In Transition: Real Time Location and Behavior Evolution of a Motorized Bench

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Abstract

Current implementations of computational design in architecture are often spatially present, but rarely evolve their behavior beyond a simple response mechanism, if any. We are interested in creating a bench that not only reacts to its environment, but evolves its behavior and location as a result of these interactions. Specifically, we are interested in how a bench can evolve its relationship with its occupants and the space it occupies. To do so, we developed a model using vibration for interfacing with occupants, as well a model using position and orientation for interfacing with its space. For each of the models, we explore applying the output to a multi-armed bandit problem so that its responses are constantly evolving. Physical prototyping led us to understand that vibrations were not effective to alert occupants, but physical movement of the bench was. While the current bench prototype is rather sparse, only including pressure sensors and motors, we would like to continue the work by utilizing other sensors (light, distance, temperature) as well as other evolution based algorithms such as contextual bandits.

1 Introduction

Nicholas Negroponte once proclaimed the creation of architecture machines that are able to continuously adapt and change in reaction to their environments (Negroponte 1975) . Yet so far, such projects have typically been automated demos that propose an evolutionary behavior (Barkow and Leibinger 2014), some manifestation of a spatial screen (Unsangdong Architects 2012), or are limited in scale and presentation (Ishii et al. 2015, 687–694; Dean and D'Andrea 2001).

While these projects are spatially present, they remain aliens to the spaces they occupy, or otherwise have spaces built around them. We are less interested in this, but rather the idea of evolving behavior on a lower resolution. By taking existing architectural elements and modulating them to be discretely evolutionary, we create pieces that are better integrated with their environment.

Benches are well suited for this experimentation. In many public spaces, they form the primary interaction between occupants and the space. Further, there are intuitive, low resolution parameters that can be evolved such as spatial positioning and interaction with occupants.

2 Methods for Evolution

Evolutionary design is nothing novel (Jefferson and others 1990; Bentley 1999) Designs will attempt to evolve their configurations in order to better suit a certain objective function or behavior. While the desired configuration may not be known from the beginning, the point of evolutionary design is to learn such configurations. In recent years, renewed development in “exploitation and exploration” algorithms (March 1991, 71-87) within machine learning and artificial intelligence allows us to approach evolutionary design with a new toolset.

Two popular methods used today are reinforcement learning (Kaelbling, Littman, and Moore 1996, 237-285) and multi-armed bandits (Bubeck and Cesa-Bianchi 2012, 1-122). In our case, reinforcement learning is less useful because it operates under the assumption of stateful decision making. In evolutionary design, certain outcomes and rewards may not necessarily rely on previous configurations. And as a result, the class of multi-armed bandit algorithms are better suited for us. By assigning a certain design configuration to an arm, we can then apply traditional bandit algorithms such as upper confidence bound (Auer, Cesa-Bianchi, and Fischer 2002, 235-256) in order to evolve design behavior and configuration.

This approach can be extended further by using contextual multi-armed bandits (Langford and Zhang 2008, 817-824) and having different sets of configurations to choose from depending on environmental variables.

3 Model

We chose to define two relationship models of interest. The first was how the bench interacted with people occupying it and within its vicinity by vibrating. The second was how it interacted with the space it occupied by repositioning itself using motorized wheels. The two models are related to each other by a state machine for the entire bench (Figure 1).

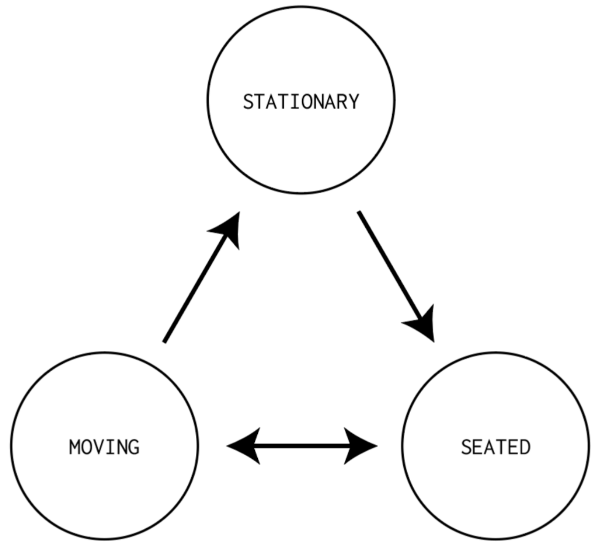

Figure 1. The three different states the bench can be in. The model for occupants applies to the stationary and seated states whereas the spatial model applies to all three.

3.1 Model While Occupied

In relationship to its current and potential occupants, we developed a model in which the bench would “offer itself” to a person either by drawing their attention to it or by forcing its current occupant off (Figure 2). A subtle device to do so is by using a vibration motor on the seat. By vibrating when a person walks by, the bench can draw a person’s attention. Similarly, vibration can be used to force an occupant off in order to offer itself to another person. By evolving the manner in which the bench vibrates, we can define a way by which the bench learns different ways to offer itself by giving it a positive reward if it becomes occupied by a new person and negative if not.

