Digital Roots: Exploring Plant-to-Plant Interactions Through Capacitive Sensing and Mechanical Stimulation

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Introduction

In a global society, humans are scattered across the world, yet connected through society. Those bonds we create with other people traditionally materialize through physical connection. While the Internet gives us a way to stay in touch with loved ones despite great distances, it lacks this important physical connection. Traditionally digital communication is mediated through man-made interfaces. As the prevalence of these interfaces in our surroundings has grown so have the concerns on human wellbeing/cognition and the environmental impact of these devices.

Often online social interaction such as video calls or social media, lacks the physical aspect which is key to maintaining healthy relationships. Recently we have experienced the heavy emotional impact of a lack of physical interaction during the COVID-19 Pandemic (Orben et al., 2020). Not having social interaction in physical spaces creates dissatisfaction with quality connection and would ultimately impact our mental health (Sikali, 2020). However, recent developments in electronic and material science have helped us revamp the form, interfaces and energy sources of interaction devices. This creates room for exciting new possibilities to naturally integrate digital tools into our daily lives. For instance, Tsetserukou (2010) designed a wearable haptic display device integrated with a 3D virtual world, generating pressure and patterns that are similar to those of a human-human hug.

Furthermore, recently, plants, especially indoor potted plants have been a significant focus in studies related to human-computer interaction (HCI). Plants play a crucial role in creating healthy living conditions and workspace. In *Behavioral Activation Therapy*, plants have been used to aid youngsters with mild depression or address loneliness in older adults (Bhat et al., 2021). During the COVID pandemic, Dzhambov et al., (2021) suggested that the mental health-supportive effects of indoor plants were largely explained by increased feelings of being away and facilitating physical interactions with others, while at home. An example of human-plant-computer interfaces that have been invented, is the cyborg botany project by MIT Media Labs (Sareen & Maes, 2019). In this project, they explored how plants could be used as sensors, displays, and actuators. A similar project was developed by Disney Research in which plants were turned into musical instruments (Sato et al., 2012). In our project, we seek to let indoor plants serve as a physical proxy for our virtual interactions. The goal is to display, stimulate, and enhance human digital communications by using I/O on plants. According to Bhat et al., (2021), “interfaced plants use various HCI strategies to facilitate their outputs in formats that can be recognizable and relatable to humans.”

As a project, we would like to create an interactive system where individuals in different locations can communicate through houseplants. Users from one location will interact physically with their plant, which, equipped with touch-sensitive technology and a machine-learning algorithm, will subsequently stimulate another plant of another user, hence creating a “digital root” between two users. While working on this project, we also reflected on the ethical dilemmas of anthropocentric viewpoints in the context of *More than Human Design*: plants should not merely become a symbol of human interaction - acknowledging their agency will also lead to a more sustainable future in terms of human-plant-computer interaction(Giaccardi & Redström, 2020; Loh et al., 2023).

Related work

1) For Plants (”real plants that are the beneficiaries of care provided by humans through a variety of technological devices”). An excellent example of technology working *"For Plants"* is the *"Telegarden"*. where remote plant care is managed by a robotic arm controlled online via a web-based interface (Kahn et al., 2005).

2) Useful Plants (”use of plants with technological devices to address sustainability, cultivate individual or collective change or awareness towards the natural environment”). "The Networked Communal Watering System" enables residents in a block of flats to collectively care for plants, which are augmented with basic IoT devices, letting the residents share the responsibility of plant maintenance, hence improving social connections through plant life (McDonald, 2018).

3) Interfaced Plants (”use of various HCI strategies to facilitate their outputs in formats that can be recognizable and relatable to humans”) For this category, leaves of real plants or their stems could function as joysticks to activate actions such as the direction of clouds on a computer screen (Steer et al., 2015).

4) Using Plants (”plants designed with an additional purpose to promote activation of other ideals“) A great example of this category is the “Go and Grow” project, where a plant’s health (received amount of water) is influenced by the user’s level of activity (Botros et al., 2016).

5) More than Plants (”augmented or enhanced so that they do not behave as the kind of plants we are normally accustomed to in their natural habitat”). When plants are given anthropomorphic qualities, they tend to enhance human interaction with them. In PotPet, a potted plant robot can move autonomously. The PotPet moves toward sunlight from shade; when it needs water, it will move toward the user (Kawakami et al., 2010).

6) Not real Plants (No longer engaging with real plants and using nature-inspired metaphors to design interactions) Not real Plants are usually artworks or public awareness projects. It could be a virtual plant that lives on your desktop or a plant-like interactively wearable device (Ozkan, 2015).

