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GESTURAL DESIGN - HAND TRACKING FOR DIGITAL DRAWING

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Abstract

Computational design is increasingly interested in the active feedback between the user/designer and the digital space. Often, our initial instinct as designers comes from a gesture, a movement of the hands that gets translated into sketches and 3D models via the tools available to us. While the physical realm allows for muscle memory, tactile feedback, and creative output via movement, digital design often negates the body of the designer as it sequesters us into a screen-mouse-hand relationship. Moreover, current CAD software tools often reinforce this standardization, further limiting the potential of physical bodily gestures as a vehicle for architectural form-making. Seeking new opportunities for a gestural interface, this research explores how Machine Learning and parametric design tools can be used to translate active movements and gestural actions into rich and complex digital models without the need of specialized equipment. In this paper, we present an open-source and economically accessible methodology for designers to translate hand movements into the digital world, implementing the MediaPipe Hands tracking library. In developing this workflow, this research explores opportunities to create more direct, vital links between expressive gesture and architectural form, with an emphasis on creating platforms that are accessible not only to design experts, but also the broader public.

Keywords

Machine Learning, Hand-Tracking, Gestural Drawing, 3D Printing, Agent-Based Modelling

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ABSTRACT

Computational design is increasingly interested in the active feedback between the user/designer and the digital space. Often, our initial instinct as designers comes from a gesture, a movement of the hands that gets translated into sketches and 3D models via the tools available to us. While the physical realm allows for muscle memory, tactile feedback, and creative output via movement, digital design often negates the body of the designer as it sequesters us into a screen-mouse-hand relationship. Moreover, current CAD software tools often reinforce this standardization, further limiting the potential of physical bodily gestures as a vehicle for architectural form-making. Seeking new opportunities for a gestural interface, this research explores how Machine Learning and parametric design tools can be used to translate active movements and gestural actions into rich and complex digital models without the need of specialized equipment. In this paper, we present an open-source and economically accessible methodology for designers to translate hand movements into the digital world, implementing the MediaPipe Hands tracking library. In developing this workflow, this research explores opportunities to create more direct, vital links between expressive gesture and architectural form, with an emphasis on creating platforms that are accessible not only to design experts, but also the broader public.

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ملخص

يهتم التصميم الحوسبي بشكل متزايد بالتغذية المرتجة النشطة بين المستخدم أو المصمم والفراغ الرقمي. غالبًا ما تأتي غريزتنا الأولية كمصممين من خلال لفظة، وهي حركة للأيدي تترجم إلى رسومات ونماذج ثلاثية الأبعاد عبر الأدوات المتاحة لنا. بينما يسمح الواقع المادي بذاكرة العضلات وردود الفعل المسببة والإخراج الإبداعي عبر الحركة، فإن التصميم الرقمي غالبًا ما ينفي جسد المصمم لأنه يعزلنا في علاقة بين الشاشة والماوس. علاوة على ذلك، فإنه غالبًا ما تعزز أدوات برامج CAD الحالية هذا التوحيد القياسي، مما يحد من إمكانيات الإيماءات الجسدية كأداة لصنع النماذج المعمارية. في إطار البحث عن فرص جديدة لمواجهة إيمائية، يستكشف هذا البحث كيف يمكن استخدام التعلم الآلي وأدوات التصميم البارامتري لترجمة الحركات النشطة والإجراءات الإيمائية إلى نماذج رقمية غنية ومعقدة دون الحاجة إلى معدات متخصصة. نقدم في هذا البحث منهجية مفتوحة المصدر ويمكن الوصول إليها اقتصاديًا للمصممين لترجمة حركات اليد إلى العالم الرقمي، عن طريق المكتبة التتبعية لـ MediaPipe Hands. وفي إطار تطوير سير العمل هذا، يستكشف هذا البحث فرصًا لإنشاء روابط حيوية ومباشرة أكثر بين الإيماءة التعبيرية والشكل المعماري، مع التركيز على إنشاء منصات يمكن الوصول إليها ليس فقط لخبراء التصميم ولكن أيضًا للجمهور الأوسع.

