible. In other words, it is easier to integrate microcontrollers, sensors, and actuators and thus enables us to move from a passive form of responsiveness to a more active one where the interactions between environment, object, and human, are more direct and simultaneous.

In order to have an active architecture, in which geometric changes occur as a means of adaptivity during the use of the building [5], we need to have a certain level of intelligence that not only can respond to environmental stimuli, but also can initiate, act, and interact.As much as a living organism is capable of adaptation, and compatibility it is also capable of communication and interaction. These kinds of responses are dynamic and interchangeable. we need a A holistic bio-inspired architecture that embodies multiple performance criteria akin to natural systems, which integrate structural, infrastructure performances throughout the growth of an organic body[6].

All these progresses have made it possible to not only create a system of form generation that would respond to stimuli, but also would be able to change its responses through time, by moving toward an intelligent system, a system that can learn through time and experience those learning to relearn. This parametric process can be in constant interaction with space and would even pave the way for new forms of interactions. This system would change the traditional understanding of the form and structure as something finished, static, and rigid to dynamic, changing, and a evolutionary process. In recent years, new fields in design have emerged that are investigating relations between products, buildings, systems, and their environments[7]. There is a certain strength in this form design, As Neri Oxman describes it:

> "designers are now able to compute material properties and behavior built-in to form-generation procedures. Combined with the designer's capacity to analyze structural and environmental forces, the enabled mediation between matter and the environment through fabrication appears to be as powerful as the ethos of craft itself."[8]

One of the questions that would help us in choosing the appropriate approach is: how do we implement this computational ability, to our physical system. The computation ability can vary from a bunch of mechanical pieces controlled by a microcontroller [9], to a natural cellular structure with a nervous system that would respond to certain stimulants. These vast numbers of alternatives are very important because it would also indicate how difficult and complicated the fabrication process and our approach for each system is.

Through past years extensive research has been done in both fields, a digital and mechanical system, and a more bionic like material system driven from the biology and its cellular structures. To better understand the different approaches we can simply point to existing examples in other fields of study such as Robotics and soft robotics. Robotics has been a pioneer in integrating electronics with mechanics for years now, and they have made a lot of progress as well. Sensors in robots can provide the necessary data needed for interactions to happen, and the motors and mechanical pieces would respond to those stimuli as the result of the data process. The ones that can have great implementations in architecture as well are soft robotics. In soft robotics you can find leap, and step further, than the use of mechanical means. Soft robotics stands in a point that is both bio inspired and mechanically actuated at the same time, Incorporating soft technologies will also expedite the evolution of robots that can safely interact with humans and natural environments. Finally, soft robotics technology can be combined with tissue engineering to create hybrid systems[10].

The properties of such soft technologies can be the perfect medium in which architecture can be reimagined and explored. A bio-inspired entity that can be a key to keep architecture uptodate and open to innovation once again. A lot is needed to achieve such a goal like: expertise, expenses, technicality, technology development but it would not be unreachable based on all the possibilities that have been discussed. This thesis has tried to explore such a physical system within a limited framework.

CHAPTER 2: LITERATURE REVIEW

There has been different usages for the term physical computing in different fields of science, but the mostly used definition is the one used by Dan O Sullivan and Tom Igoe [11] sensing and controlling the physical world with computers.

> "Physical Computing" will not only change the way you use your computer, it will change the way you think about your computer-how you view its capabilities, how you interact with it, and how you put it to work for you. There have been several other books about this topic because they are mostly about the applications of physical computing and introducing different ways that we can cultivate physicality through computation power.

In order to have a better understanding over sensors and actuators some related projects are discussed in Make book [9] and some more related projects in operation system based micro controller have been used in Raspberry Pi Projects[12].

To focus on parts of physical computing that are also relatable to our topic we can mention these projects and researches. One of the projects that have the most similarity in sense of performance is the Hyposurface [13], which is about Interactive surfaces that have perceptual, interdisciplinary existence but in spatial aspect. Between the range of space and perception, interactive surfaces that can carry the perceptual boundaries to different scales. In this way, experience is variable and it exceeds the spatial perception. Which includes architectural scale and perception of space.

There are of course several attempts to animate the design using technological development, specifically in robotic field, in naming some of close relatives we can mention the efforts of MIT media lab on developing the circuit robots [14], in which they developed a novel manufacturing technique, where such robots can be produced at a flexible electronics factory. Using a lamination process, and were able to integrate air pouches or shape memory alloy (SMA) inside a polyamide-based flexible circuit to produce bending actuators. The implementation of SMAs and flexible materials would enable the design to act multi-functionally and reach different spatial qualities. For some other precedents from the same lab we can definitely mention the projects of the tangible media group which try to discover new possibilities in design; Aeromorph, which investigates how to make origami structure with inflatables with various materials. Introducing a universal bending mechanism that creates programmable shape-changing behaviors with paper, plastics, and fabrics[15]. This shape-changing design is particularly interesting due to its simplicity of form and details and the vast dynamic possibilities that it introduces.

The KinetiX is also another very interesting approach toward form manipulation [16],auxetic-inspired material structures that can transform into various shapes upon compression. Changing the form under load or force is an interesting intake of this project as it tries to figure out how it changes and benefits from such a system not only by compression but also by shrinking or expanding. There are other approaches in making a soft and kinetic surface that would respond to its environment as well, the research on Using Tensegrity and Folding to Generate Soft Responsive Architectural [17] is another one. The purpose was combining concepts stemming from both tensegrity structures and folding mechanisms, and developing a prototype that changes dynamically to produce varying facade patterns and perforations based on sensor-network data and feedback. This is more related to architectural space and tries to close the gap of industrial design and architecture. As mentioned it would be in the Kinetic Architecture category which is also a very close family of the physical computing in mechanics.

There are a lot of projects trying to exploit kinetic design to create new forms and visual qualities. We can name one of recent designs by Heatherwick and Foster and partners, the Bund finance center in Shanghai[18], which creates a link between interior and exterior of the building. Kinetic architecture covers most mechanical parts, mechanisms, and their properties and how they are used in architecture[19].

Machine learning is an evolving branch of computational algorithms that are designed to emulate human intelligence by learning from the surrounding environment. They are considered the working horse in the new era of the so-called big data. Techniques based on machine learning have been applied successfully in diverse fields ranging from pattern recognition, computer vision, spacecraft engineering, finance, entertainment, and computational biology to biomedical and medical applications [20].

To reference a previous architecture research we can certainly mention the work by Philip Beesley, Hybrid Sentient Canopy [21] which emphasizes on An implementation and visualization of proprio receptive curiosity based machine learning. This study is also about the actual kinetic systems which are already in place and they are designed for certain functionalities. To name a few more, the works of Keith Evan Green, and his studies on the use of such a kinetic systems can be a good example, Animated Work Environment [22], which is about a user-programmable robotic work environment that dynamically shapes and supports the working life of architects, designers and their new and more traditional collaborators working with both new and old, digital and analog materials and tools. Which in some part explains the use of robotics in design and how it enables the designer. The projects developed by Hoberman are another good use of mechanical components, joints and movement, through the dynamic shading [23].

The experience of such a responsive environment is also a part of the research which is very well discussed by the work of Krueger [24], which perceives human behavior and responds with intelligent auditory and visual feedback. There is other research that would go in depth with the experience of a form active designs, through which we can mention Interdisciplinary Research-based Design: the Case of a kinetic form-active Tensile Membrane[25]. Membrane surfaces comprise the basic component of the hybrid system developed, whereas any form modification is activated through the system cablenet and struts. The interactive platform of investigation, based on physical- and digital modelling serves for the definition of the systems adaptability, its composition and the structural components design.

CHAPTER 3: METHODS

Since the project proposal consists of two systems, a is a physical system, and an intelligence system, that work hand in hand, each of them would be discussed separately. The methodology is based on observations, records, experiments. The fabrications and manufacturing is dependent on availability of materials specially for the physical system. The previous works have been closely studied and most of fabrication and data collection were made possible by collaboration of available labs and studios at UNCC.

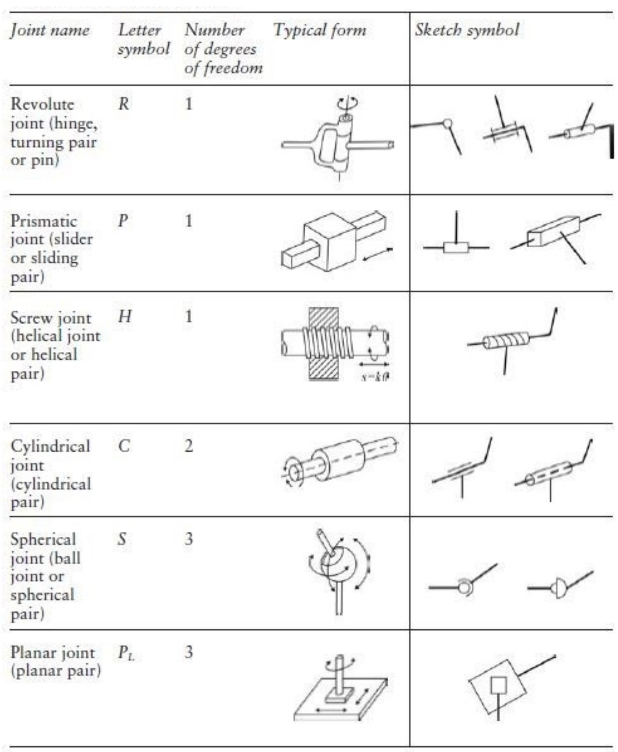
3.1 Physical system

The research proposal for the type of built environment consists of several parts that each of them require their own specifications. In general, the physicality of the project must consist of dynamic, soft, and interactive parts to be able to adapt to different built environments and also to change their form and shape based on feedback of the intelligence system. The physical system is evaluated based on the degree of freedom of the whole form [26]. fluidity and softness amplifies as DOF increases. For further evaluation of the different elements of physical system, it has been analyzed in following sections: Actuator, Membrane, and Sensor.

3.1.1 Actuator

There have been a lot of discussions in types of movement both in Architecture as Kinetic architecture and in Robotics as basics of mechanical science. Kinetic Architecture can better assist architects to acquaint the need to enroll motion in the built environment. The technological achievement in different divisions of engineering such as structural, mechanical and materials engineering as well as information and communication technologies has an enormous effect on kinetic design. There are several conceptual framework for classification of kinetic Architecture [27]. The part that matters most in this thesis is the role of Actuators and different forms of movements that are made possible by them.

Actuator is a device that moves the system which is supplied with a power source that is usually electrical, hydraulic or pneumatic power and turns it into movement. It is the last part in a series of controls and is responsible for the movement of the body in accordance with the orders given by the control system. There are actuators which depend on pressure such as; hydraulic pistons that are pressurized fluid or pneumatic muscles which produce linear movement[19]. The part that needs more investigation are types of actuators and their movement. Many complex physics objects require the use of joints. Joints are a means of keeping individual bodies together, and they define the freedom of movement between the connections[28].



Joint name	Letter symbol	Number of degrees of freedom	Typical form	Sketch symbol
Revolute joint (hinge, turning pair or pin)	R	1		
Prismatic joint (slider or sliding pair)	P	1		
Screw joint (helical joint or helical pair)	H	1		
Cylindrical joint (cylindrical pair)	C	2		
Spherical joint (ball joint or spherical pair)	S	3		
Planar joint (planar pair)	P_L	3		

Figure 3.1: Different types of joint.

Mechanical movements can always be reduced to basic types of movement: Rotation, Translation and a combination of the two. This classification is used regardless of where the hinge or joint is located and without considering gravity. Here the function of the movement is considered rather than the precise mechanical or theoretical elaboration of a sequence of movements [29].

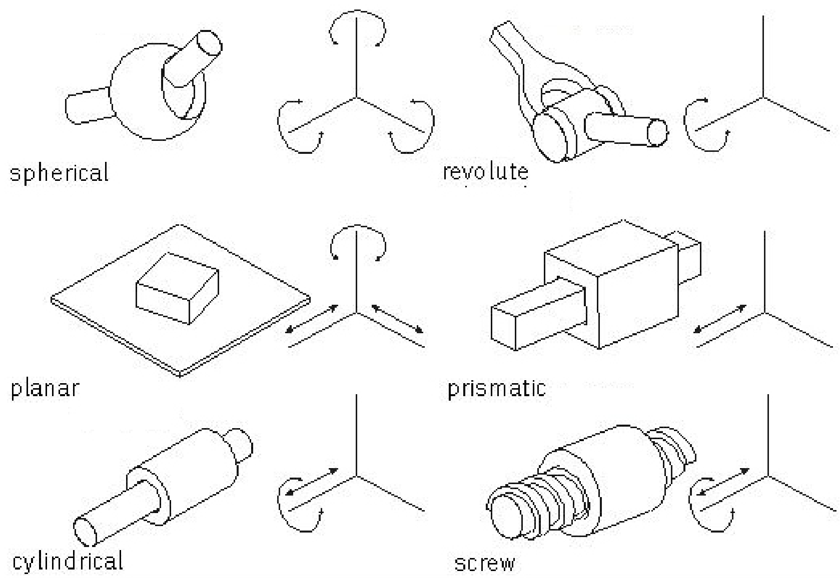


Figure 3.2: different types of kinematic Movement.

3.1.2 Membrane

For the purpose of soft interaction and soft technology we need the membrane to be adaptable to different deformations of the envelope, and also must be capable of bearing the certain loads such as tensions that may apply by user or structure. Being able to stretch and resist puncture is also of great importance. In addition to all these properties it should be capable of having a composite behavior, which would allow integration of different properties to it. In order for that we need the composite to act as a container that holds the needed elements in place. casting and forming a membrane needs certain elastic properties to resist the deformations as a result of interactions with the environment. The core material must support interactions and function according to human needs and conditions. Various other parameters are also involved such as heat resistance, electrical properties, weatherability, and elasticity are of the most importance [30].

Elasticity is the most important one as the need to deformation requires extension freedom to be able to adapt to different positions and functions. Material elastic features are characterized by the modulus of longitudinal elasticity Stress = (elastic modulus) * strain [31].

Rubbers are a good candidate for such a demanding properties. The one that can be found in nature is Natural rubber, and it seems to have adequate properties to develop a soft membrane but due to its scarcity different material options are studied. Analysis of different materials in comparison to natural rubber as a reference [32].