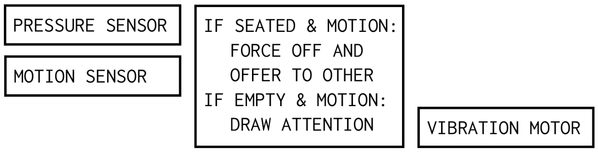

Figure 2. Relationship between pressure and motion sensor, occupant model, and vibration motor.

3.2 Model in Space

In the second relationship, we were interested in how different locations and orientations of the bench in a space might affect how occupants interface with it. The model developed (Figure 3) was one where the bench's movement was dependent on an occupant giving it the energy to continue its search for an ideal location and orientation. For each configuration, a reward is given as the fraction of time seated over the time in that configuration. Other reward functions could incorporate sensor data as well.

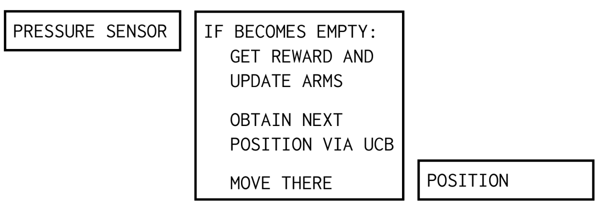

Figure 3. Relationship between pressure sensor, spatial model, and position.

4 Stool Prototype

While we were designing the bench prototype, we also began by creating a temporary prototype. The purpose of this initial prototype was to research which sensors provided the richest information for our models and to determine the efficacy of the model while occupied.

Because benches often allow multiple occupants, we wanted to test our model first on a single occupant analog, such as a stool. In using a stool, we were still able to test different sensors as the results could be easily translated to a bench.

The sensors that we were interested in using included pressure sensors, PIR motion detectors, and Sharp proximity sensors (Figure 4). By putting these on the stool, we were able to determine which were more useful for our specific models. Off the shelf Arduino libraries were used in order to obtain some measurements.

In addition to this, a vibration motor was placed on the stool top.

Figure 4. Stool including pressure sensors on the feet, an array of motion detectors and proximity sensors on each side, and a vibration motor on the stool top.

In testing the different sensors, we found that while both proximity sensors and motion detectors could be used for our model, the former were more useful if we wanted to revise the model to only trigger within a certain radius. We also used basic thresholding for pressure sensors to determine state. The pseudo code is given in (Figure 5).

Figure 5. Pseudo code for stool prototype.

```
run():
    if pressure detected:
        state ← seated
        update rewards
    if motion detected:
        pick vibration from UCB
```

4.1 Experiential Results

Once implemented, we asked passersby to interact with the stool. Our goal was to determine whether or not the model using a vibration motor was effective. In several cases, the person was hesitant to sit on the stool because of all the wires protruding. In the cases in which the person sat on the stool, it was observed that the vibration motor was not powerful enough to force the person off. Rather, they often mistook it for the vibration of their own mobile devices. We asked one person to stand nearby without mentioning the stool, and then produced a vibration pattern. They reacted by assuming that it was someone's phone vibrating.

We concluded that while this model was still interesting to pursue, vibration motors overall were not convincing. However, the prototype did allow us to determine which sensors to include in the bench prototype.

5 Bench Prototype

Our goal for this prototype was to build a scale model of a motorized bench and implement the spatial model. Based on experience from the first prototype, we included slots for proximity sensors, wiring, and wheels. In particular, we focused on a lightweight wooden design (Figure 6) using laser cut pieces so that geared 12V DC motors could be used.

Figure 6. Laser cut bench prototype with specific slots for proximity sensors and wiring. Width of the legs is wide enough for motors and wheels.

In particular, special attention was given to the wheels. Mecanum wheels (Gfrerrer 2008, 784-791) were used so that different motion behaviors could later be tested in order to determine which was most interesting. This was important in conveying the sense that the bench was in fact searching and not moving at random.

In addition, we developed an elastic suspension system (Figure 7) so that the only load on the motor would be that of the bench. Once occupied, the bench would sink so that the load would be on the frame and not the motor assembly. This also gives the impression that the person is actively affecting the bench.

Figure 7. Wheel assembly held independent of frame using elastics so that load can be shifted to frame when seated.

The final prototype included four motors connected to H-Bridges, two proximity sensors, and two pressure sensors on a diagonal (Figure 8).

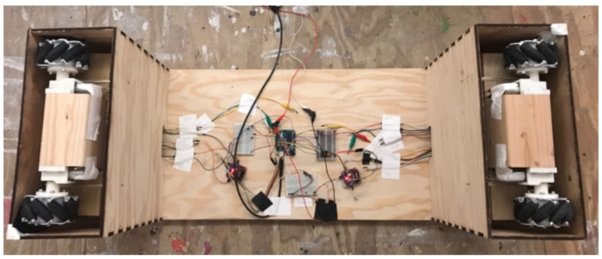

Figure 8. Underside of bench, with electronics hidden from viewer. Proximity sensors located on the side of the bench; pressure sensors located on the legs.