الكلمات المفتاحية: التعلم الآلي، تقنية تتبع الأيدي، الرسم عن طريق اللفظة، الطباعة ثلاثية الأبعاد، النمذجة المبنية على الوكيل.

1. INTRODUCTION

From the inception of architectural drawing, architects have relied on tools to generate exacting drawings that are later used as a communication tool for construction. The craft of architectural drawing grew out of the drafter's capabilities to translate intuitive physical gestures into coherent and legible inscriptions. The "human error" or "makers marks" inherent in this project provides a method of individualization for the final product (Jenny et al., 2018). The introduction of computer aided drafting and digital design has abstracted this process and progressively introduced a distance between the hand and the surface of representation. (Sunshine, 2021). While there have been extensive developments of a plethora of algorithmic approaches aimed at introducing variation or indeterminacy in the drawing process, for the most part, these do not originate in the hand or the gestural expression of the human body.

The process of translating gesture into design is often frustrating, especially as we consider the multi-sensory essence of gestures and the current limitations of the tools for interfacing with digital design platforms. While digital design initially developed as an analogue to hand-drawing, in recent decades, it has been able to explore new realms of digital expression. However, digital tools exist within the limited range of human-computer control devices, such as the mouse and keyboard, which tend to reinforce the visual regime of representation and design thinking, at the exclusion of more tactile engagement with form (Oliveira, Nedel and Maciel 2018). This Human-computer interaction, thus, becomes a critical element of creative output (Yasen and Jusoh, 2019). This research seeks to explore dynamic methods of interaction with virtual environments for the purpose of architectural design, improving upon the current tools of digital design by leveraging the power of Machine Learning and data organization in Grasshopper for Rhino.

The development of human-computer interaction via hand gestures rather than keyboards and mice has allowed for a more fluid and flexible interaction with 3D virtual environments, laying out the foundation for Virtual Reality Aided Design (VRAD). While in VRAD hand gestures continue to be understood as controlling gestures, in architectural design gestures are often communicative, borne out of an initial instinct to design with our hands, a movement that is later translated into sketches and 3D models via the tools available to us. Virtual Reality (VR) is a human-computer interface in which the computer creates an immersive environment that is controlled by the behaviour of the user (Abdelhameed, 2012). The most common system for VR is that of Head Mounted Displays (HMDs), where the user wears a set of goggles that provide deep immersion and a set of hand-held controllers to interact with the digital space (Balzerkiewitz & Stechert, 2020). VRAD has a great deal of potential for a more direct connection between bodily gestures and digital form making and presents an important avenue for future exploration in this area. However, in terms of the current and near-term future technology, VRAD has a few notable limitations. First, it remains a fairly computationally intensive and expensive technology, and thus accessible to a limited number of people; second, the ability of VR interfaces to capture fine motor gestures in the fingers, hands and wrists is somewhat limited in typical handheld controllers; and third, entry into "virtual space" inherently involves a kind of disembodiment that detached the user from concrete physical space, materiality, and experience.

In the search of a less mediated gestural interface, this research engaged the development of hand-gesture recognition in the field of computer vision. The evolution of user interaction is a well explored topic in computer vision, where alternatives to keyboards and mice in 3D virtual environments have been sought in areas such as Human Computer Intelligent Interaction and Perceptual User Interfaces (Mohamed, Mustafa, and Jomhari 2021; Wu and Huang, 1999b). Visual-based gesture recognition techniques first endeavoured to understand gestures, classifying them into conversational, controlling, manipulative, and communicative gestures (Wu & Huang, 1999a). For the purposes of computer-vision, hand gestures are used to activate a virtual environment thus falling into the classification of controlling gestures. As such, hand motions are translated into actions within the digital space.