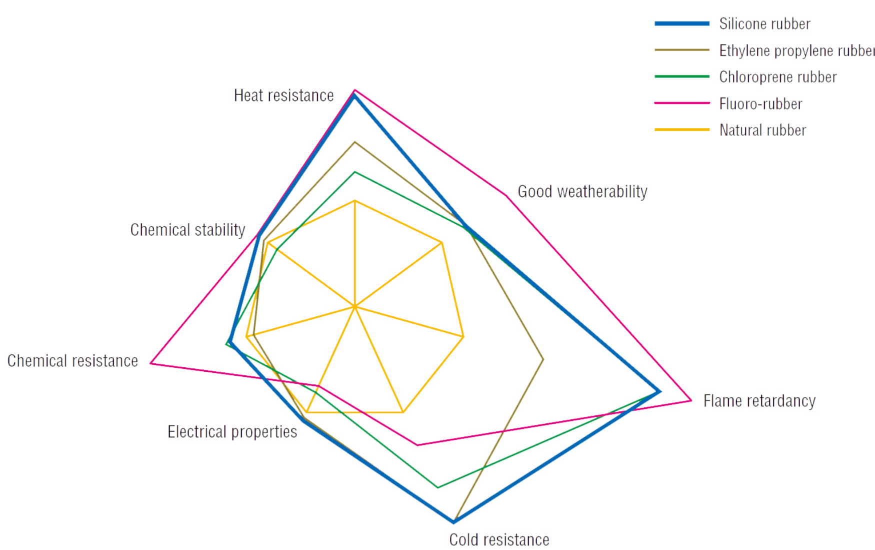


Figure 3.3: Comparison of properties of various Rubbers using Natural Rubber as a reference.

Although, a side by side comparison based on Characteristic properties of these materials are important, the availability of material on the market and how accessible the compound is, also plays a great role in our evaluations.

3.1.3 sensor

] Digital systems, however complex and intelligent they may be, must receive information from the outside world that is generally analog and not electrical. Sensors are interface devices between various physical values and the electronic circuits that "understand" only a language of moving electrical charges. In other words, sensors are the eyes, ears, and noses of silicon chips [33]. Sensors are devices that can sense and measure physical properties of the environment, e.g., temperature, size, weight, luminance, resistance to touch, etc. The term sensor differs from the term transducer. Transducers convert one type of energy into another, whereas sensors convert any type of energy into electrical[34].

Sensors	**Functions**
Touch	Sensing an object's presence or absence
Vision	Detecting edges, corners, holes
Force	Measuring force along a single axis
Sound	Presence, frequency and intensity of sound
Light	Presence, color and intensity of light
Proximity	Non-contact detection of an object
Physical orientation	Co-ordinating the objects in space
Heat	Infrared wavelength (IR) or ultraviolet (UV) rays, temperature, magnitude and directions
Chemicals	Presence, identity and concentration of chemicals

Figure 3.4: Comparison of different Sensors.

Other than how the sensor function there are other criteria that would help us evaluate the choice of sensors. All sensors can be characterized by various properties describing their capabilities, such as sensitivity, linearity, measurement, dynamic range, response time, accuracy, repeatability, resolution or bandwidth [35].

3.2 intelligence system

Intelligent systems are technologically advanced machines that perceive and respond to the world around them. the approach we are taking to intelligence systems includes Artificial intelligence system as well. An artificial intelligence system for accepting a statement, understanding the statement and making a response to the statement based upon at least a partial understanding of the statement. The system is characterized by its interaction with a user, which may be a person or machine, in gathering additional statements through inquiries to develop the most specific understanding possible by matching of the statements with a data base [36].

Intelligent systems use artificial intelligence and machine learning. This helps machines to learn in much the same way humans do. With machine learning, computers take in data and train themselves based on that data. They run tests to ensure they are interpreting the data correctly. They then pass it through classification algorithms to figure out what in the current situation is familiar and what is less well known. After the computer's algorithms have been trained to make the right decisions, they can use this decision-making ability to perform tasks[37].

We can decide which machine learning approaches/algorithm to select based on the problem statement, its an interaction with the environment and what type of data and inputs are going to be. But in general, we can categorize the machine learning algorithms in two groups: 1) Learning algorithms and 2) Similarity algorithms. The similarity algorithms further used as a learning model based on the types of problem environment [38].

In short Learning algorithms are the most popular and basic algorithms in AI. They can adapt to the problem environment. They consist of: Supervised Learning, Unsupervised Learning, and Semi-Supervised Learning[39].

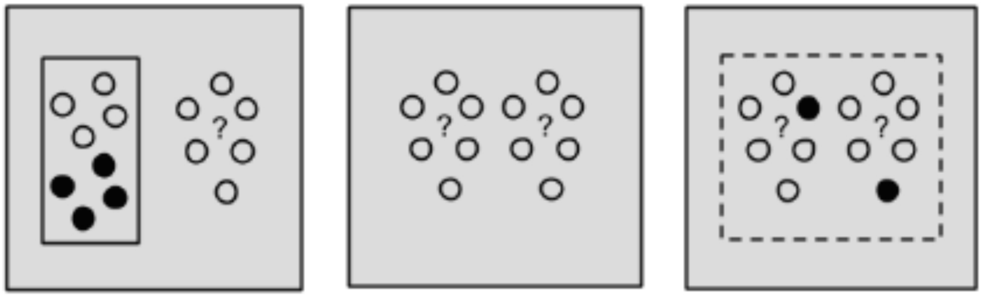


Figure 3.5: Comparison of different Learning Algorithms.

Similarity algorithms are grouped by similarity of their function. here are some of the most popular machine learning algorithms: Regression Algorithms, Decision Tree Algorithms, Artificial Neural Networks, and Support Vector Machine. Since, The similarity algorithms further used as a learning models we can expand on their functionality a little more.

Statistical machine learning has co-opted regression methods because of the modeling the relationship between variables. Regression algorithms can iteratively refine these relationships to predict a better outcome. [40]. To name a few we can point to Linear, Logistic, polynomial.

Decision Tree Algorithms construct a model of a decision made based on the several input variables. Decisions are forked based on the attributes and input variables in a tree structure. Decision trees are like a binary tree, each decision node is a single input variable and that node further split into leaf nodes or more decision nodes.

Artificial neural network (ANN) is also known as a connectist system. ANN is inspired by the brains neural network of the living organism. ANN is a framework of various machine learning algorithms which work together to process complex datasets[41].

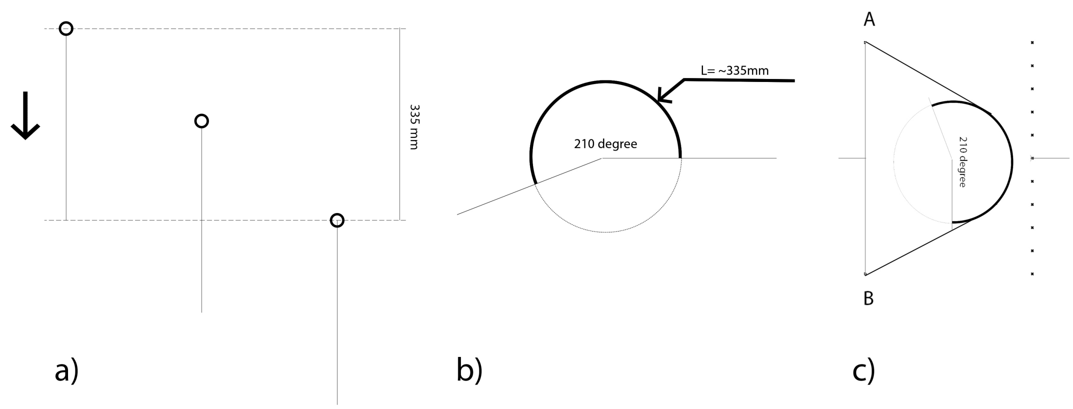
Support Vector Machine is related to the supervised learning approach and used for classification and regression. In training dataset, each data point is marked whether it belongs to class 0 or class 1, then trains a model based on the training dataset to predict whether the new data points fall into class 0 or class 1[39].

CHAPTER 4: FINDINGS AND CONCLUSIONS

Making of physical systems that integrate Physical and intelligence systems in architecture is dependent on sensible use of Materials, Mechanisms, and computation. As discussed in methods of this research the physical parts need a meaningful entanglement with the intellectual parts. This correlation is essential to optimize the functionality, movement form, and interaction possibilities. As the same principles and relations exist in organisms. The similarities of these two systems have pushed the study to look for similar characteristics in its core, under consideration of the actual limits of fabrication, Time, and budget.

4.1 Fabrication

A physical interactive system is highly dependent on its ability to move and change its state. Prismatic Joints enable the actuator to move exactly in a certain direction and this would make the control of them much easier in spite of their limited kinematic degree of freedom; DOF=1. eventually the DOF of the form would increase as we add more joints; DOF= NumberOfJoints. The length of the joint would also impact the range of movement. As the range is dependent on travel distance from top to the bottom of the sliding part. Our selection of the joint and size of is a determining parameter in overall design and fabrication process as well. The length of the slider is dependent on the fabrication technology and availability of the Materials. The magnitude of movement would impact the intensity of interaction for this study. The Workspace is another important information which will be helpful to optimize the dimensions of a robotic manipulator[42]. The length of the slider is 335mm which also affects the workspace. Electric Motors used to power actuators. Among those, Servos and steppers allow you to control the position of the slider. Servo motors are a better choice for systems requiring high speed, high acceleration, and high accuracy. The trade-off is a higher cost and complexity[43]. Because of availability of servos the cost benefit of the motors pushed the mechanisms to be servo based. For this Physical system The HS-322HD Standard Heavy Duty Servo motors is used, which can rotate up to 201Â° when given a PWM signal ranging from 553 to 2450 microseconds[44]. in order to connect the Motor to the slider a 6mm strong belt is used. In order for the slider to make the maximum travel we need a gear that at has as least that amount of circumference between 0 to 210 degree of rotation possible by servo motor.



(a) Displacement of slider (b) Gear Rotation and Arch length (c) gear and slider position

Figure 4.1: Gear and Slider dimensions and their position in relation to another.

As it is demonstrated the gear size would limit the displacement of the slider as it can not move beyond the height of gear. The other issue is the cable length of such a movement as in Prismatic joints the slider movement parallel to the position of the gear it would result in inconsistent cable length changes. which is about 13 percent of total length of the Cable.

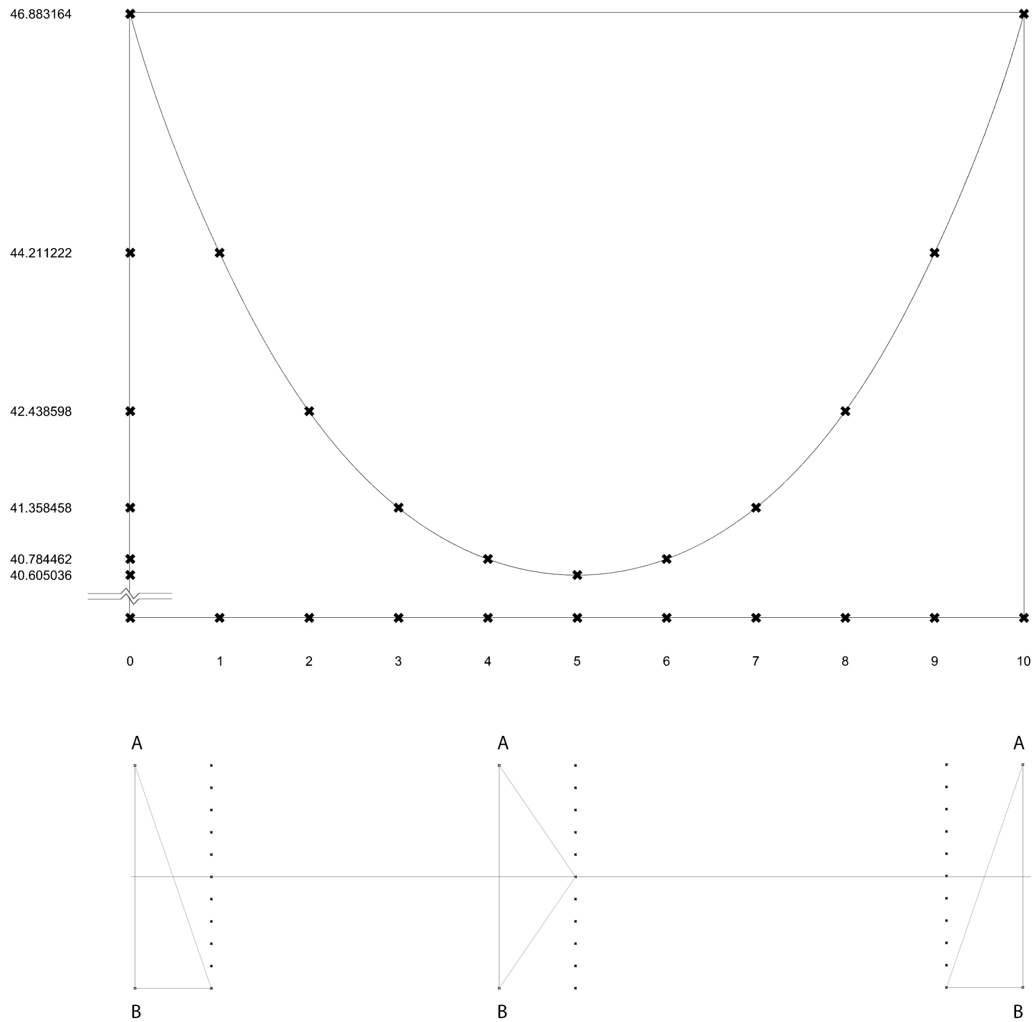


Figure 4.2: Inconsistent Cable Length Domain.

To solve these two problems: 1.gear shape that limits the domain of the slider, 2. over 10 percent inconsistency in cable length changes. An elocutionary optimization algorithm is used. the use of evolutionary systems as computational processes for solving complex problems, is a tool used by computer scientists and engineers who want to harness the power of evolution to build useful new artifacts[45].

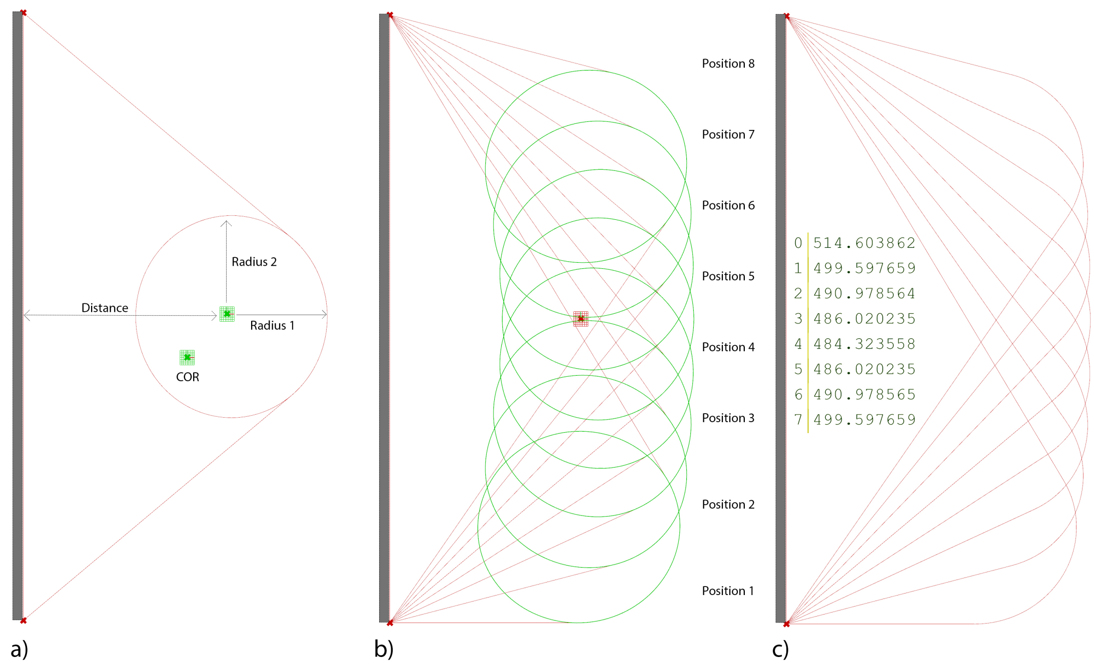
Evolutionary algorithms are characterized by the existence of a population of individuals exposed to environmental pressure, which leads to natural selection, i.e. the survival of the fittest, and in turn the increase of the average fitness of the population [46].