Technical Scope

Frequency Swept Capacitive Sensing

The technique at the basis of turning a houseplant (or any other conductive surface) into a sensor is based on capacitive sensing. Capacitive sensing, as the name implies, is based on the workings of a capacitor. A capacitor has two conductive surfaces separated by a non-conductive layer. It's like a tiny battery. It charges fast when you send a signal and discharges when the signal stops. This delay happens because it takes time to charge and discharge the capacitor. The sensor, a conductive surface (in this case the plant) will start working as a capacitor the instance another conductive surface (such as skin) comes into proximity. The amplitude of the build-up charge can be measured as the difference in voltage. In swept capacitive sensing the sensor sweeps over a range of alternating current (AC) frequencies and measures a pattern in voltage changes instead of just one instance. This creates a more complicated signal that differs upon how the sensor is touched. In turn, these signals can be used to classify incoming signals into different touch gestures.

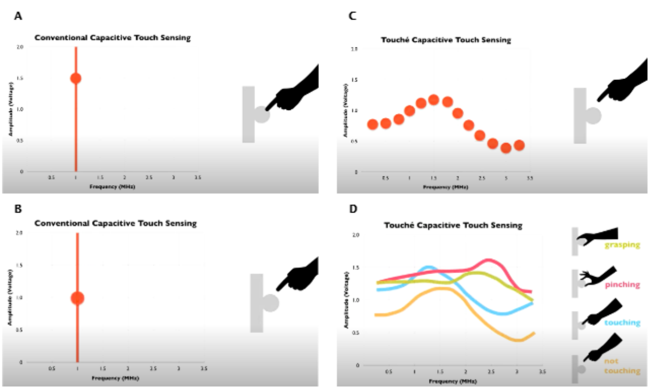


Figure 1 Overview Swept Frequency Capacitive Sensing: Plots **A, B, C** and **D** portray the workings of swept frequency capacitive sensing. In Figure, **A** it is seen that a build-up of potential in Voltage (y-axis) is observed when the finger touches the conductive surface (doorknob) versus when it is not touching the doorknob. This is taken at an AC frequency of 1Hz (**B**). Figure **C** portrays a similar effect of touching the doorknob, however sampled at a range of AC frequencies creating a signal. In figure **D** it is shown how each way of touching the conductive surface results in a characteristic voltage series. Image taken from, a video demonstration of the project by *Sato et al., (2012)*.

The Capacitive Sensor

An online guide on how to adapt the Touché technology on an Arduino was provided as a reference for the capacitive touch sensing circuit prototype[1] (The components, circuitry, and methodology described are the same as described there). An overview of the circuit and its parts can be seen in Figure 2.

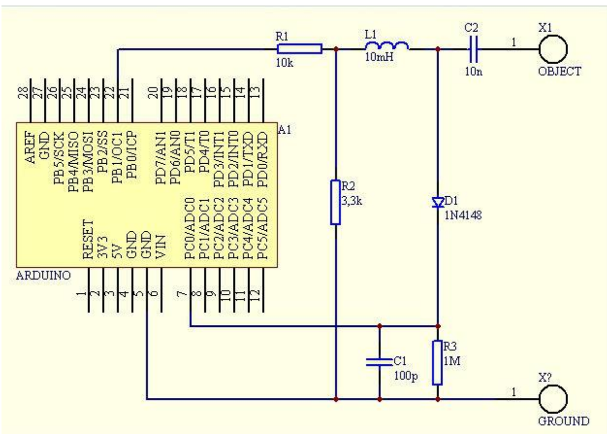


Figure 2 Circuit diagram sensing unit: Components: Arduino (A1), Resistors: 10kΩ (R1), 3.3kΩ (R2), 1MΩ (R3), Capacitors: 100pF (C1), 10nf (C2), Diode: 1N4148 diode (D1), Coil/Inductor: 10mH (L1). Component specifications and circuit design were taken 'Touche for Arduino: Advanced Touch Sensing' Instructables guide (URL: https://www.instructables.com/Touche-for-Arduino-Advanced-touch-sensing/).

An important note for this adaptation is the choice of generated AC frequencies. In the original Touché paper, a Direct Digital Synthesizer IC synthesizer was used, creating high-resolution frequencies between 1kHz and 3.5MHz with high resolution. The Arduino is not capable of creating such high frequencies with high resolution. As the guide reported this resulted in a messy signal with a low frequency resolution. Instead, they adapted the circuit by measuring the signal after an inductor coil (*L1*) which resulted in a smooth signal. Initially, visualization of the incoming signal was done through Java Processing.

[1] *https://www.instructables.com/Touche-for-Arduino-Advanced-touch-sensing/*).