This field has developed several algorithmic approaches to analyse hand positions, segmenting hands into features such as fingertips, finger directions and hand contours (Wu & Huang, 1999b). These segmentations provided a basis for commonly found landmarks, such as fingertips, knuckles, and particular areas in the palm. However, it was recognized that a temporal dimension, one that could capture the stroke and movement of a gesture, was needed. An approach to capturing the temporal dimension is by generating a wireframe model of a hand

based on landmarks. The wireframe model, connecting the landmarks via primitive components such as spheres and cylinders, becomes a digital proxy that is then controlled by the user via gestural commands. This approach, however, is computationally expensive as it relies on a redundant method of landmark finding (to first generate the digital proxy) and landmark controlling (using landmark recognition to activate the digital proxy) (Jaimes & Sebe, 2005).

An emerging alternate approach relies on Machine Learning. Machine Learning is a probabilistic approach for pattern finding via the training of a neural network. The neural network is trained using a large and as varied as possible dataset. Once the neural network is trained, it can accurately approximate the patterns it has learned. For hand-tracking, a neural network would be trained on static hand positions with their related marked landmarks. Once trained, the model can be used to recognize landmarks in real time using very little computational power. By using Machine Learning, the potential of a light-weight real-time feedback without the need of external tools is possible. (Cheok, Omar, Jaward 2017; Pavlovic et al., 1997).

In search of a more flexible, accessible, and computationally light approach this project opted for an open-sourced, thus free, Machine Learning model. The MediaPipe Hands library, developed in 2020 by Google Research, is a real-time hand tracking solution that predicts a hand skeleton of a human from a single RGB camera input (Zhang et al., 2020). The hand tracking consists of two models, a palm detector, and a hand landmark. The palm detector is enacted on the input image from the RGB camera, where the palm is segmented and cropped from the background. The palm is then transformed into a bounding box with a direction, which reduces the area of probability of where to find the fingers. The palm detector is only enacted at the start of the model, or if the palm is lost in the subsequent image. This means that the palm detector model is only used as needed, lowering the required computational power. The hand landmark model performs precise landmark localization of 21-point coordinates in a 2.5D space (see figure 1), which is done through a regression neural network. The hand landmark model provides an x, y, and relative depth, as well as the possibility to discern left from right. The goal of the MediaPipe Hands library is to become so lean that it can achieve hand-gesture recognition on mobile devices in the future (Zhang et al., 2020). With such a computationally light model that requires nothing more than an RGB camera, and that can capture the movement of the knuckles of each finger, this project began to explore the translation of active movements and gestural actions into rich and complex digital models without the need for specialized equipment.

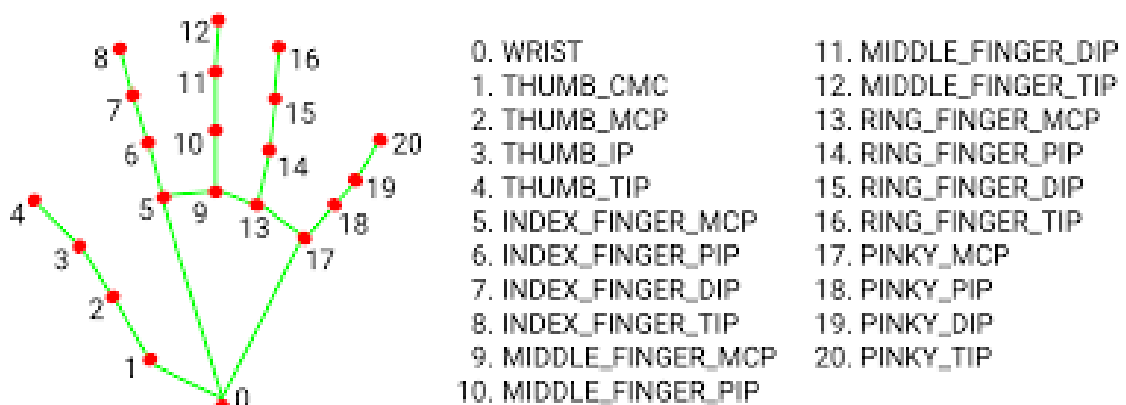


Fig.1: Hand landmarks for MediaPipe Hands Library.