In this scope the Variables are: Shape of the Gear (symmetrical), center of Rotation, distance to the slider.

Constrains are: slider Length= 335mm, gear rotation degrees= 0 to 210, gear circumference > slider Length.

Fitness Parameter: Minimizing Length of Cable in 8 different gear positions.

Goals: consistent cable Length, Maximizing the slider movement.



(a) Optimization Variables (b) Gear positions (c) Cable Length in eight gear positions

Figure 4.3: Gear and Slider Parameter evaluation for optimization.

For evolutionary optimization Galapagos is used. This plugin comes standard within Grasshopper and is very helpful to optimize complex design questions with lots of variables. The Process would Minimize the sum of length differences at these eight gear positions by changing the variable values.

Figure 4.4: Evolutionary Optimization using Galapagos for Grasshopper.

The Gear shape that is optimized is a elliptical geometry with rotation domain of (-96.765 to +96.765) which is less than 210 degrees possible by servo motor, The results demonstrates values of:

Radius 1 = 49.757mm

Radius 2 = 59.991mm

COR: u=0.205 , v= 0.5// in a domain of (0 to 1) in which the 0.5 for v means symmetry.

distance = 114.73mm from center of ellipse to slider.

This optimization has Minimize the sum of length differences at these eight gear positions to 2.8mm which means 0.35 mm cable length difference for each gear position. This value is less that extension possible by the rubber belt that is used as connecting cable.

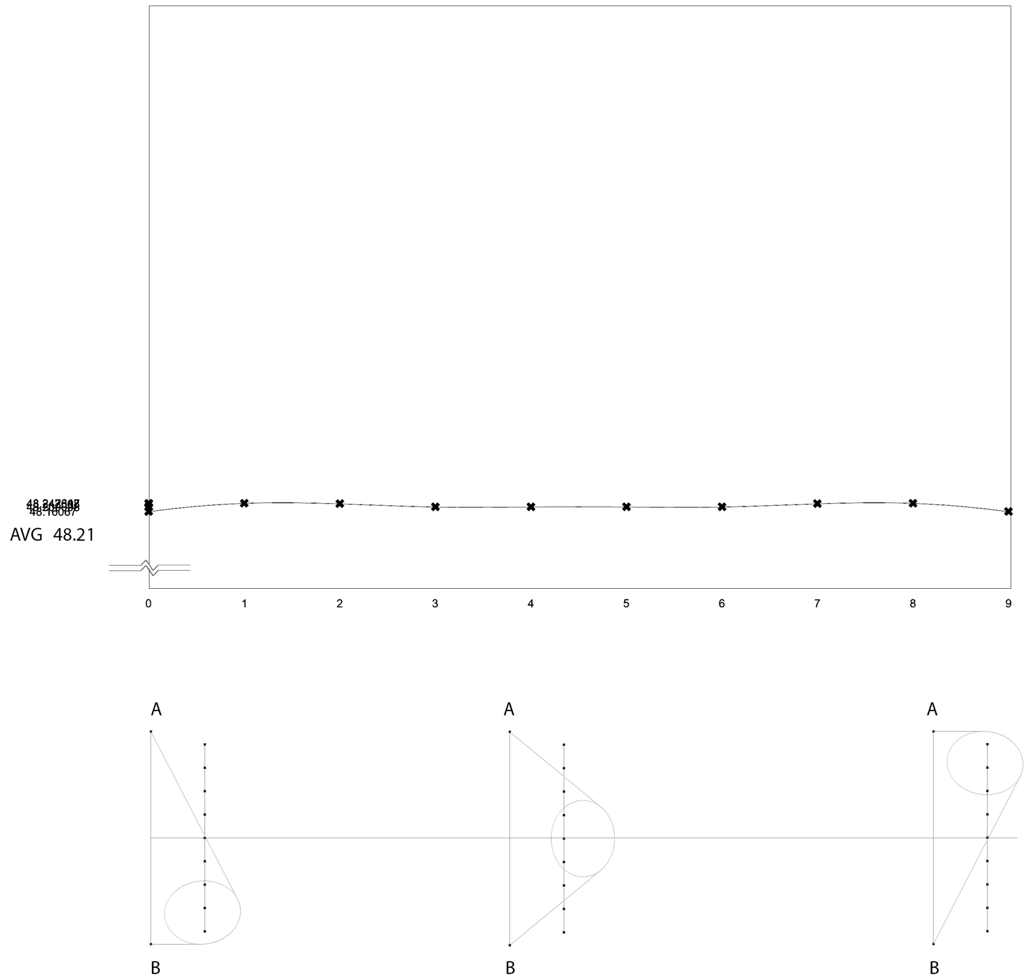


Figure 4.5: consistent Cable Length Value.

based on the values concluded by the optimization the following gear mechanism would be adaptable to timing belt that is employed with Pitch of 2mm and Width of 6mm.

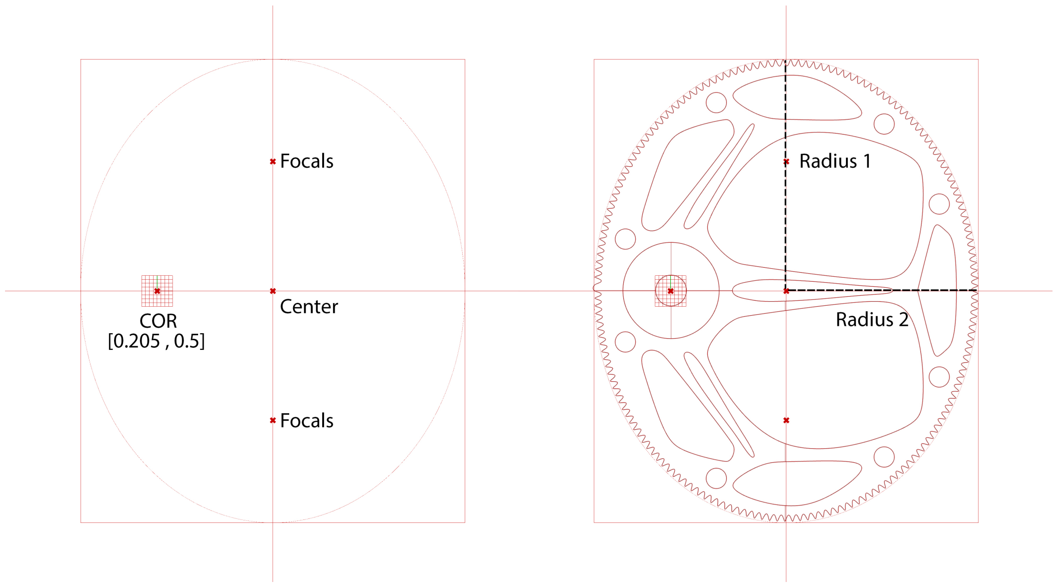


Figure 4.6: Gear details base on Optimized Geometry.

The properties of such a mechanism would also maximize the motion range of slider as the COR is moved to the side. this would enable the mechanism to move to almost full length of the slider which is 335 - 20 = 315mm.

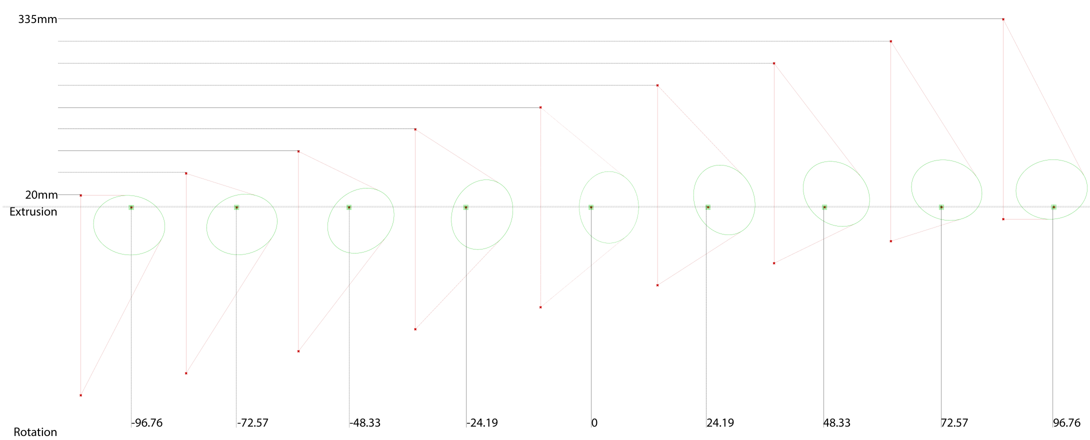


Figure 4.7: Movement of Prismatic Joint by Gear.

To maintain the stability of the mechanism as it is a form of moving tensegrity structure, the slider is being fixed by three supporting mechanisms to avoid the deformation of the slider and maintain the direction of the movement. We can control the position of the slider by having a minimum of three cables fixing the position of the construction angle of 120 degrees. This configuration works like guyed mast supports in which tensioned cables are designed to add stability to a free-standing structure. The Role of this tension cable in a moving mechanism is to fix the verticality of the slider in order to withstand additional and side forces.

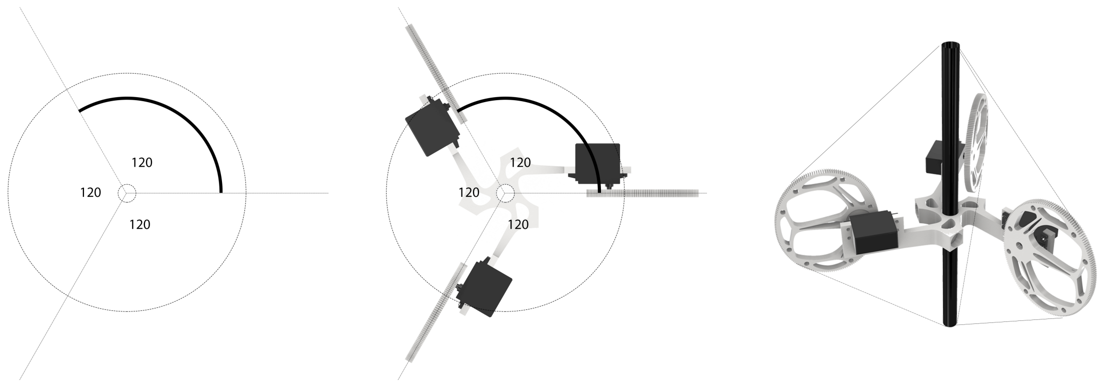
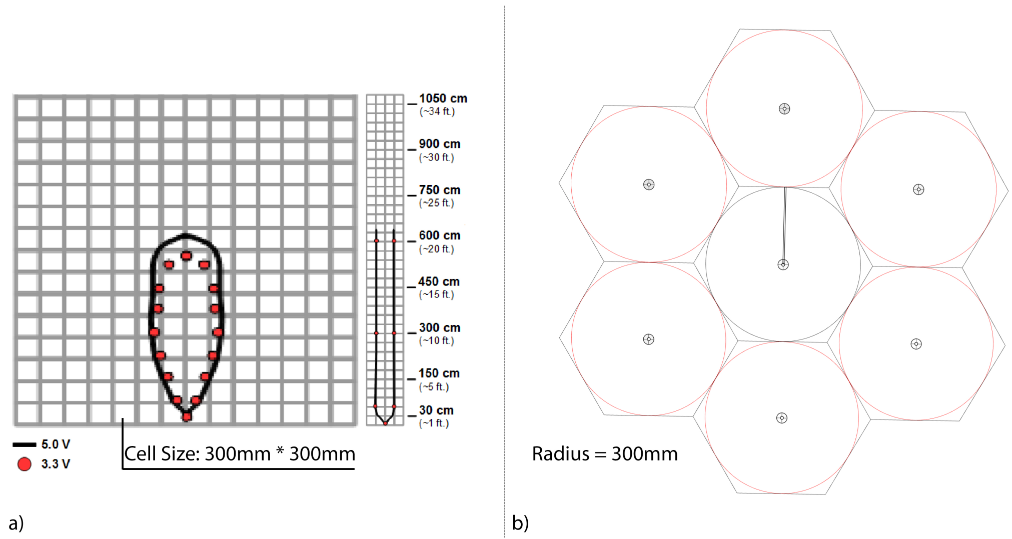


Figure 4.8: Triple formation of Mechanisms.

This three side formation if expanded would result in a hexagonal pattern in which the vertices would hold the mechanisms and each prismatic joint is connected to neighbor joints by connectors.

The scale of the resulting hexagonal mesh is dependent on how the physical system perceives the environment. For this physical system Proximity and range finder sensors have been used. These sensors would make the system expandable and modular. The proximity Ultrasonic Range Finder can operate with great accuracy and on a low voltage. They can detect objects from 0-inches to 254-inches (6.45-meters) and provide sonar range information from 6- inches out to 254-inches with 1-inch resolution [47].



(a) Sensor Accuracy (b) Sensitivity Pattern

Figure 4.9: Relationship between Sensors and size of the physical system.

This dimensions would give us a clear idea on dimensions of the connector geometries. Based on the idea of modularity and cellular development we can set the length of connectors. The Modularity would allow us to develop the system as needed.