Signal Analysis

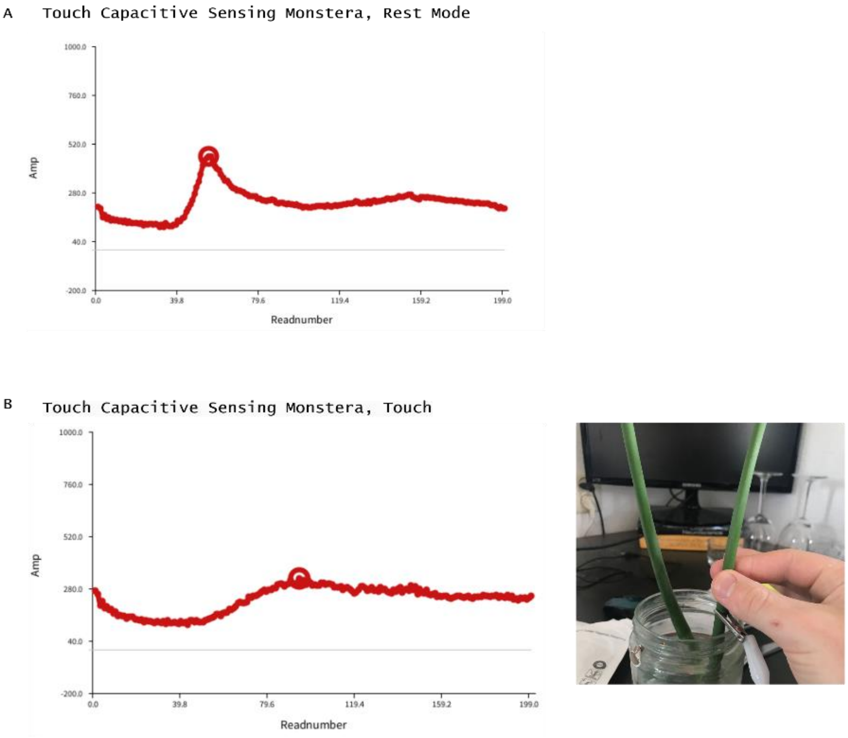


Figure 3 Examples of plant capacitive sensing: Plot **A** features series voltage amplitudes against AC frequencies ranging from 0 to 200Hz. The red circle marks the highest point measured in the signal. +- 500 and +- 300 for plots A and B respectively. Plot **A** is the standard signal received with no physical contact with the plant. The image next to Figure **B** shows the electrode attached to the plant stem of a Monstera deliciosa. In this instance, the plant is being touched on the stem near the electrode using two fingers.

As a receptor plant, we used *Monstera deliciosa*, a very popular ornamental plant commonly known for its ease of cultivation and tolerance of a wide range of conditions making it an ideal plant to try and get a robust signal from. As a starting point for creating plant gestures, we chose to collect frequency samples of four different gestures including the rest state. An overview of the gestures, their averages and their distribution can be seen in Figure 3. For training purposes we chose to capture at least 10.000 samples per gesture, resulting in at least 40.0000 data samples with accompanying labels. The data-capturing procedure can be described as follows. We divided one branch of the plant into three sections: the branch near the electrode, the branch between the electrode and leaf, and the leaf. Touching the plants in each of these sections corresponds to a certain gesture, and therefore gets a matching label. During data collection, within a timeframe of about 10 seconds, 500 data points were sampled while touching the plant in one of the sections. This was repeated 20 times per gesture resulting in approximately 10.000 samples per gesture. An overview can be seen in Figure 4.