Introducing the MediaPipe Hands library frees the user from the limits of keyboard and mouse interface and allows for an enriched exploration of the virtual environment. In this research, we tested a workflow for translating from physical hand gestures to a digital point-cloud model using the MediaPipe Hands library and a computer webcam. We then developed one possible process for translation that point-cloud into a robust geometry, and finally, to translate that resulting digital geometry into a physical form via 3D printing. By closing the circle from physical gesture to digital form to physical form, this research sought to initiate a feedback loop that could allow for an iterative exploration of the design possibilities in the intersections of physical gesture and digital geometry. Ultimately, this research sought new ways to introduce “makers mark” and gestural expressiveness back into the digital design process.

2. METHODOLOGY

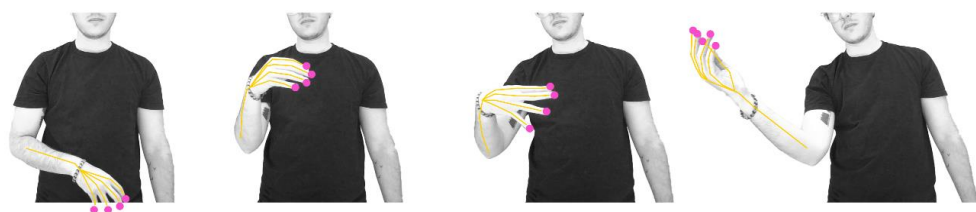
2.1. From Physical to Digital: Mapping Gesture Coordinates

Making use of the MediaPipe Hands library, a python script was developed to track five landmarks, one for each fingertip. The MediaPipe Hands utilizes the ML Pipeline to detect and track hand motion, identifying the palm, cropping the image, and identifying hand and finger landmarks on each image frame of the video.

The Hands model operates in two modes - detection and tracking. Detection is more computationally intensive and relies more on image detection to formulate the hand model; tracking relies on prediction based on previous states of the model. If the tracking confidence of a model falls below a certain threshold, then the model will switch to detection mode (MediaPipe Hands). In our experience, this switch occurred during rapid changes in hand position or movement during a gesture and would result in a significant decrease in the frame rate at which the model ran. To create a consistent sampling of the hand landmarks through the gesture, our implementation of the Hands model recorded the coordinates of the tracked landmarks at a regular time interval. The resulting series of sets of coordinates (one set for each tracked finger landmark, one series for each recorded frame) were then exported into a CSV file, whose length is a changeable variable and can be adjusted according to the desired outcome. For the purposes of this paper, the length of the CSV file varied between 80 and 200 captured frames. This meant that we were able to collect five landmarks, each with an x, y, and relative z, for each frame, depending on the length of the gesture.

The python script, when activated, uses an RGB camera, for example a laptop webcam, and begins capturing landmarks as soon as a palm is detected. Upon this detection, the user can move their hands in space, expressing a particular gesture or design motion, which is then captured as coordinates in space. The series of coordinates begins to capture the stroke of gesture over time, rather than a static hand motion. Once the recording was complete, the coordinates were imported into Rhinoceros 3D and converted into point geometry with the scaling factors applied to create an accurate digital map of landmark locations over the time of the recorded gesture.

To convert the results of the model recording from a pixel-based unit system to one that corresponded to the spatial measurements of the hand gesture, a series of validation recordings were made before the gesture recordings. These validation recordings consisted of simple hand movements of known distances and directions, which were then used to calculate scaling factors for x- (right to left), y- (up and down), and z- (distance to camera) coordinates. These scaling factors were then applied to the coordinates of each recorded point, to ensure that the digital model accurately represented the physical space of the gesture. The z-coordinate values deviated from the x- and y- coordinate values because the Hands model used the image depth map to calculate these values, and therefore required a much larger scaling value.