In testing, we found that the pressure sensors were far enough apart so that we could detect whether there was a single occupant or multiple occupants on the bench. We also discovered that the motors were not nearly powerful enough to move the bench laterally so that we were only able to move it linearly.

Due to time constraints, proximity sensors were not integrated. This meant that spatial awareness was limited to running motors for a certain number of seconds. The pseudo code, which can be applied to a fully functional prototype, is given in (Figure 9). In addition, an example diagram illustrating ideal execution of the prototype on four predetermined positions over a period of time is given in (Figure 10).

Figure 9. Pseudo code for bench prototype running once per second.

```
run(state):
  if state is moving:
    if person seated:
      stop moving
      begin counting sitting timer
      begin counting stationary timer
      add new position to arm list
      state ← seated
    else if position is destination:
      stop moving
      state ← stationary
    else:
      keep moving
  else if state is stationary:
    begin counting stationary timer
    if person seated:
      begin counting sitting timer
      state ← seated
  else if state is seated:
    if person no longer sitting:
      reward ←time seated/time stationary
      update reward in UCB
      get next position from UCB
      begin moving to new position
      state ← moving
```

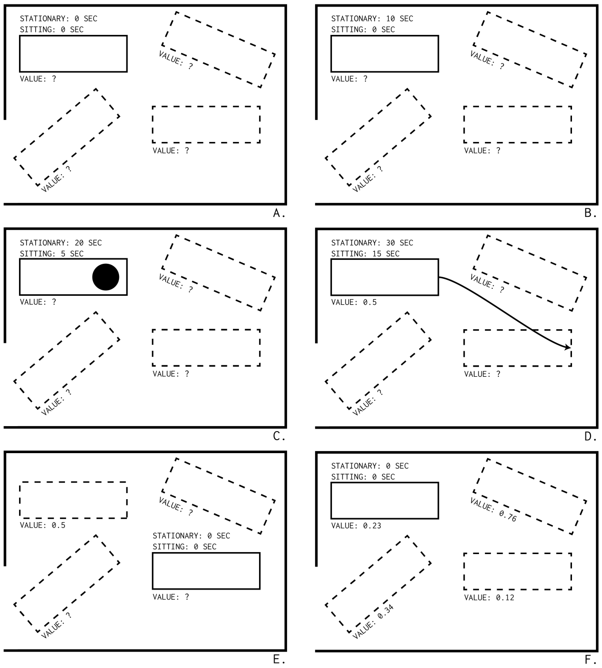

Figure 10. Example execution of prototype using a UCB bandit algorithm with reward determined as the fraction of time seated over the fraction of time stationary. Each position is an arm, initially with unknown value. (A.) The initial state at time 0. (B.) At 10 seconds, the prototype remains stationary but continues counting. (C.) At 20 seconds, a person sat on the bench at 15 seconds. (D.) At 30 seconds, the person gets off the bench, giving a reward for that position as 0.5. The algorithm first gets values for all unknown positions, so it chooses another unknown position and moves to it. (E.) Once in its new position, the counters reset and the stationary counter begins counting. (F.) After a certain amount of time has elapsed, each position has a certain value, which UCB uses to determine which position to choose next. Note that at this point in time, the current position's value is not the highest. This is an illustration of the "exploitation and exploration" aspect of bandit models.

Because of the mechanical and physical challenges in building the prototype, we only had a brief amount of time for experimentation.

5.1 Initial Results

In initial experimentation with the prototype, we set positions certain time steps apart and limited it to moving linearly. This was done to reduce complexity while still providing enough spatial difference between positions to run the algorithm with effective results.

When a colleague sat on the bench, she was no longer unnerved by its presence. However, she was surprised to see the bench move after getting up, asking whether or not it was moving randomly.

In the future, we will try to further discretize an actual space, as well as allow for movement in all directions. In addition, more testing is needed to determine the behavior by which the bench moves. One possible behavior would be to have the bench move only when it does not think others are around.

6 Conclusions

While we have discussed only an initial prototype with this paper, we believe that this bench provides a thought provoking peek into Negroponte's original vision for architectural machines. Whereas many current projects are focused on demoing possibilities or confined to being aliens in a space, this bench is a working prototype of an architectural entity that continues to evolve its behavior without completely defining a space.

We have shown that applying multi-armed bandits to computational evolutionary design yields interesting results and are keenly interested in developing this further.

In the future, we hope to further refine the behavior of the bench in order to give it a less robotic and random personality, as well as make it fully autonomous so that it can run for days without interruption. Afterwards, we hope to integrate more sensors so that the bench can respond accordingly to inputs such as daylight and temperature. Finally, we plan to couple this with contextual bandits so that the bench can truly respond and adapt to its environment.

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