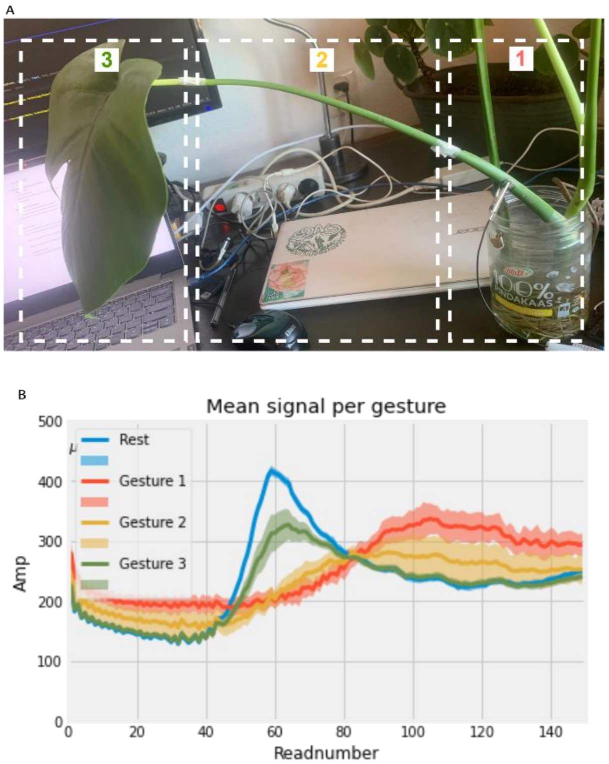


Figure 4 The four gesture signals: A) *Monstera deliciosa* branch divided into three different sections corresponding to each gesture. **B)** For each of the recorded gestures the mean (μ) (given by the lines) and standard deviation (σ) for each gesture category. The shaded areas provide the deviation from each particular frequency read number. Resting-state μ = 233.74 with σ = 71.65 and 10000 data samples. Gesture 1 μ = 254.61 with σ = 56.85 12000 data samples, Gesture 2 showed μ = 226.59 with σ = 50.11 and 14000 data samples. Lastly, Gesture 3 had μ = 222.54 with σ = 55.12 and 10000 data samples. The entire dataset existed out of 46000 samples. The signal was clipped after 150 read numbers as this contained most of the characteristic data points for each condition based on visual inspection.

As can be seen in **Figure 3B** there is some overlap between the different recorded gestures. More specifically between gesture 3 (*touching the leaf)* and the resting state and between gesture 2 (*touching the mid-stem)* and gesture 1 (*touching near the sensor)*.

Signal Classification

The next step was to recognize the incoming gestures using the signal data. To achieve this a small neural network was programmed in Python. The network fed the 150-dimensional signal input forward through the input layer to a 20-neuron hidden layer to a 4-neuron output layer. Sigmoid activation layers were used to scale the probabilities between 1-0. Furthermore, the training involved stochastic gradient descent, training the network over 30 epochs with a learning rate of 0.01. Weights and biases were randomly sampled from uniform distributions. The described network architecture was coded manually with the help of online guides[2] and AI chatbots (*ChatGPT and GitHub Co-pilot*). Such a basic network structure was chosen to suffice as a learning exercise to better understand the use and training of machine learning networks. The evident potential for improvement in both the network architecture and training regimen will be briefly addressed within the evaluation section

The voltage signals were trained as raw signals, Z-score normalized and min-max normalized datasets separately to see which would yield the highest accuracy. Training and testing were performed

[2] *https://medium.com/typeme/lets-code-a-neural-network-from-scratch-part-1-24f0a30d7d62*

separately with an 80 to 20 ratio. Weights were calculated and exported for each scaling method. The results of the training can be seen in **Table 1.**

Training Regime	Testing Accuracy (%)
Raw	29.9
Z-score normalized	29.8
Min-max normalized	100.0

Table 1 The neural network processed a 150-dimensional signal input through an input layer to a 20-neuron hidden layer and then to a 4-neuron output layer. Sigmoid activation layers were employed to normalize the probabilities between 1 and 0. The training employed stochastic gradient descent over 30 epochs, utilizing a learning rate of 0.01

The same weights are loaded into the final signal classification function and used to transform the incoming signal into a corresponding gesture label. As can be seen in the table the Min-max normalized outperformed both the other scaling methods by a great margin. However, its 100% testing accuracy can be indicative of overfitting, which could negatively impact the data classification of the incoming capacitive sensing signal. This is still only the classification of a single signal. We had to implement it in such a way that it was able to classify a live incoming signal. This was done by sampling signal classifications over a short time frame and the output signal corresponded to the label transformed the most.

After classification, the label was sent to the client end that initialised the right action through Arduino communication. As soon as the action was complete it sent a signal back to the client, which forwarded this back to the server. The plant briefly goes into rest mode after which it starts receiving input again. See the flowcharts.

Serial Communication

After the classification of a signal, the label needs to be sent to a client-server connected to the actuator that performs the right response. To achieve this bidirectional communication between a client and a server using sockets, enabling IP communication. Subsequently, the receiving end sends signals to an Arduino board through serial communication. A Python script was written to establish a connection to the specified server, listen for incoming messages, process received data to trigger actions on the Arduino controller and send back a signal as soon as the action is complete. See flowcharts **B** and **C** in the appendix for a more detailed overview of the communication. Communication was performed on local network ports.