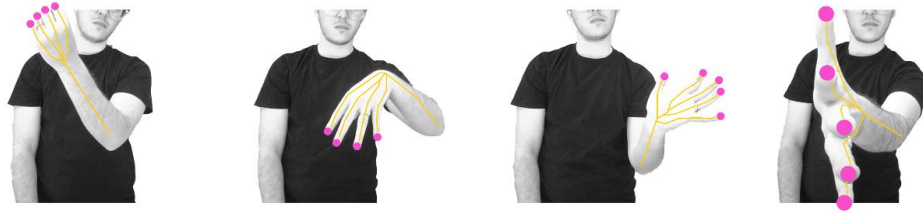


Fig.2: Collecting coordinates of hand landmarks with MediaPipe Hands.

2.2. Transforming the Points into Surfaces

With the points in space inside the Grasshopper environment, the user/designer can make decisions based on their desired outcome. There are several ways these points in space could be translated into volumetric geometry (lofting, isosurfacing, etc.). In this research we focused on the motion of hands in space and time; therefore, the decision was to make lofted surfaces that follow the order in which the landmarks were captured. Each fingertip motion was traced by a line and after these lines were lofted with each other. The results are complex and organic surfaces that capture motion, not hands. At times, these surfaces overlap creating knotted looking meshes, and other times the surfaces are elegant ribbons in the virtual 3D space. The lofted surfaces have an ethereal lightness and can be argued to capture the emotive quality of the gesture in some form (see figure 3).

The hand gestures tried for this project ranged from fast motions and complex pirouettes to simple and slow directional movements. However, the steps followed to generate lofted surfaces had yet to translate the intensity of the hand gestures. The resulting geometry represents an index of the gesture's intensity, variation, finger movement, etc.

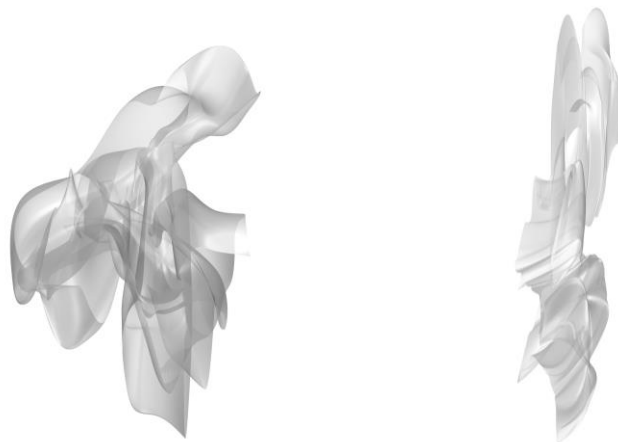


Fig.3: Lofted surfaces in Ghosted view to showcase overlapping.

2.3. Implementation of Agents on Surface

To further explore the geometric potential of these meshes, and to reconstitute the sense of movement in the original gesture, a system of agent-based modeling was implemented. Agents are components that provide multi-object behaviours, thus creating dynamic interactions. Luis Quinones developed Culebra.NET, a grasshopper plug-in developed in C#, where the user can enact agents upon a surface and establish behaviours such as flocking, wandering, mesh crawling, etc. The user can specify how many generations of agents are to be summoned, at which locations, if they are to have one or multiple generations, and how they will behave. Although there are many agent-based plug-ins for Grasshopper, Culebra was chosen because it offers a “graphics-only” exploration of agent behaviours before transforming them into geometries. This graphics-based approach makes it so computers with limited GPU power can perform complex behavioural iterations

in a short period of time. For this research, the number of agents was relative to the speed of movement based on the distance between points at each framerate. If the distance values were constant between points, then a single point for agent spawning was generated and a simple mesh crawl behaviour selected. However, if the distance became greater, then a second point of agent spawning was generated this time with a flocking behaviour, following the first generation of agents as they proceeded with their mesh crawl (see figure 4). In this way, the agents responded both to the surface geometry and the velocity of the original gesture at any given point in its duration. Though clearly abstract, this was intended to enhance the connection between the original gesture and the final geometry.