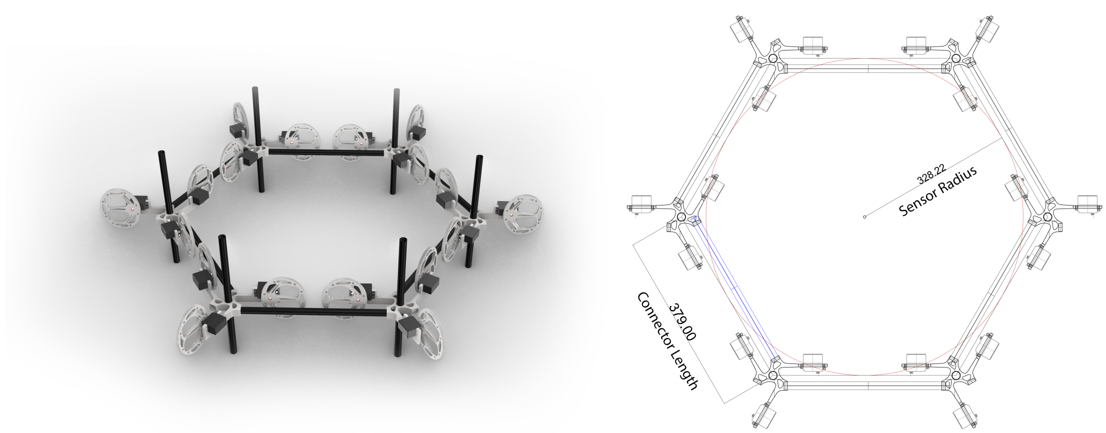


Figure 4.10: Module dimensions Related to Sensor Radius.

complexity of the movements increase so does the DOF of movement. As a result the control of movement would also be much more complex. Certain Criteria for evaluating the amount of complexities are Manufacturing, control, and maintenance abilities. these limits would greatly impact the formal complexity of physical systems.

In order to have some initial simulation on how the material would stretch under pressure we need to have a basic stress test to better understand the capabilities of the silicone rubber. To test the mechanical properties achieved by this composition the material is tested by a Tensile stress/strain device in UNC of Charlotte duke engineering building.

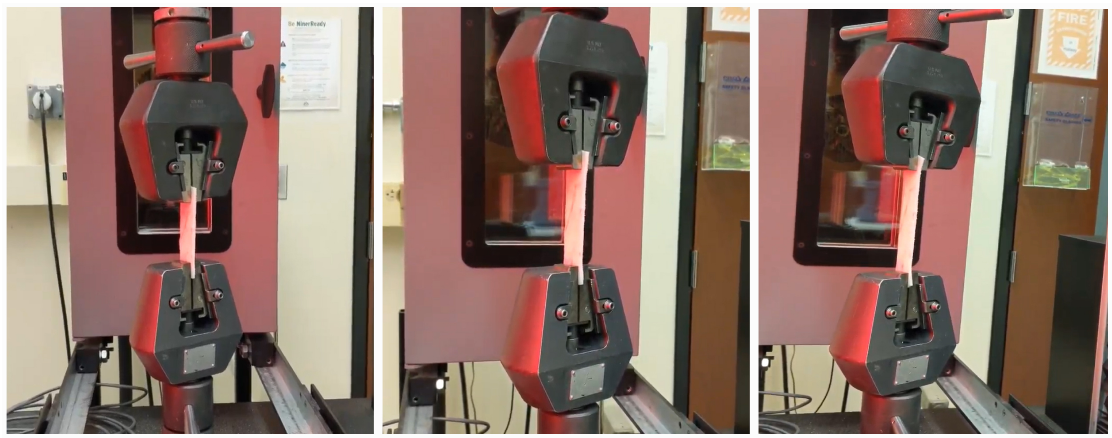


Figure 4.11: Tensile stress/strain test material.

The results demonstrated a reasonable stress to strain evaluation for three different specimens that have been tested. To have an accurate account for the amount of extension possible based on the stress, three different specimens tested and average amount of extension is derived by Stress = (elastic modulus) * strain [31]. Which results in 2.3 times extension at max.

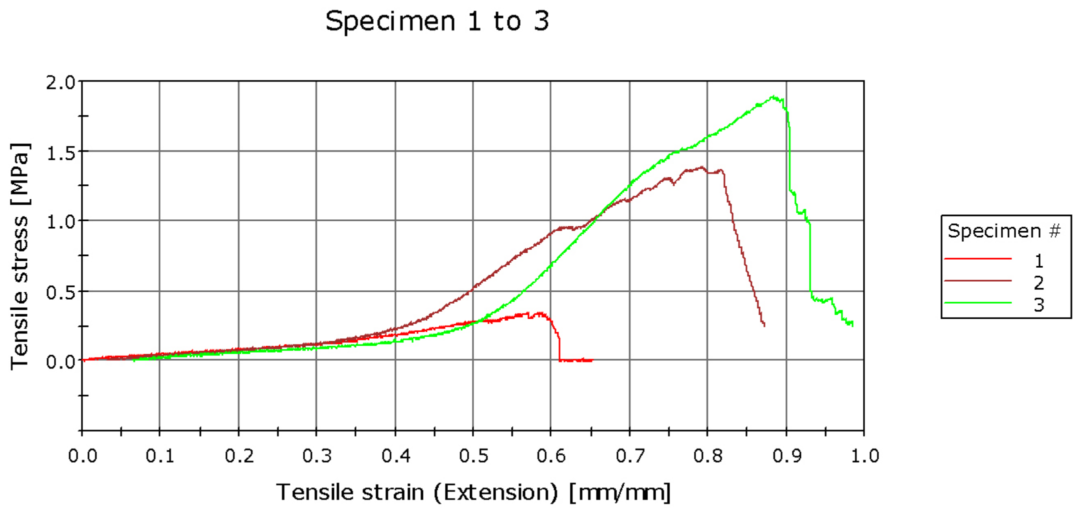


Figure 4.12: stress/strain test for three specimen.

In order to investigate the different formal limits based on the above mentioned extension a series of deformations is simulated to further analyze the possible deformations as the result of 2.3 elasticity module.

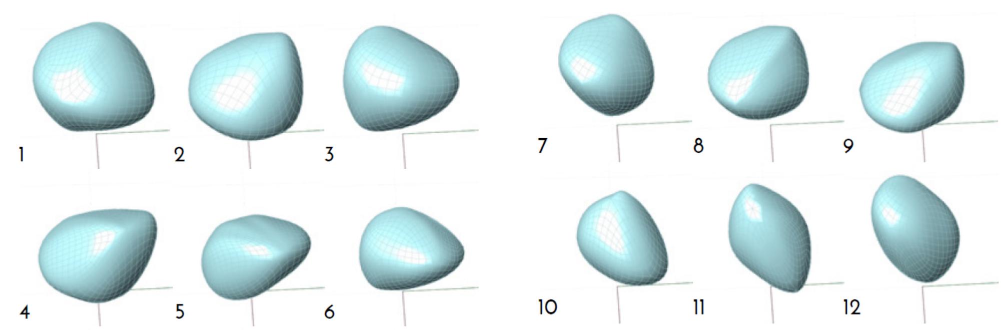


Figure 4.13: possible form deformations according to elastic module.

the other important property is stiffness, which is a measure of the load needed to induce a given deformation in the material. The stiffness is usually measured by applying relatively small loads, and measuring the resulting deformation. Since the deformations in most materials are very small for these loading conditions, the experimental problem is largely one of measuring small changes in length accurately[48]. The thickness the most important geometrical properties that would affect the stiffness. As the Thickness increases the elasticity would decrease. This effect would help us model the proper thickness variation so that the extension would be ubiquitous as possible.

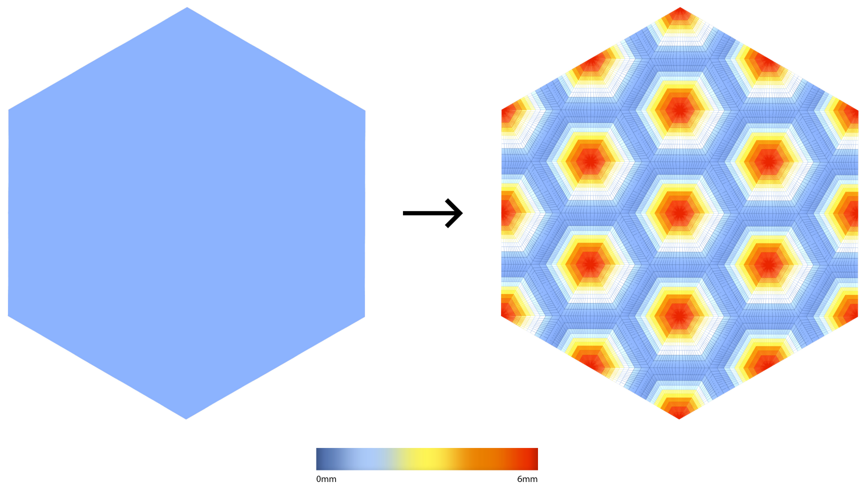


Figure 4.14: Evaluation of thickness on the extension properties of the Material.

The resulting 0 to 6 mm thickness changes would allow the extension to be ubiquitous as the tension in thinner areas increases. As the membrane gets thinner the elasticity would increase and we can say we have different elastic values for different thicknesses of the membrane.

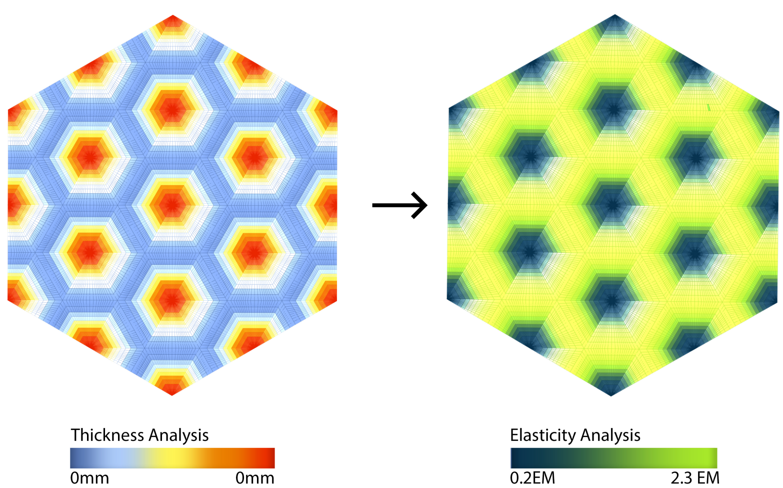
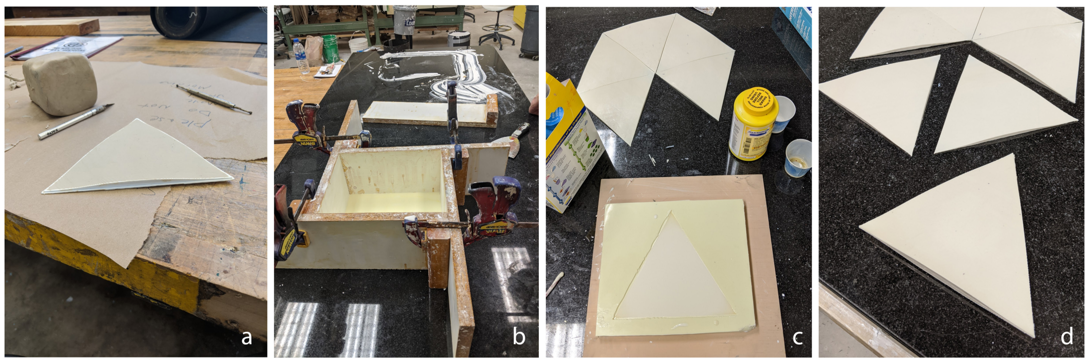


Figure 4.15: Evaluation of Elasticity based on Thickness of the Material.

The Fabrication process begins by making of the such a membrane. First a positive mold of the smallest sub-module have been created, this sub-module then is used to make a larger negative cast for real scale negative module.



(a) sub-module Positive Mold (b) Making a Negative cast from positive one (c) Casting Plastic sub-module (d)sub-modules for negative full module cast

Figure 4.16: Casting Process of sub-modules needed for a full negative membrane.

A total of 24 sub-modules are needed to make a full hexagonal negative cast for the membrane. Then these parts have been sanded down and re aligned. For the filing of the parts silicone glue has been used.

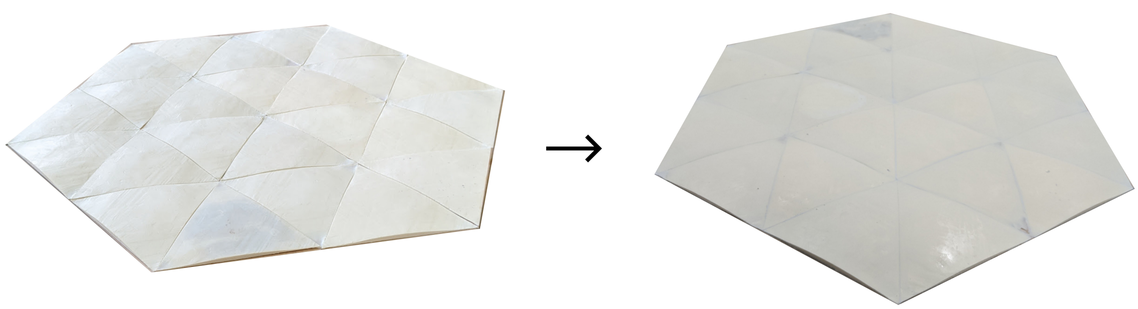


Figure 4.17: finishing the 24 parts for the final negative cast with silicone glue.

Dragon skin silicone rubber from smooth on have been used as the casting material for the final membranes and also neodymium magnets were used as connectors. Here I need to again mention that all these processes were made possible by the help Sculpture group at UNCC and with consultant of Professor Marek Ranis.

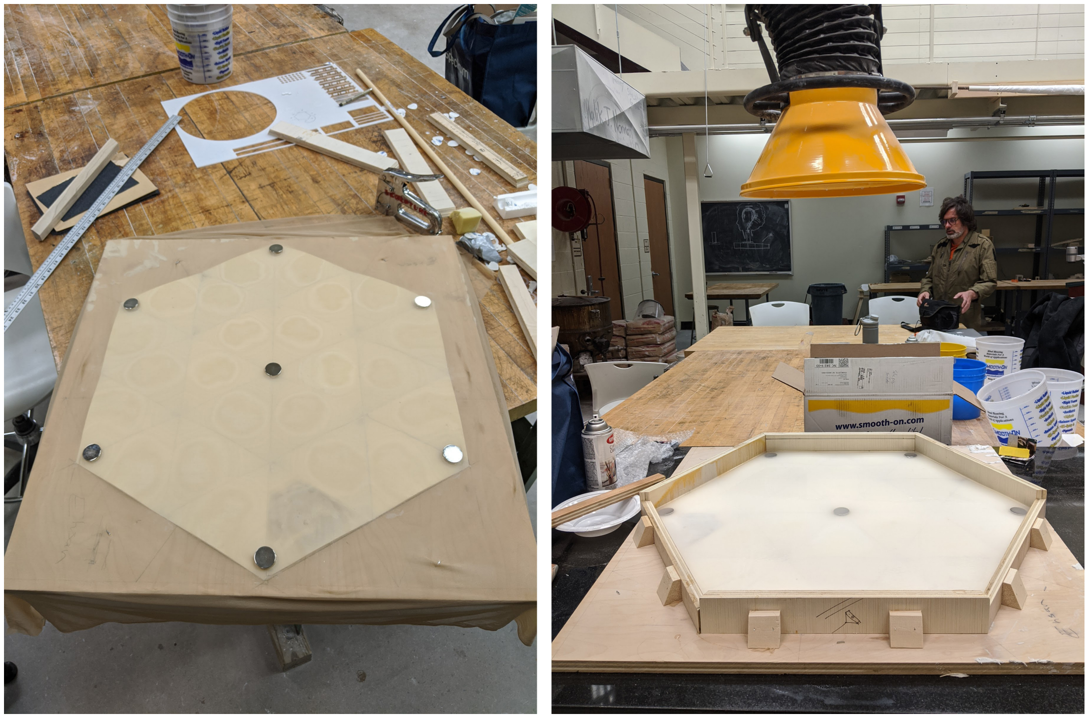


Figure 4.18: Final Casting Setup for Silicone Membrane.