Actuator

Physiological Stimulation

As soon as the receiving end gets an incoming message with the gesture label it elicits a response in the actuator. Originally, we envisioned creating a visually perceivable reaction by utilizing plant physiological properties. Initially, the intent was to use the *Mimosa Pudica,* also referred to as the *sensitive plant touch-me-not* or *shame-plant*. The *Mimosa Pudica* is famously known for being one of the few plants that have a human-visible physical response. This is in the form of a unique defence mechanism triggered by touch. When stimulated, specialized cells at the base of its leaves swiftly release water, causing the leaves to close and droop. This rapid response startles potential animal threats to the plant. Interestingly, besides reacting to touch, the plant also exhibits nyctinastic movement—its leaves droop in darkness and reopen in daylight. This also influences its receptibility to touch, being mostly reactive during daylight and unresponsive at night (Adalarasu, 2022).

Due to its unique properties, it is also heavily featured in research on plant mechanoreception. Greg Gage, a prominent neuroscience researcher focused specifically on electrophysical stimulation of the *Mimomas Pudica*. In his project *Backyard Brains* he demonstrated sending an action potential straight from a Venus flytrap to trigger a response in a *Mimomas Pudica* plant[3]. We figured it could also be done by translating a signal captured through capacitive sensing into an electrical stimulus to activate the mimosa plant. Previous research has demonstrated that reaction in the Mimosa plant could alternatively be induced by an electrical stimulus between 1.3 and 1.5V supplied over 10s (Volkov et al., 2010). However, we soon realized that adapting the setup was beyond the scope of the project and our current knowledge of plant physiology. More on this in the project evaluation.

Mechanical Stimulation

As a substitute for the physiological stimulation of a plant, we decided to go for mechanical stimulation of the Mimosa plant. This, however, had other challenges. The initial setup utilized piezoelectric buzzers driven by an Arduino Uno microcontroller. However, the buzzers were found not to be a suitable choice, being too heavy and difficult to adhere to the mimosa's *pulvinus,* a sensitive area of the plant that when touched triggered the characteristic drooping response of the *Mimosa Pudica*.

In a second approach to create a visually perceptible reaction, we took inspiration from Sareen & Maes, (2019) and decided to stimulate the plant mechanically to create visual movement. This was tested using different plants, that were selected based on characteristics that we figured would enhance any physical movement exerted on the plant (e.g. long, thin bendable branches with lots of small leaves that shake easily). In the final setup a servo motor, based between the main branches of the plant was used. The main branches of the plant were wired to the motor to ensure they moved along during mechanical stimulation. See the appendix for this schematic. A complete overview of the interaction between the sensors can be seen in the flowcharts featured in the appendix. Both the sensor and actuator were coded in Arduino and signal interpretation, network training and classification were performed in Python. The reference code is documented on GitHub[4].

Design and Interaction

The project primarily concentrated on the technical aspects of crafting a sensor and actuator from plants, but it also factored in design considerations for the interaction on the go. The primary goal was to develop a Naturalistic Interface that offered intuitive usability. During testing, questions arose regarding gestures: "How might one interact with a plant?" and "Which touch gestures effectively convey specific messages?" We brainstormed how to capture the user's attention through plant movements and how these movements could signify different types of information. To maintain simplicity given the gesture format and duration, we opted for concise, universal messages in this design.

The transmitter plant design at this point was confined to signal analysis, neural network training, and classification schemes during signal input. For ease, we adhered to our initial gestures showcased in Figure 4. Figure .. features an overview of the current setup.

On the actuator side, we aimed to embody three distinct movements: Curious, Chirpy, and Alarming. Initiating the Curious movement involved gently touching the plant's leaves, prompting brief, random twitches in the actuator plant. The Chirpy movement, triggered by touching the middle to upper stem, resulted in short sways from side to side at irregular intervals. Lastly, the Alarming movement entailed a regular, alarm-like swaying of the plant from side to side.

[3] *https://backyardbrains.com/*
[4] *https://github.com/HendrikScheeres/DigitalRoots.git*