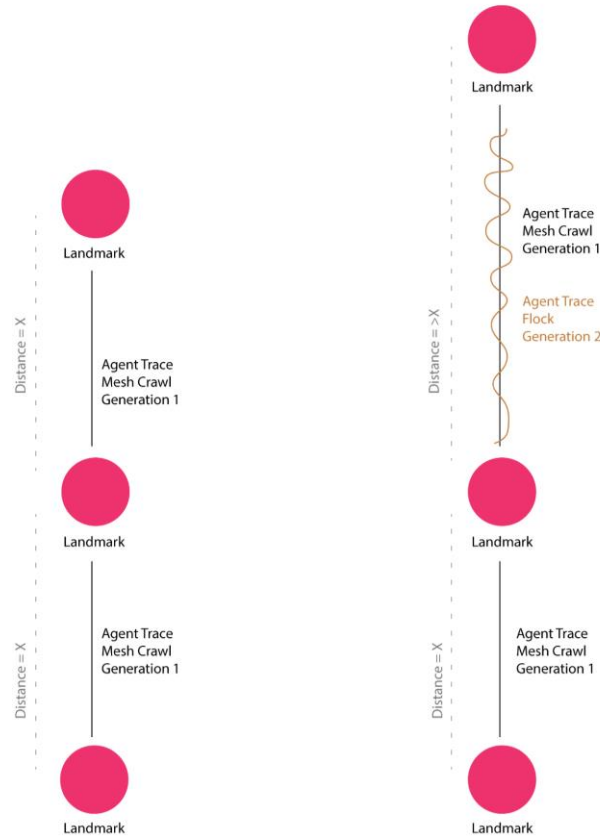


Fig.4: Agent spawning behaviour

The implementation of agents resulted in rich and complex models, where the tracing of motion through space became enhanced by the beauty of the models. The varied densities and spawn locations of the agents help reconstitute the original hand gesture through their interactions with the lofted geometry. The agents, thus, highlight the motion of the fingertips creating not just one line per fingertip landmark but rather multiplying the impact of the hand motion.

2.4. From Digital to Physical: 3D Printing

As a method to close the loop between physical gesture to physical form, the resulting digital gestural models were prototyped through 3D printing. To do this, the traces generated by the movement of the agents had to be optimized and interconnected so they could support one another. While the agent traces in the digital space could exist without concern for gravity or material thicknesses, once we began 3D printing the traces had to be converted into pipes, and these pipes had to connect to one another so that the model could self-sustain. Once again, the use of distances was selected as a factor for decision making. By subdividing the agent traces into evenly spaced segments, we could then measure the distance between these newly identified segment points. If the segment points were close enough to one another, such that the pipes intersected, then no additional geometry was added. If the points were beyond this intersection threshold (i.e. the diameter of the pipe), then a line was generated connecting the two segment points. This line was then piped as

well, to create a supporting “strut” between the various agent pathways. The threshold for when to place a connecting line was also based on the scale of the model, where the physical characteristics of the 3D printing material had to be taken into consideration. These small connectors allowed us to generate digital models that would be self-supporting. Three small scale prototypes were printed, showing that generally the connecting lines were only needed when the hand gesture was slower, resulting in fewer agents and therefore fewer interconnecting pipes.