Preparing the casting and mixing of Materials for each panel takes about three hours. The air filtration is needed to maintain proper air quality. The room temperature is recommended for optimal fusion of the Silicone Parts.

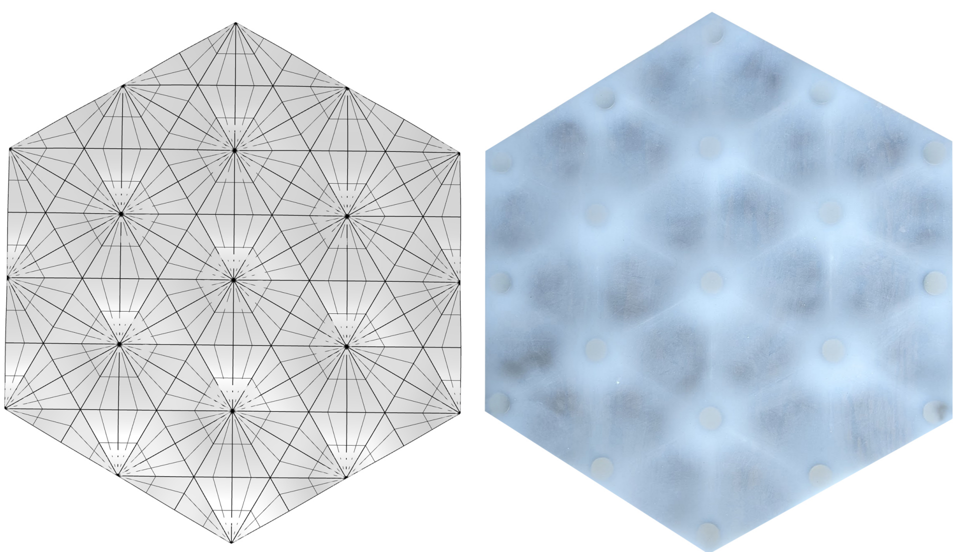


Figure 4.19: Final Membrane design and fabrication.

Actuators are 3d printed using a home 3d printer because of the special circumstances. It took about two weeks to finish the mechanisms. about 2kg of PLA filament has been used for printing of following parts.

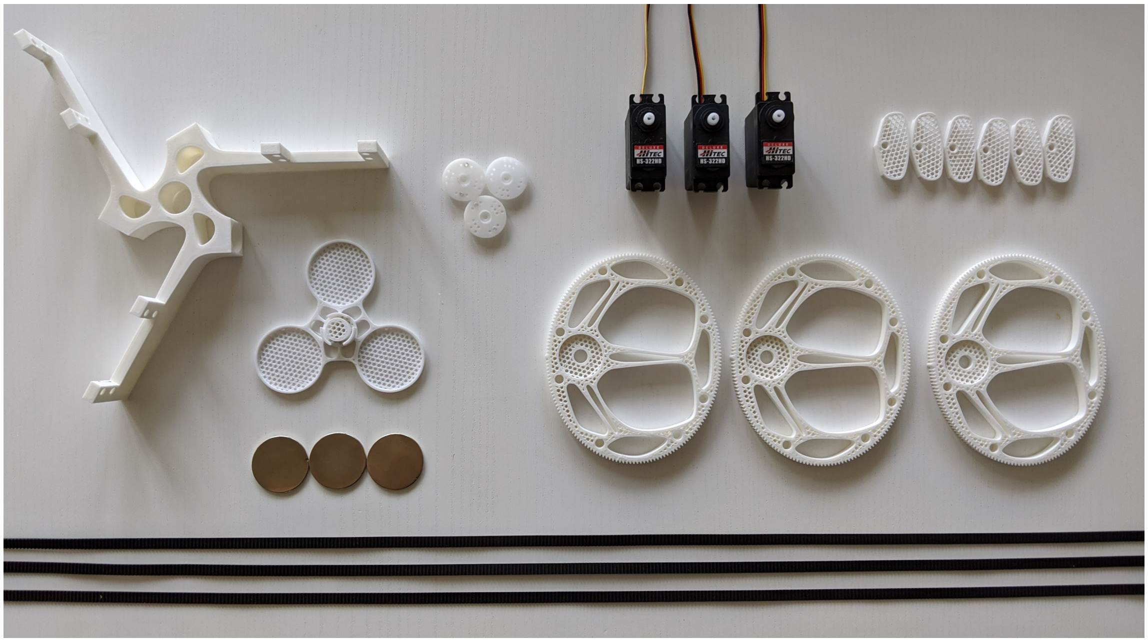


Figure 4.20: 3d printing of the parts needed for one Actuator.

A step by step process would start by adjusting servo motors to 90 degrees, adjusting the Gears in Place, mounting the gears on the Tri-Arm, adjusting the Belt in place, installation of the holders and caps, setting up the slider, and mounting aligners. The Assembly of a gear would take about 2 hours and the testing of the motors is done by a Raspberry pi 4 micro controller. Since motor voltage is in 3.5 to 5.5 v range the output 5v pin on raspberry pi was sufficient enough for initial adjustment of the Rotor.

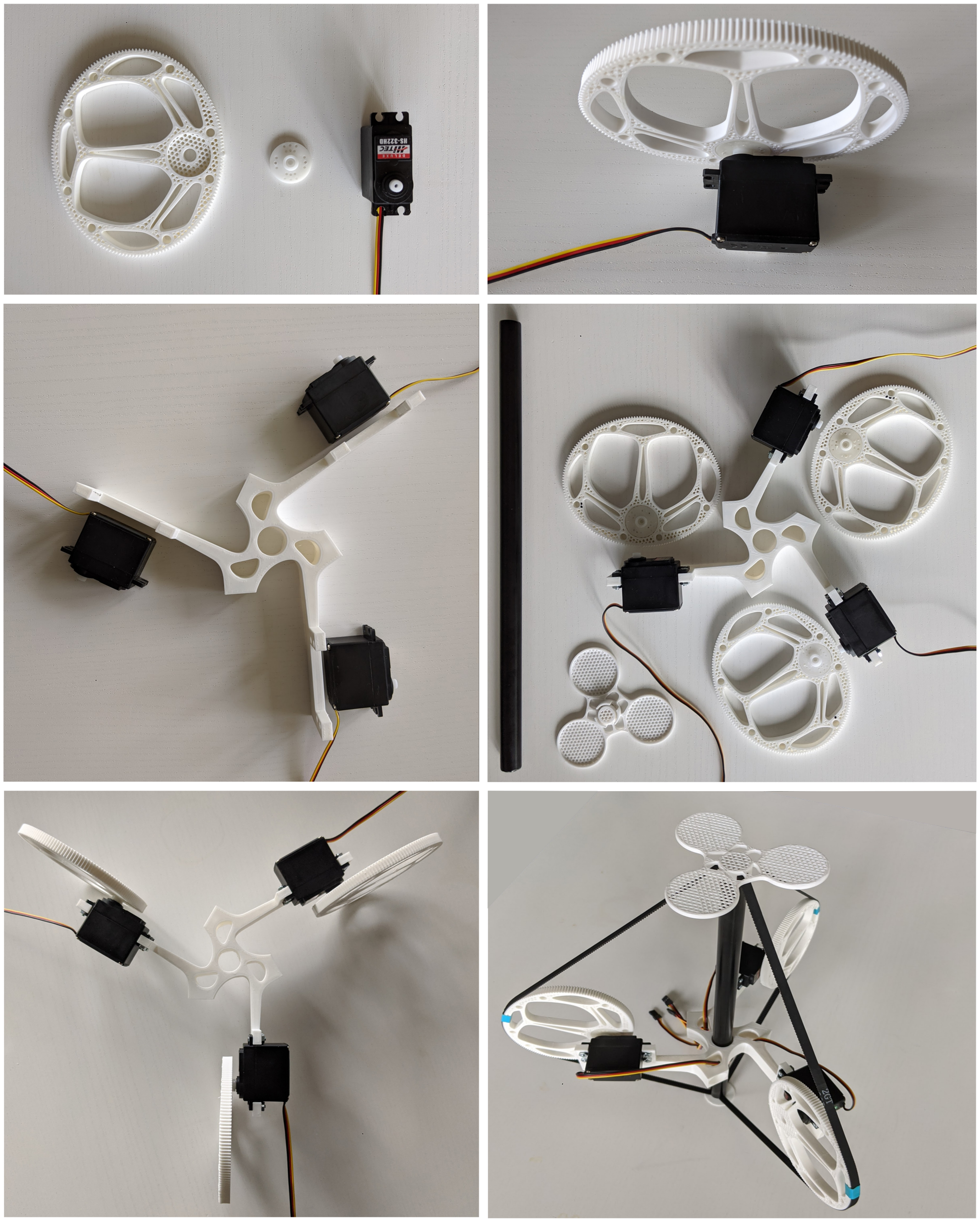


Figure 4.21: Assembly Process of a Actuator.

for each hexagonal panel we need 6 sets of actuators. Connectors then would connect the actuators together.

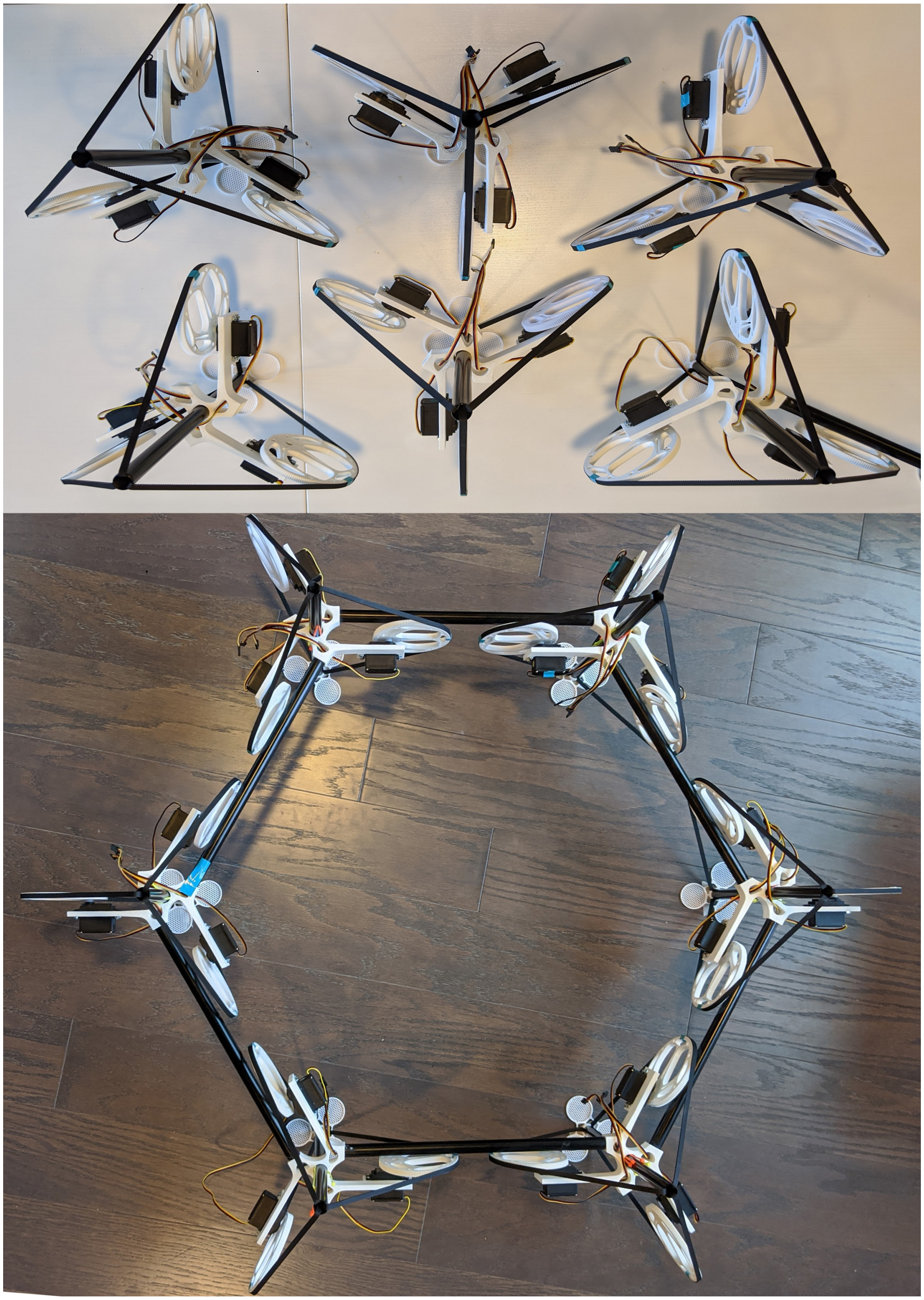


Figure 4.22: Assembly Process of a Panel of 6 Actuators.

The membrane would be mounted on top of the panel using Permanent magnets as connectors. This would make them interchangeable and would also ease the maintenance of the actuators.