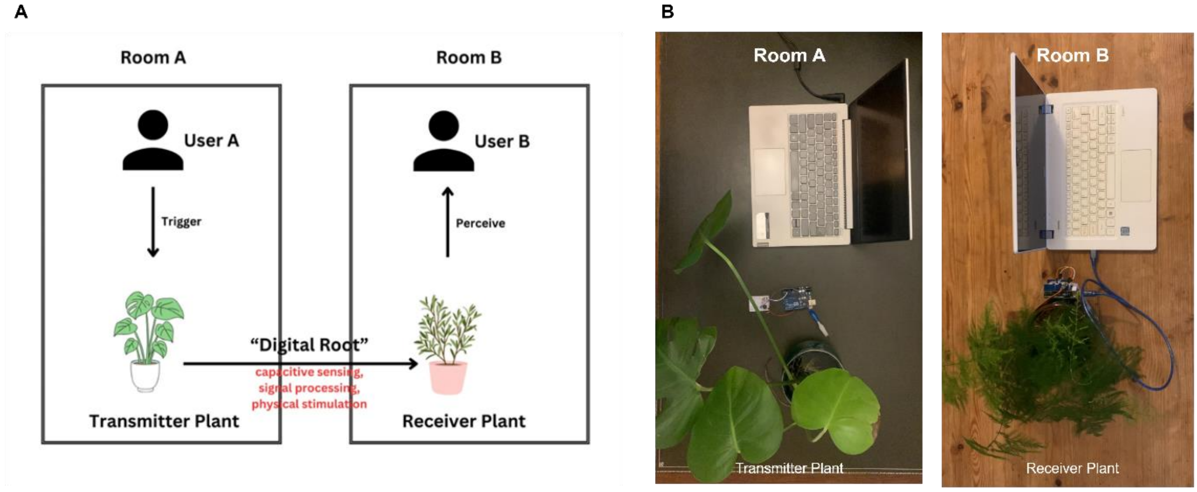


Figure 5 Installation setup. Schematic **A** and image **B** both feature an overview of the final setup. The Transmitter plant is connected through the computer of *user A*, which connects using an IP socket to the computer of *user B* that sends a signal to the receiver plant that performs the action corresponding to the transmitted signal from Room A.

Results

A video demonstration of the final interface can be viewed using the following link. See **Figure 5** for the final setup.

Discussion

This project aimed to use indoor plants as a physical substitute for our digital interactions. We successfully demonstrated how through the use of capacitive sensing and a simple neural network, plant touch responses can be measured, classified and sent to another user where the message is carried out by movement in another plant. In other words, plant-to-plant digital interaction. Below we will briefly discuss some of the technical and design limitations of the project, and finally touch upon future work in this mode of communication.

Firstly, we will touch upon the technical limitations. The plant signal was measured at different gestures and the variation in gestures was visually analysed. This gave a glimpse into what factors that could affect the resulting signal. However, a more elaborate inspection of the range of frequencies and the resulting voltages would give a deeper insight into the potential of using the plant as a sensor and transmitter. In turn, a better understanding of the signal will also aid in a more informed design of what sort of touch interaction the plant permits. For example, in transforming the signal during interaction with the plant signals were grouped into 0 (Rest), 2 (Chirpy), and 3 (Curious). The network seemed to have difficulty with correctly classifying the signal as gesture 1 (Alarm) and instead classified it as 2. As can be seen in Figure 4 there is a lot of overlap between gestures 1 and 2. This rigidity could also be the effect of overfitting the network. As can be seen in Table 3 the network scored a 100% score during testing. This is generally a sign of overfitting and thus something to be avoided. Proposed techniques to counter overfitting that could be considered are data augmentation or implementing dropout mechanisms.

Another reoccurring problem was that the min-max scaling during training did not yield the same results during min-max scaling during live signal interpretation. Namely, the signal during live measurements seemed to have a standard lower maximum signal strength. This theorize is mostly due to differences in plant physiology during training and live classification. Our measurements are based on the conductive properties of the plant. Thus fluctuations in this conductivity also impact our measurement. Previous research has demonstrated that the time of day influences the water in plants and thus its conductive properties. This could potentially explain sudden fluctuations in the incoming signal that we experienced (Turner, 1991).

The simple neural network used for this classification problem could be heavily improved. First of all, implementing machine learning packages such as *Keras* or *Tensorflow* would be straightforward options to create more elaborate network structures that can classify the data more robustly. As a classification scheme, we chose to implement a real-time classification with dynamic response activation. While we do think that the inability to distinguish between gestures 1 and 2, mostly has to do with the proximity of these signals alternative forms of real-time signal classification could also be a potential solution to better classify the gestures. This could involve using more complicated network structures such as recurrent neural networks.

The most profound challenge we faced was that of trying to manipulate living materials to align with our intentions. This was exemplified especially by our use of the *Mimosa Pudica*. Firstly, the plant required specific care, thriving best in humid conditions. Secondly, our extensive experimentation led to the plant expending significant energy and water, impeding its natural response mechanism. Insufficient recovery time resulted in the plant drying out. Previous research done by Adalarasu, (2022) and (Volkov et al., 2010) are valuable references to guide future setups for electrical stimulation of the *Mimosa Pudica* and a deeper understanding of plant physiology. This knowledge proved pivotal in overcoming some of these hurdles and making progress in our experiments.