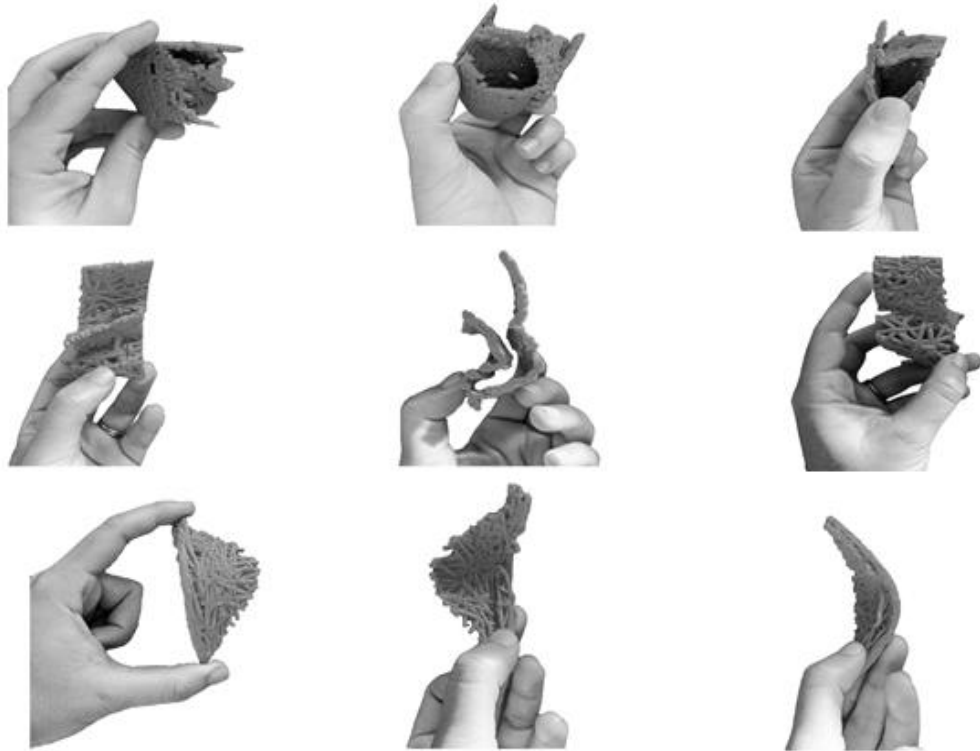


Fig.5: Sample 3D Prints

3. RESULTS

The result of this research is the development of a workflow that translates hand gestures into digital geometry and then back to physical form through 3D printing. This research explored the potential for the use of Machine Learning platforms to record and create robust digital models of hand gestures using a laptop and webcam only. This presents a new avenue for reintroducing the intricacies, individuation, intimacy, and expressiveness of hand gestures into the digital modeling process and explores a workflow to close the loop in the translation from physical gesture to digital model to physical form.

In terms of the translation from physical gesture to a digital point array, the research further validated the capacity of the ML Pipeline to accurately capture a variety of gestures without requiring intensive or specialized computer hardware (GPU, VR headsets, etc.). The scaling validation process implemented in this workflow ensured that the 3d model was accurately scaled to physical space. The decision to sample landmark positions at a regular time interval allowed for the resulting point geometry to reflect the velocity of the hand gesture at any given moment - as determined by the distance between any two points from one landmark in sequence divided by the regular time. This fact was taken advantage of in the subsequent agent modeling process, as the agent behavior responded to the variation in velocity. An alternate approach would be to sample the landmark positions at a regular frame (i.e. every 10 frames, etc.). This would have resulted in a sampling that would adjust the “resolution” of the recording relative to the complexity of the gesture. For example, when a more complex sequence of movements occurs, and the Hand model switches to detection mode, reducing the framerate of the model, the rate of recordings per second would go up. This would result in a point cloud composed of more samplings when the gestures are more complex, and less samplings when it is

less complex or more predictable. More research is needed to explore which approach produces a better representation of the gesture, and in what contexts one or the other works better.

The process of translating the digital point array into surface and pipe geometry represents one possible approach among many. The degree to which this workflow captured the “essence” of the gesture is open to interpretation. However, the development of a closed-loop design process that translates from physical gesture to digital model back to physical form opens the possibility of an iterative design process where these instances of translation can be further experimented with, tested, and refined. While the use of lofting, agent-modeling, piping, and 3D printing were not novel to this research, they did provide invaluable points of reference in creating tighter feedback between gestures and design.