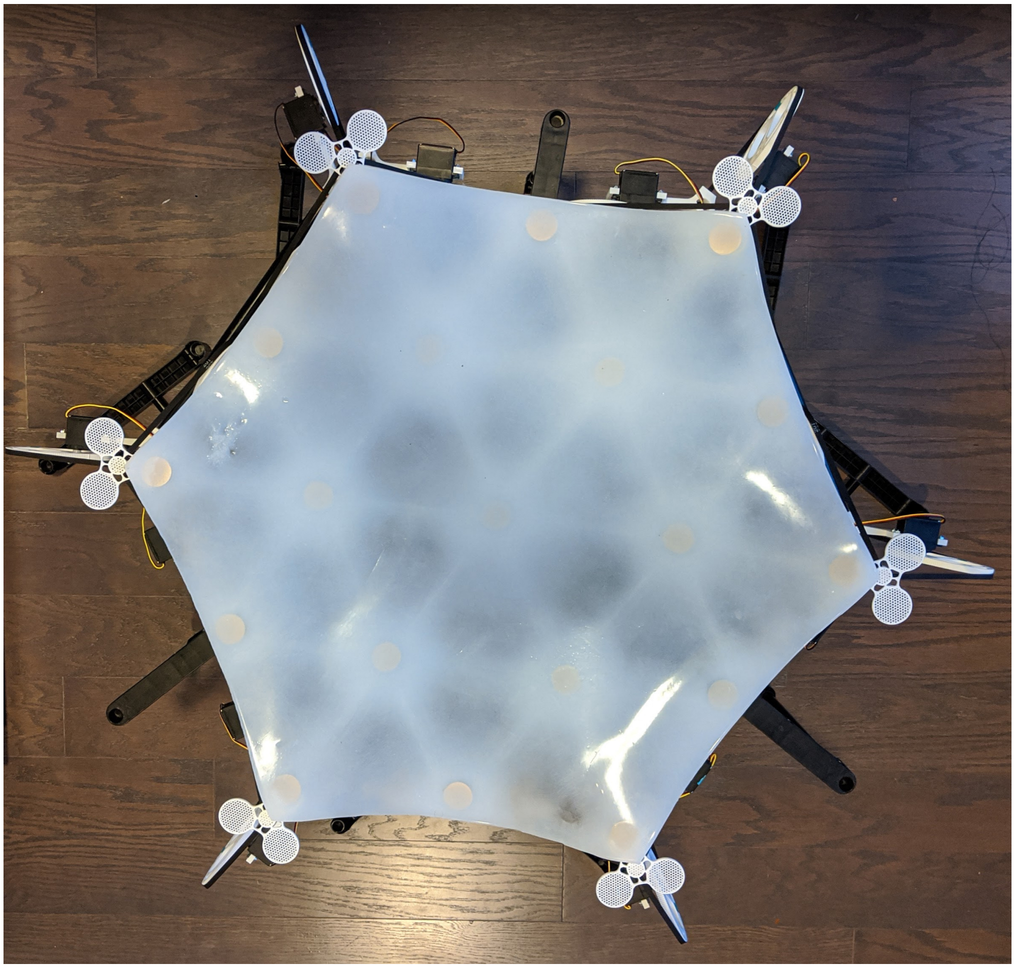


Figure 4.23: Final Assembly Process of Mechanism with Membrane and Actuators.

4.2 Integration

The data is being collected through Ultrasonic sensors as a set of numerical values. The Intelligence system is implementing a Supervised learning algorithm with ANN approach. In this process we need a learning algorithm that can predict the movement of the user and thus his/her behavior and Provide an acceptable response. A pattern recognition algorithm which is dependent on time as we collect data and store it in a database is needed for such an application. This algorithm should be able to run on a microcontroller and use the predicted data as input to process needed angular movement for the servo motors, and thus for actuators.

A time series is a series of data points indexed (or listed or graphed) in time order. Most commonly, a time series is a sequence taken at successive equally spaced points in time. Thus it is a sequence of discrete-time data. Examples of time series are heights of ocean tides, counts of sunspots, and the daily closing value of the Dow Jones Industrial Average. Time series analysis comprises methods for analyzing time series data in order to extract meaningful statistics and other characteristics of the data. Time series forecasting is the use of a model to predict future values based on previously observed values[49].

on top of that the Artificial neural network that we are using should be have a recurrent connection on the hidden state aka a loop. This looping constraint ensures that sequential information is captured in the input data also this looping constraint on the hidden layer of ANN turns our ANN to RNN or Recurrent Neural Network. This captures the sequential information present in the input data i.e[50].

The RNN technique that is implemented is used by TensorFlow. In which it uses Python and can be used by a Rasbian Microcontroller. Time series is a structures data algorithm that can use TensorFlow resources. For data collection a Raspberry pi4 with a coral accelerator that Accelerates the calculations and thus the response time. The Packages that I am using with TensorFlow Time Series Algorithm are matplotlib, numpy, and pandas.

To start integrating data we need to set up a test space, this would help in data collection and prediction.

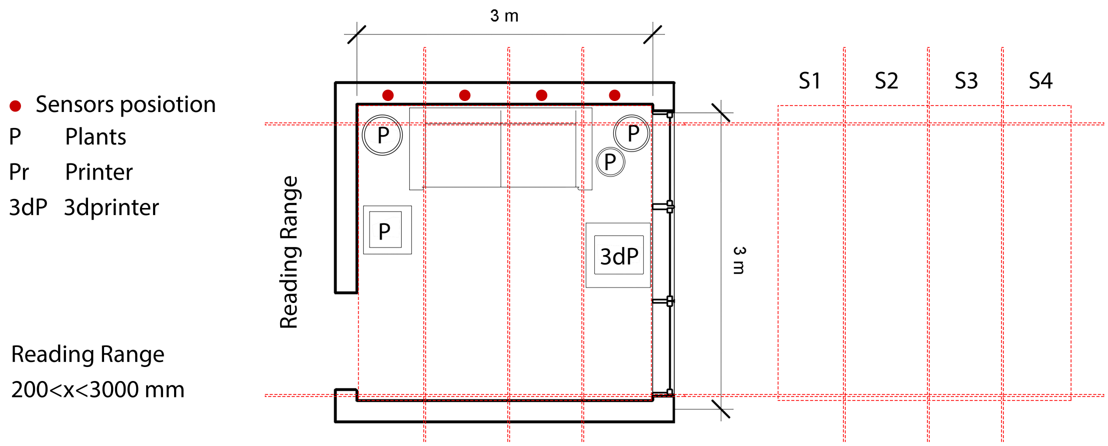


Figure 4.24: Test Space for Data Point collection.

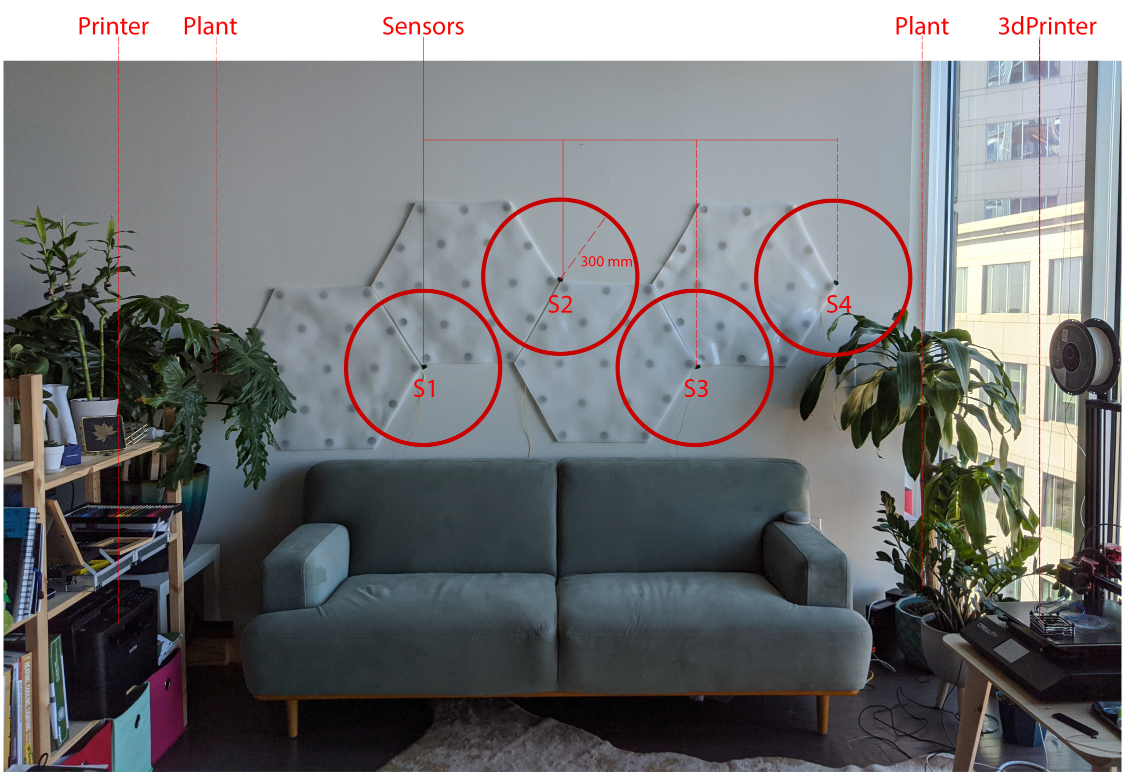


Figure 4.25: 3d Test Space for Data Point collection.

Considering the sensor Radius of about 300mm and in different heights the following configuration is chosen for test space. The sensors are set to read ranges between 200mm to 3000mm which is the depth of the test space. The Reading is thus divided to Four strips in which each sensor is reading its own variables.

A simple baseline test shows the True Future based on the History of the data. The following is a baseline method used for sensor one in which the baseline method looks at all the history and predicts the next point to be the average of the last 20 observations.

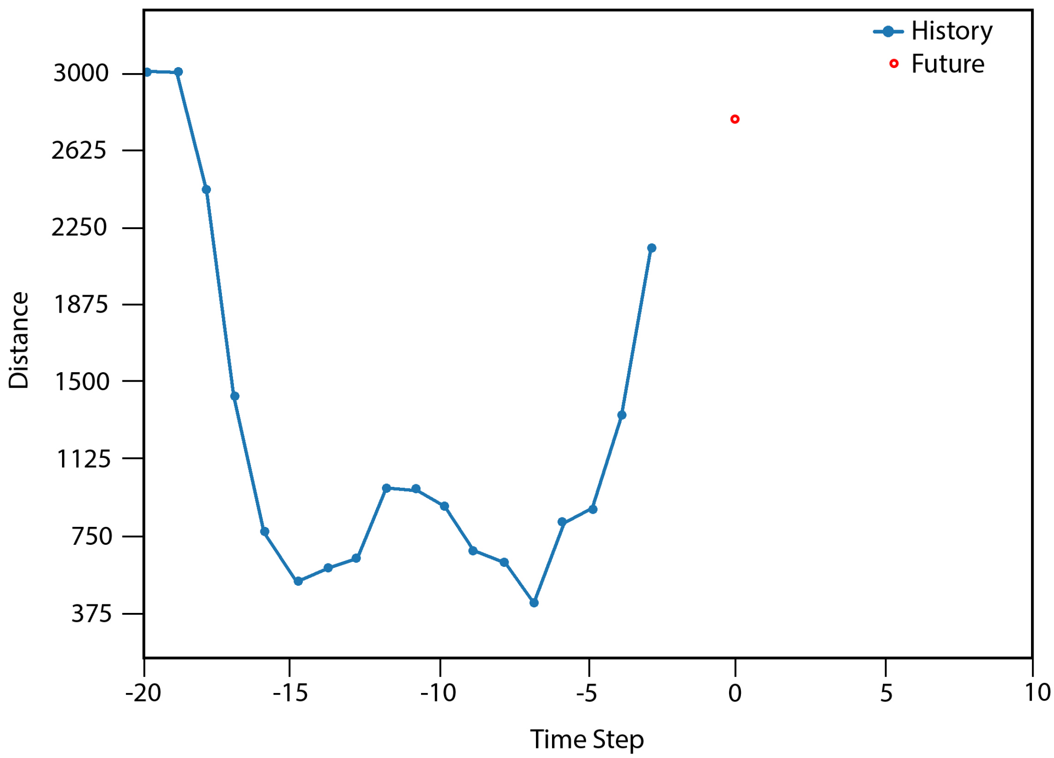


Figure 4.26: Baseline Method for sensor1(S1).

This would show the Motion of an object in space toward the sensor and back to the door. base on the baseline method the predicted position of the person would be the future point(red circle).The Data Cleaning would null the values which are greater than 3000 mm or less that 200 mm.

RNN process a time series step-by-step, maintaining an internal state summarizing the information they've seen so far. A batch data set would be separated into train and validation.A specialized RNN layer called Long Short Term Memory (LSTM) is used. LSTMs are explicitly designed to avoid the long-term dependency problem. Remembering information for long periods of time is practically their default behavior [51]. This would help the system to adapt as it spends time with the user or built-environment.

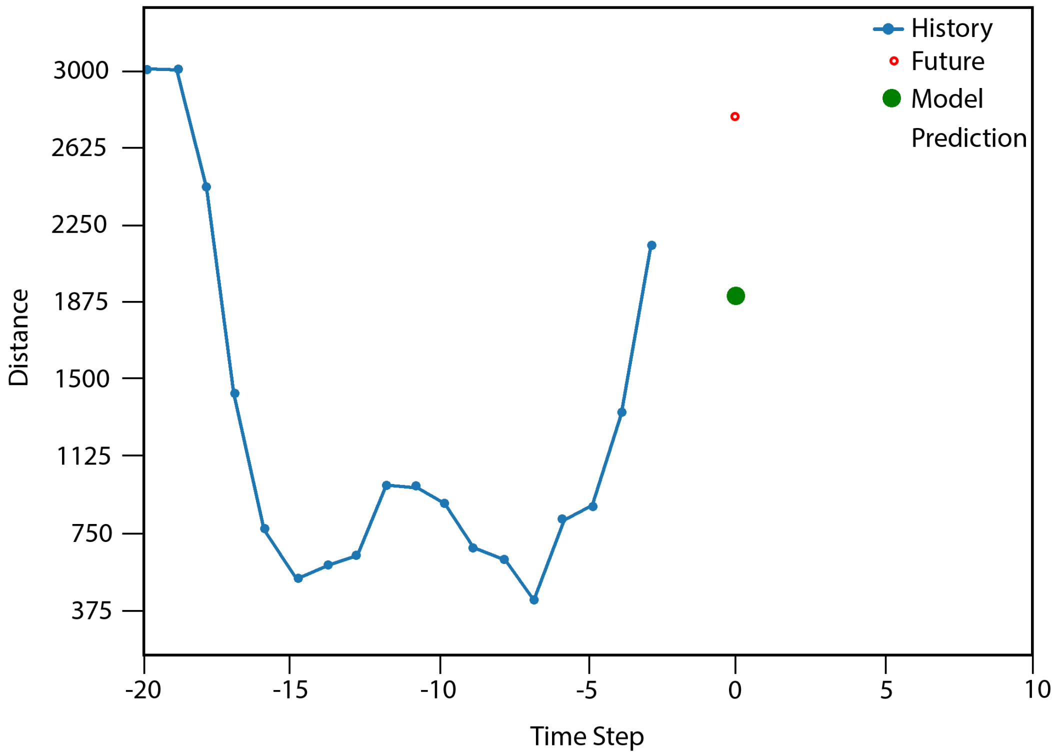


Figure 4.27: Model Prediction for sensor1(S1).

The setup collected data for 5 days, every second for four sensors. which is about 1.7M distance points. after cleaning the data and remove the values greater that 2990 and smaller than 200 mm. The resulting database was about 500k. For this research purposes about 60K data points for each sensor have been used. The following is the data collected for just one user in the test space. so we can have a continuity between sensor in the time steps. This Continuity is preserved by cleaning of data greater that 2990 mm. this way as a sensor is not reading an object it would generate no time steps as well. Merging of the the time steps would result in a efficient data collection which means to collect the data only when the test space is being used, otherwise we would have a lot of redundancy. The Feature space is in consist of 4 sensors in place:

features-considered =['S1(int)', 'S2(int)', 'S3(int)', 'S4(int)']

In a single step setup, the model learns to predict a single point in the future based on some history provided The below function performs the same windowing task as below, however, here it samples the past observation based on the step size given. here the the network is shown data from the last five (5) days. For the single step prediction model, the label for a datapoint is the position 10 sec into the future.