Another important factor to better analyse for future research is the effects of the plant's surroundings on stomatal conductance which in turn affects the capacitive sensing abilities of the plant. During testing, a drop in the measured voltages was experienced in the evening and at night. This seems in accordance with literature focused on external factors influencing *stomatal conductance* Other factors that play a role are the nutrient status of the soil or water. Also, a rise in air temperature increases conductance and plant transpiration. For a future implementation it would be interesting if the conductance of the specifically chosen transmitter plant could be monitored in different settings to adjust signal classification accordingly (Turner, 1991).

While the emphasis has been on the technical aspects, there ample improvements in the context of design considerations. An important missing point in this design paradigm is testing with a wider audience. Exploring user behaviours, preferences and responses would aid in fine-tuning the technology, but also give new inspiration and ideas for intuitive and impactful interaction. In addition, this could help testing and improving the technical aspects of the project as well, resulting in a more robust end product.

An intriguing future addition would be to incorporate two-sided communication fostering a more profound interaction between users at both ends. Moreover, adopting a 'more than human' design approach holds promise for creating more sustainable and healthier modes of digital communication. Acknowledging the agency of plants, and integrating their needs and responses into this digital dialogue could be the touch needed to create a more caring interaction between technology, nature and humans.

References

Adalarasu, A. (2022). *Electrophysiology of Mimosa pudica L* [Preprint]. Open Science Framework. https://doi.org/10.31219/osf.io/wk4vu

Bhat, A. S., Boersma, C., Meijer, M. J., Dokter, M., Bohlmeijer, E., & Li, J. (2021). Plant Robot for At-Home Behavioral Activation Therapy Reminders to Young Adults with Depression. *ACM Transactions on Human-Robot Interaction*, *10*(3), 1–21. https://doi.org/10.1145/3442680

Botros, F., Perin, C., Aseniero, B. A., & Carpendale, S. (2016). Go and Grow: Mapping Personal Data to a Living Plant. *Proceedings of the International Working Conference on Advanced Visual Interfaces*, 112–119. https://doi.org/10.1145/2909132.2909267

Dzhambov, A. M., Lercher, P., Browning, M. H. E. M., Stoyanov, D., Petrova, N., Novakov, S., & Dimitrova, D. D. (2021). Does greenery experienced indoors and outdoors provide an escape and support mental health during the COVID-19 quarantine? *Environmental Research*, *196*, 110420. https://doi.org/10.1016/j.envres.2020.110420

Giaccardi, E., & Redström, J. (2020). Technology and More-Than-Human Design. *Design Issues*, *36*(4), 33–44. https://doi.org/10.1162/desi_a_00612

Kahn, P., Friedman, B., Alexander, I., Freier, N., & Collett, S. (2005). *The distant gardener: What conversation in the Telegarden reveal about the user experience of telepresence*.

Kawakami, A., Tsukada, K., Kambara, K., & Siio, I. (2010). PotPet: Pet-like flowerpot robot. *Proceedings of the Fifth International Conference on Tangible, Embedded, and Embodied Interaction*, 263–264. https://doi.org/10.1145/1935701.1935755

Loh, S., Foth, M., & Santo, Y. (2024). The more-than-human turn in human-plant interaction design: From utilitarian object to living co-inhabitant. *International Journal of Human-Computer Studies*, *181*, 103128. https://doi.org/10.1016/j.ijhcs.2023.103128

McDonald, S. (2018). What Impact Does a Networked Communal Plant Watering System Have On A Sense of Community Cohesion? *Companion of the 2018 ACM Conference on Computer Supported Cooperative Work and Social Computing*, 105–108. https://doi.org/10.1145/3272973.3272985

Orben, A., Tomova, L., & Blakemore, S.-J. (2020). The effects of social deprivation on adolescent development and mental health. *The Lancet. Child & Adolescent Health*, *4*(8), 634–640. https://doi.org/10.1016/S2352-4642(20)30186-3

Ozkan, B. (2015). Fall: An interactive garment that mimics nature’s responsive system of defoliation through an embedded electronic mechanism. *Adjunct Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2015 ACM International Symposium on Wearable Computers*, 617–621. https://doi.org/10.1145/2800835.2801675

Sareen, H., & Maes, P. (2019). Cyborg Botany: Exploring In-Planta Cybernetic Systems for Interaction. *Extended Abstracts of the 2019 CHI Conference on Human Factors in Computing Systems*, 1–6. https://doi.org/10.1145/3290607.3313091

Sato, M., Poupyrev, I., & Harrison, C. (2012). Touché: Enhancing touch interaction on humans, screens, liquids, and everyday objects. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 483–492. https://doi.org/10.1145/2207676.2207743