There is room to further a multi-sensory interaction via haptic feedback by generating physical objects from the gesture-generated virtual objects. Haptic feedback is concerned with the sense of touch, often achieved by creating physical artifacts that express some aspect of architectural design. However, physical modelling of complex digital massing had been difficult to achieve before the widespread access to 3D printing. By creating a physical artifact, we shift from a visually dominated interaction and attempt to incorporate multiple senses. Introducing 3D printing as part of the multi-sensory feedback loop builds on the idea of communicating with virtual environments through our bodies, and thus accessing otherwise sequestered means of creation.

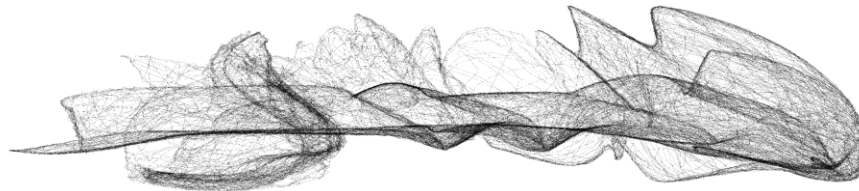


Fig.6: Finished Model B with two generations of agents. Plan view.

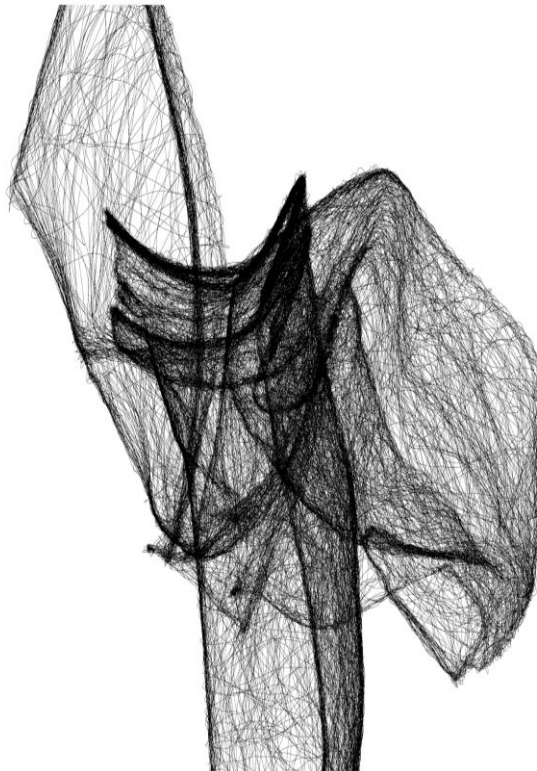


Fig.7: Finished Model C with two generations of agents. Plan view.

4. DISCUSSION

This research project began by asking how users and designers could interact with the 3D digital space without negating their corporality, and by accessing the initial instincts of design through gestural movements, without the need of specialized equipment or high-performance computer hardware. Focusing on hand gestures, the use of the MediaPipe Hands library, provided a computationally light and straightforward approach using landmarks at the fingertips of the user. This workflow was then extended into a process of digital parametric modeling and 3d printing. The project illustrates that the use of specialized equipment for interacting with 3D virtual environments is no longer an unavoidable necessity, and that other kinds of interfaces can be both technically and economically accessible to a broad base of potential users and designers.

This workflow suggests a more inclusive approach to design and digital form making. It opens the possibility of leveraging the universal language of hand gestures as a direct driver of design processes and form making. This has the potential to liberate the designer or design expert from the limitations of conventional user-interface tools, such as the keyboard and mouse, and to create a much more embodied, less mediated user interface experience. It also suggests the potential for non-experts to engage in the design process in a more direct way, allowing their expressive gestures to be translated into digital and physical form. By tying this workflow into the broader network of DIY makers, artists and designers will only expand the possibilities for form making in the future.

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