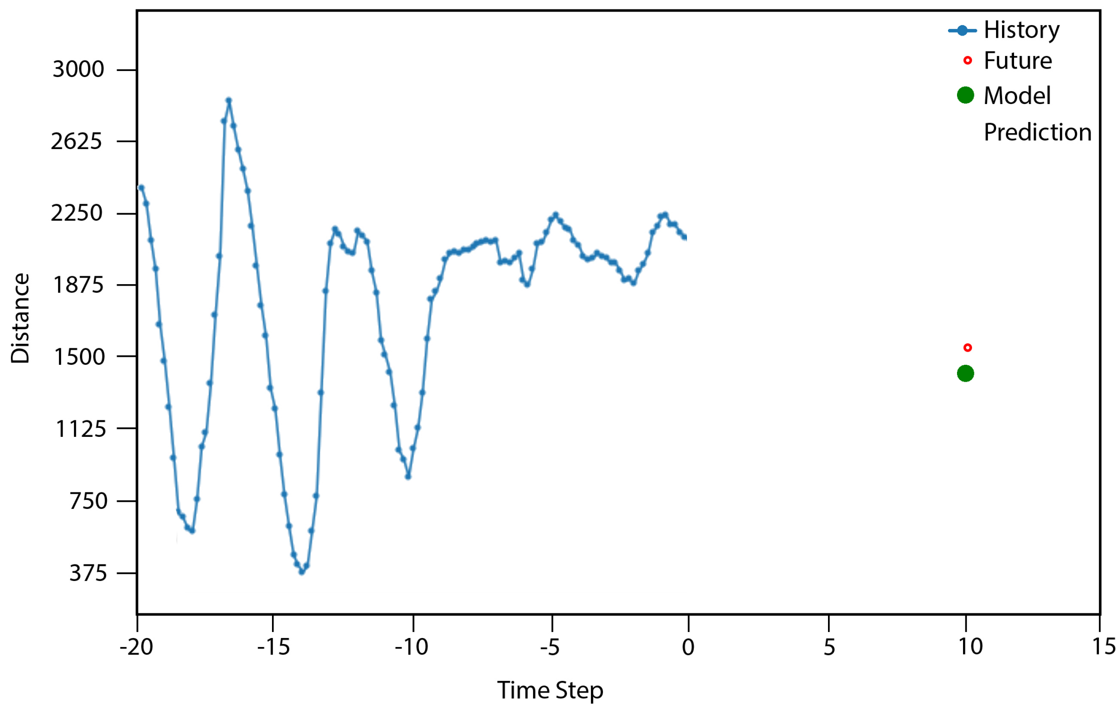


Figure 4.28: Single Step Model Prediction.

In a multi-step prediction model, given a past history, the model needs to learn to predict a range of future values. Thus, unlike a single step model, where only a single future point is predicted, a multi-step model predict a sequence of the future. the model now consists of two LSTM layers, since 40 predictions are made, the dense layer outputs 40 predictions.

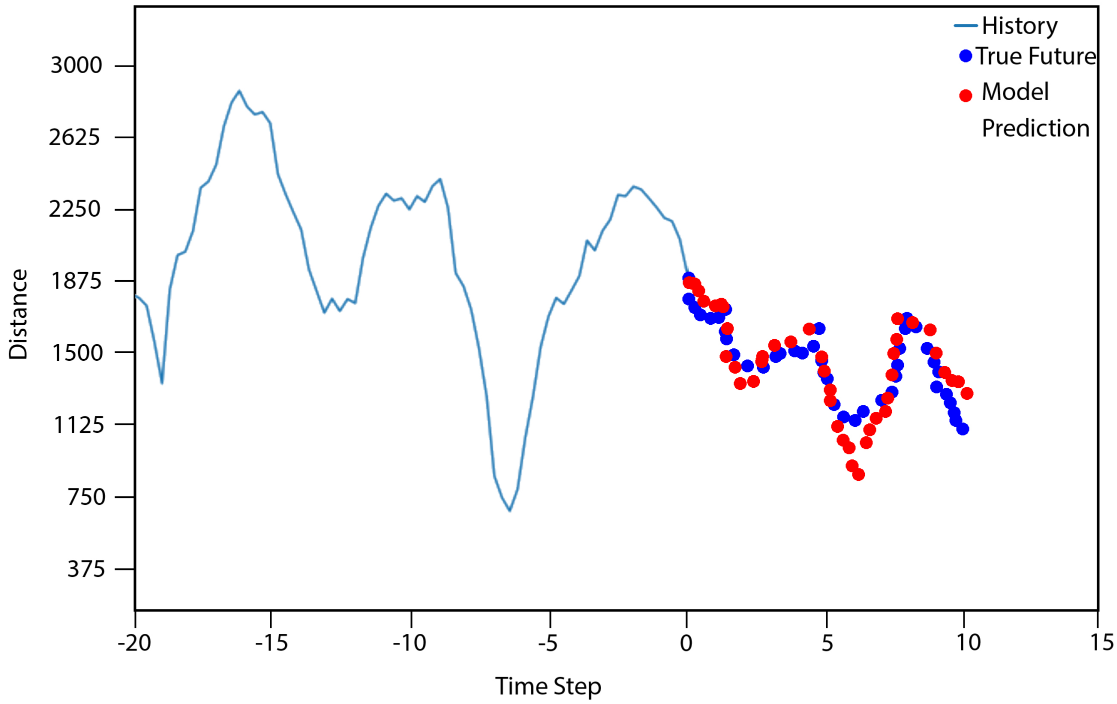


Figure 4.29: Multi Step Model Prediction.

4.3 Interaction

The Prediction then are interpreted as interaction. These Interactions are happening in our test space and are responding to different uses of the space. As depicted in the Integration, the space is set for different usages. the user can simply just walk in the space, use the free space for activities, use the printers, water the plants, or simply use the sofa. The prediction are giving us the whereabouts of user regardless of activity. Since the Intelligence system does not mind the activity and just predict the numbers that each sensor is going to receive as a range. We need to reform the Physical system based on these extracted inputs. our physical interaction are dependent on physical properties of our physical system such as geometry and scale. In real scale we are using 7 hexagonal panels with 24 nodes and 72 actuators.

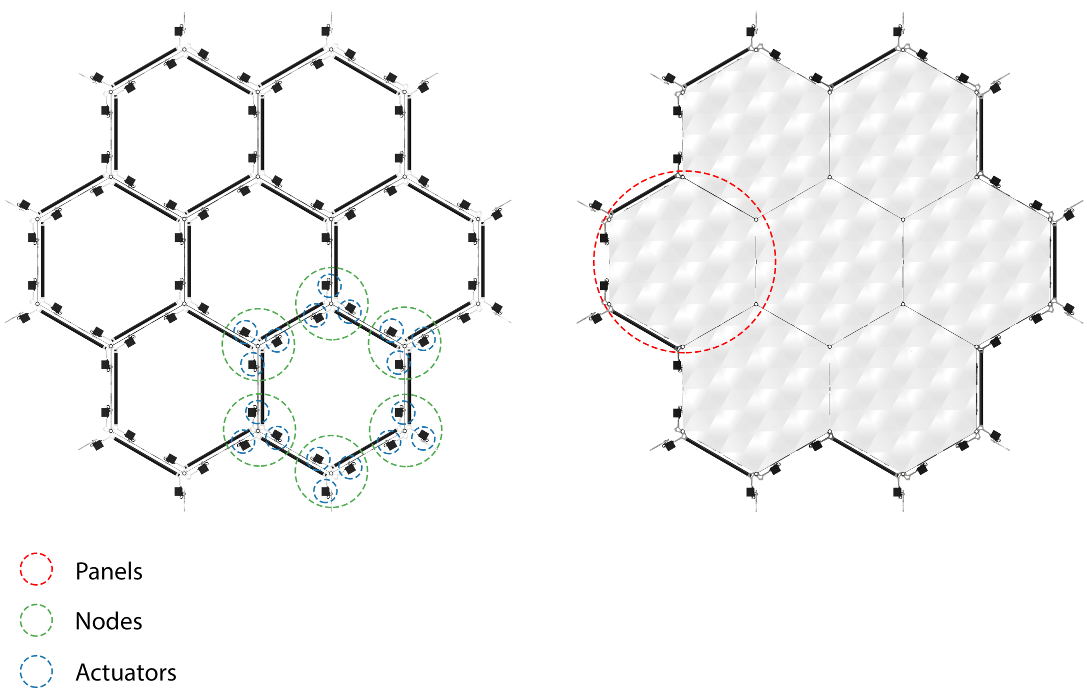


Figure 4.30: Panels in detail.

The dataset of the multi step model prediction would suggest the position on the prediction of the movement from that position. The Physical system though interact through a set of 24 angular movements that are available with servo motors (Actuators). The range is also limited to 315mm, the length of slider. Based on the 300mm radius that can be detected by the sensors a 3 by 3 zoning have created. This zones would help us to recognize different responses by the sytem.

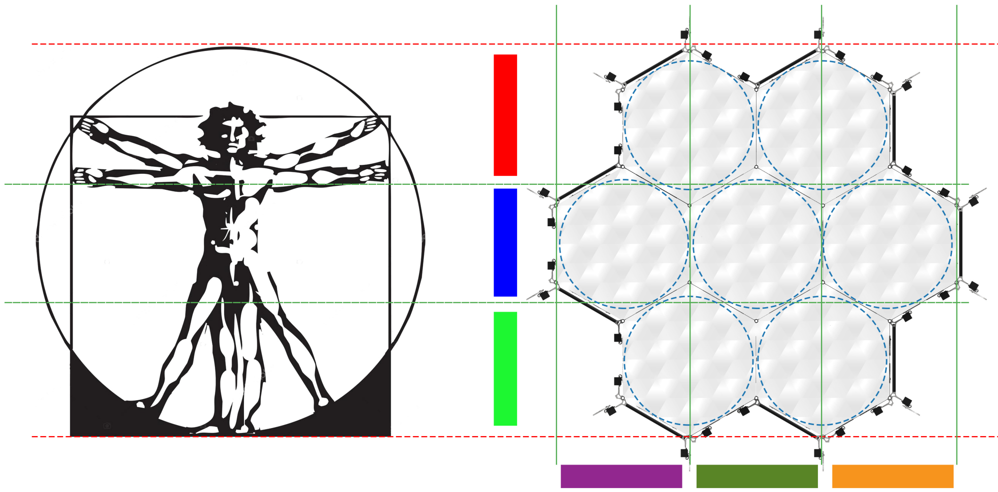
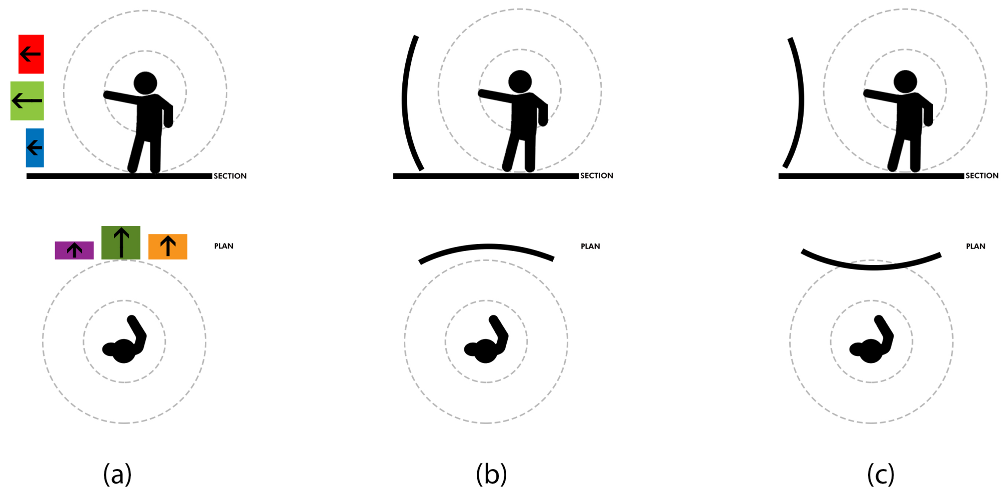


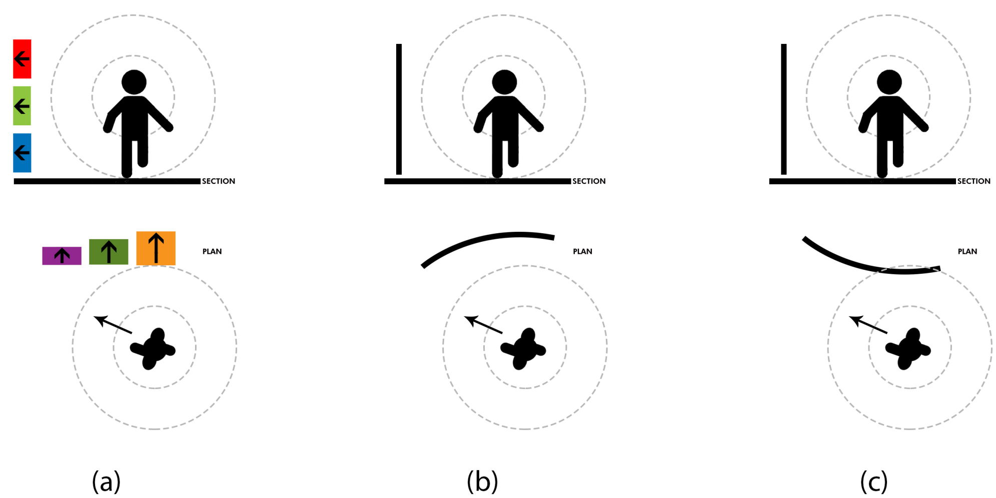
Figure 4.31: Panels in Zoning in relation to human scale.