Sikali, K. (2020). The dangers of social distancing: How COVID-19 can reshape our social experience. *Journal of Community Psychology*, *48*(8), 2435–2438. https://doi.org/10.1002/jcop.22430

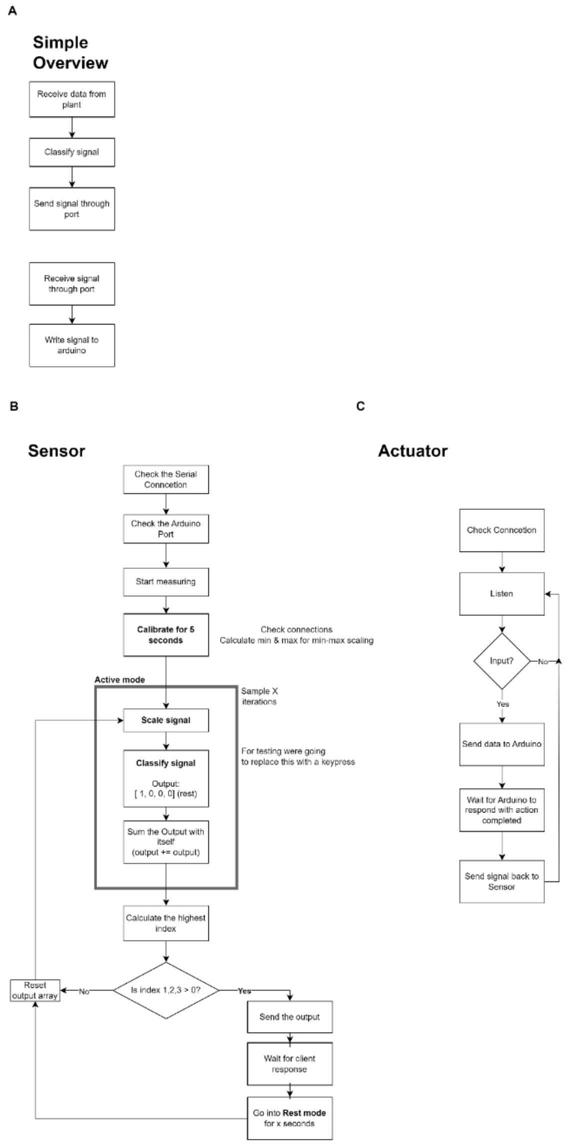
Steer, C., Robinson, S., & Jones, M. (2015). Growth, Change and Decay: Plants and Interaction Possibilities. *Proceedings of the 33rd Annual ACM Conference Extended Abstracts on Human Factors in Computing Systems*, 2037–2042. https://doi.org/10.1145/2702613.2732765

Tsetserukou, D. (2010). HaptiHug: A Novel Haptic Display for Communication of Hug over a Distance. In A. M. L. Kappers, J. B. F. van Erp, W. M. Bergmann Tiest, & F. C. T. van der Helm (Eds.), *Haptics: Generating and Perceiving Tangible Sensations* (pp. 340–347). Springer. https://doi.org/10.1007/978-3-642-14064-8_49

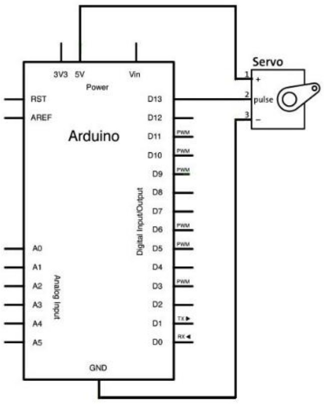
Turner, N. C. (1991). Measurement and influence of environmental and plant factors on stomatal conductance in the field. *Agricultural and Forest Meteorology*, *54*(2–4), 137–154. https://doi.org/10.1016/0168-1923(91)90003-9

Volkov, A. G., Foster, J. C., Ashby, T. A., Walker, R. K., Johnson, J. A., & Markin, V. S. (2010). Mimosa pudica: Electrical and mechanical stimulation of plant movements. *Plant, Cell & Environment*, *33*(2), 163–173. https://doi.org/10.1111/j.1365-3040.2009.02066.x

Appendix



Appendix 1 Flowcharts: A contains a simple overview of the complete setup. In **B** the sequence of steps is described to normalize the signal, transform it and transmit it to the receiver. **C** contains the actuator logic and communication with the transmitter.



Appendix 2: Servo Schematic. Schematic of servo motor wired to the Arduino board. The servo motors' power lines are connected to the 5 V and GND connectors of the Arduino board. The servo pulse line is connected to the Arduino pin D13.