According to test space limitation, functionalities, and work space limits, we can multiple sets of interactions in a range from Follow to Lead. As it is obvious in the Follow Response the Physical system would predict the position of the user and comply with that position and thus would expect you to move toward that position and would deform its panels based on the prediction as you intend to be in that position is space. The Lead Response though would React to the prediction model and act as the opposite form of the follow. The range is not limited and can sit anywhere in between these two based on the intensity of the values coming from the prediction model. Here Multiple scenarios have been demonstrated as possible forms of interaction in the Range of Lead and Follow:



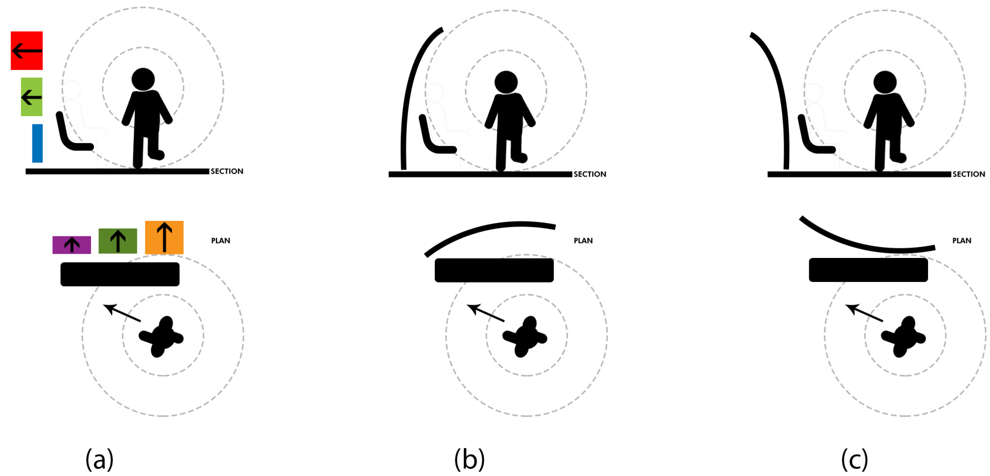
(a) Prediction model (b) Follow Response (c) Lead Response

Figure 4.32: Follow and Lead Responses for a Gesture.



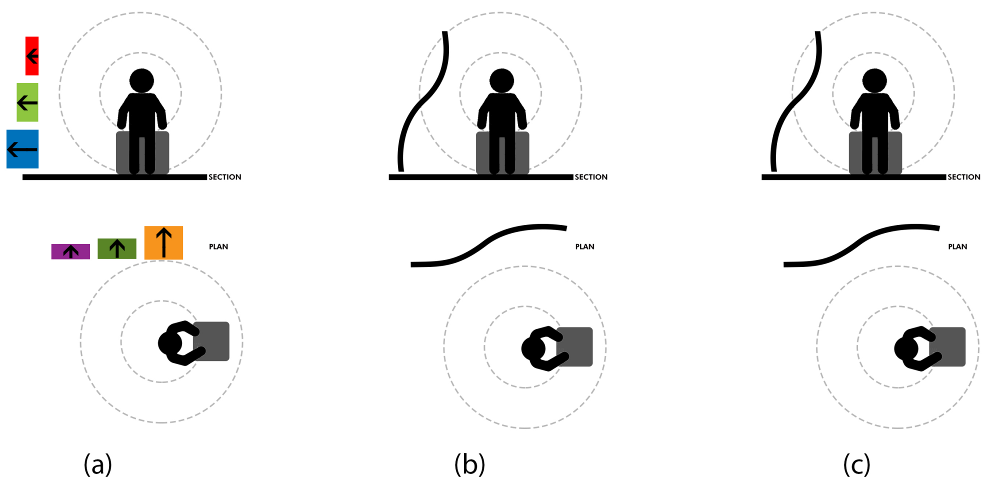
(a) Prediction model (b) Follow Response (c) Lead Response

Figure 4.33: Follow and Lead Responses for walking.



(a) Prediction model (b) Follow Response (c) Lead Response

Figure 4.34: Follow and Lead Responses for Seating.



(a) Prediction model (b) Follow Response (c) Lead Response

Figure 4.35: Follow and Lead Responses for Printing.

Based on the compliance of Prediction values and type of response, we can extract the Rotation values that are needed for the physical system. the process starts by extracting the model predictions of next 5 seconds of interaction.

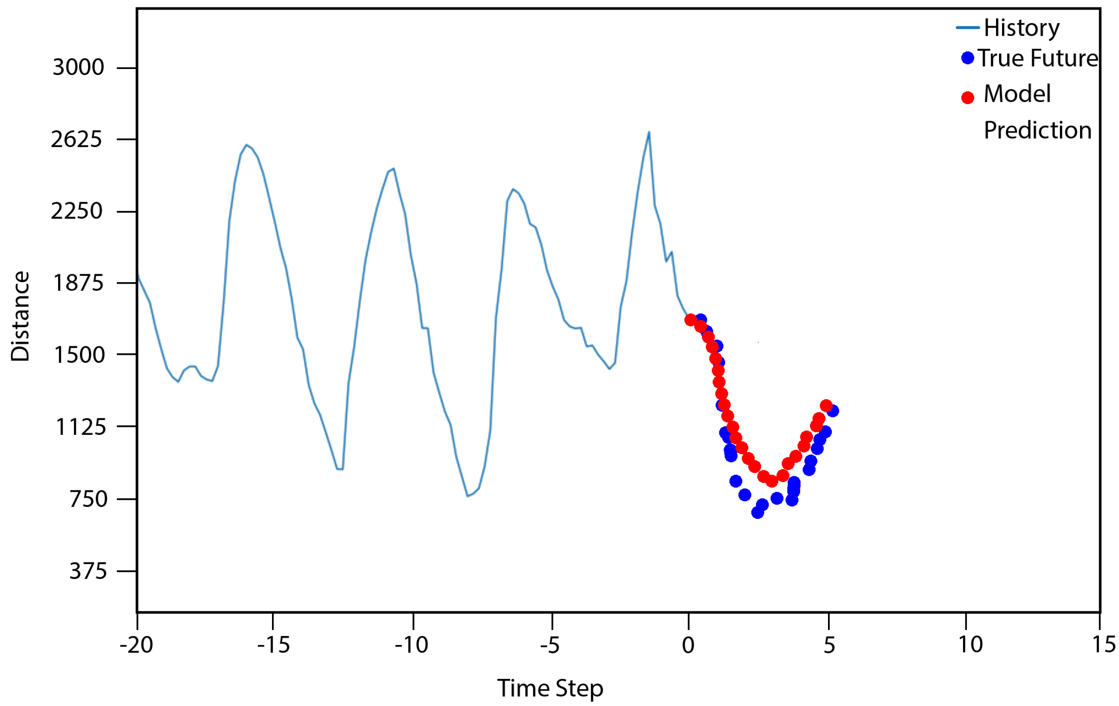


Figure 4.36: Prediction Evaluation for 4 seconds and 24 distances.

	Predicted Values	Conversion to Degrees
0	1675.008432	11.258333
1	1647.815689	9.509476
2	1599.551698	6.404493
3	1542.161477	2.712388
4	1481.09105	-1.216476
5	1418.430592	-5.247632
6	1355.163494	-9.317815
7	1292.083492	-13.375962
8	1229.916891	-17.375347
9	1169.543685	-21.259356
10	1111.70878	-24.980068
11	1055.78462	-28.577856
12	1001.116676	-32.094827
13	948.203084	-35.498935
14	898.361302	-38.705423
15	856.063624	-41.426574
16	843.000545	-42.267
17	879.023922	-39.949461
18	932.689915	-36.496949
19	990.771218	-32.760385
20	1050.156331	-28.939943
21	1109.868323	-25.098471
22	1169.538546	-21.259687
23	1229.007654	-17.433841

Assigning Degrees to actuator nodes

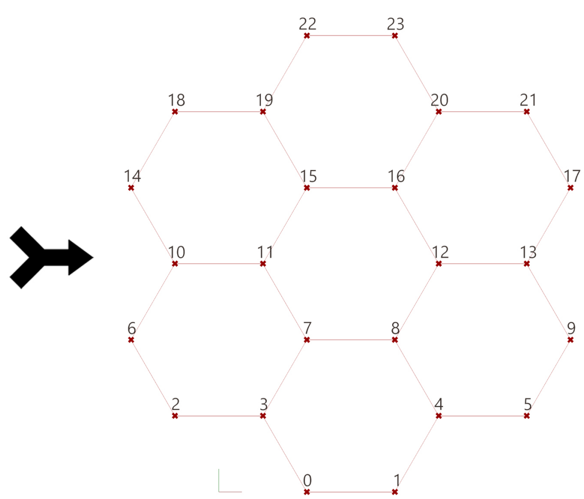


Figure 4.37: Remapping values to Degrees for Servo motors.

These changes in values are then mapped to the changes in the degrees of rotation. The resulting simulation would be the following for 3 vertical zoning of Red, Blue, and Green.

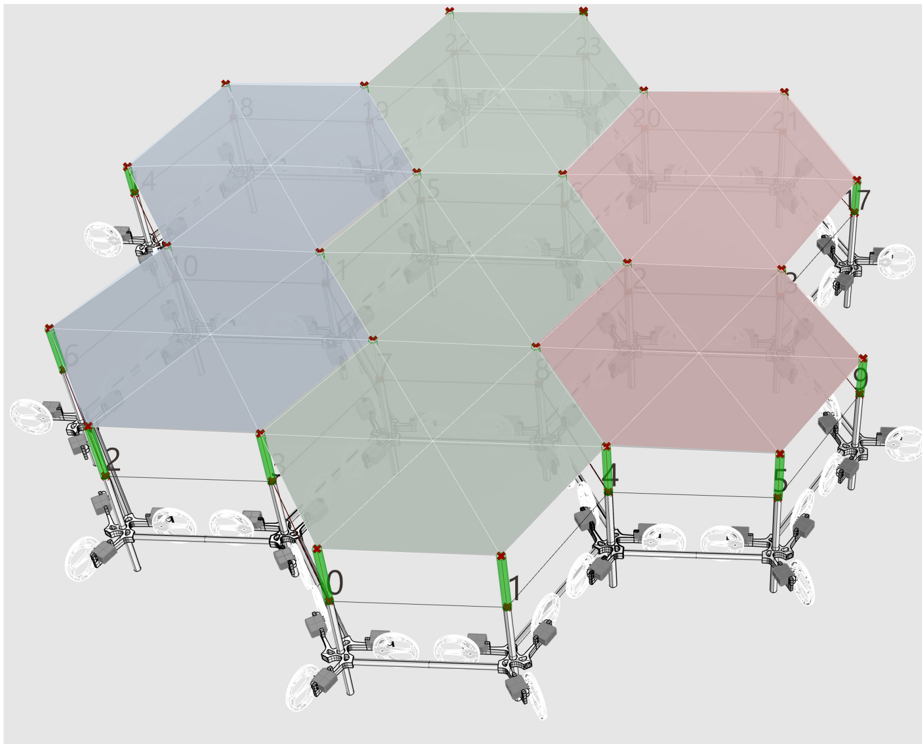


Figure 4.38: Movement of panels for each node.

The Physical system based is based on Panel 1 with the node numbers of 0,1,3,4,7,8. Panel 1 is sharing the nodes 3,4,7,8 with neighbor panels. Connectors in the middle of the panel would avoid separation of the panels. Because of the special circumstances the fabrication is limited to Just Panel 1 and the conversion of the data to angular for servo motors on the panel 1 would be the following.

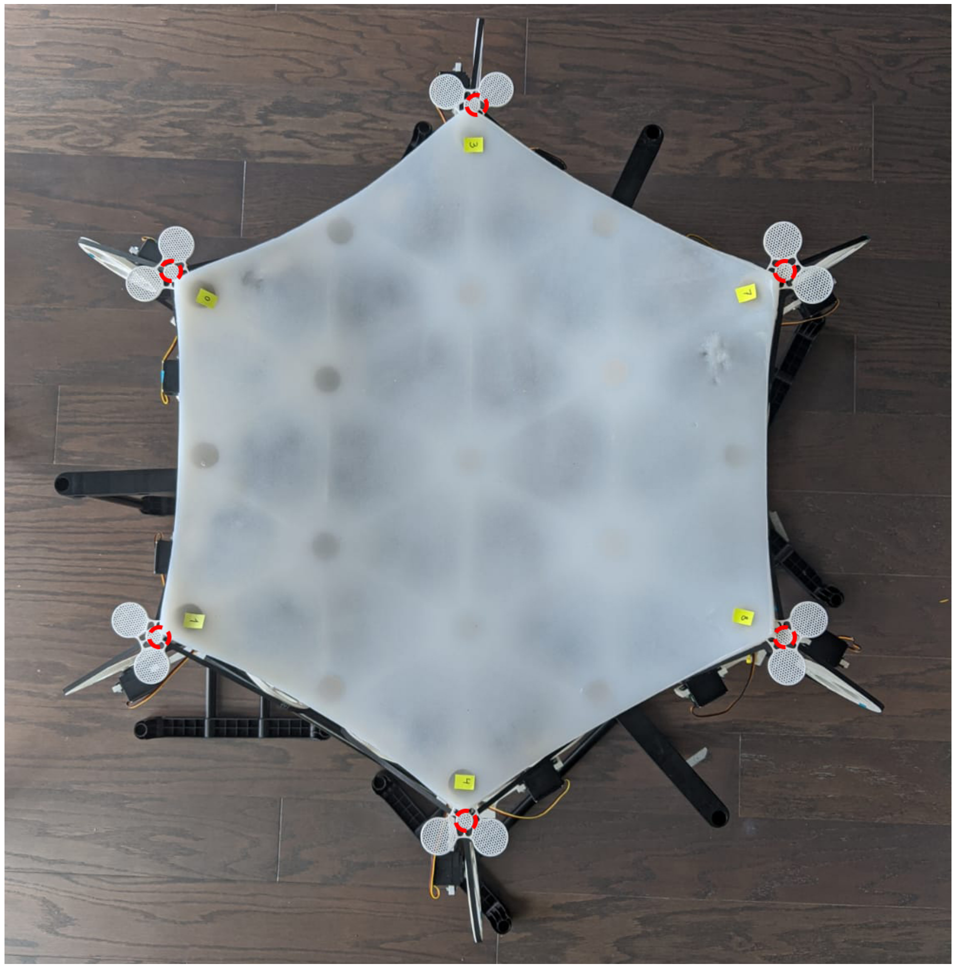


Figure 4.39: movement of Panel 1 nodes according to degree changes in Servo motors.

CHAPTER 5: FUTURE WORK

The first thing to do is to develop a full scale prototype to experience the physical system in hand. Next, A more dynamic and Interactive AI can be developed specifically for IOT uses. this AI can include actuators in a feedback loop which then would add a set of features for each of the actuators in the layers. by adding a set of sensory we can also see how we can develop a ML that can integrate different sensors and their different set of outputs to function, just like our brain that integrates the vision, touch, and other sensors.

developing a mechanism with vision and Proximity sensors would also help us tag different people and as a result different behaviors that each person has. This would result in a multi interaction space that can learn from different people.

Analyzing more convoluted and complex geometries would result in a more interactive Physical system. This would also push the interactions to be more immersive and inclusive. Developing of different sets of sliders and extruders would increase the interaction space, work space, and can potentially can handle the functionalities of the built-environment as well.

The Final goal of the developing such a Physical system is to be an essential part of the life, in which there is a close interaction between the users and the Physical system, and the envelope can take responsibly for every aspect of our lives. This close interaction need a fluidity in the structure that is possible by developing of soft technologies in Robotics.

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