THE PENNSYLVANIA STATE UNIVERSITY
SCHREYER HONORS COLLEGE

DEPARTMENT OF PHYSICS

SIMULATED HYSTERESIS IN ASYMMETRICALLY DRIVEN SYSTEMS

TRAVIS R JALOWIEC
SPRING 2022

A thesis
submitted in partial fulfillment
of the requirements
for baccalaureate degrees
in Mathematics and Physics
with honors in Physics

Reviewed and approved* by the following:

Nathan C Keim
Associate Research Professor of Physics
Thesis Supervisor

Richard W Robinett
Professor of Physics
Honors Adviser

* Electronic approvals are on file.

ABSTRACT

Memory in materials—or the ability to encode, subsequently read-out, and ultimately erase information about a system's history at will—is of value in probing and programming matter, but it is not yet fully understood. Previous work showed that shearing a jammed packing of colloids—a 2D amorphous solid—could encode multiple amplitudes from past deformations, via a generic behavior known as return point memory (RPM). However, features of these materials suggest that RPM cannot be a complete description of their memory behavior. We study a simple model of rearranging regions ("soft spots") in these materials. Unlike in past work, we shear the system in asymmetric cycles of negative strain amplitude only, which prevents encoding of RPM. Despite this, we show that memories can still be encoded and recovered. We discuss differences between these memories and those in past work, and propose experiments to study this new form of memory directly.

TABLE OF CONTENTS

LIST OF FIGURES

ACKNOWLEDGEMENTS

I would first like to thank my thesis advisor, Dr. Nathan Keim, for his patient support and guidance throughout the research and thesis writing process. I am deeply indebted to you for introducing me to the field of soft matter and helping me learn what it means to be a physicist. Thanks are also due to the other members of the Keim Lab for their contributions to enlightening discussions during our group meetings. I would also like to thank Dr. Richard Robinett for acting as my honors adviser throughout this process and my academic adviser of the last four years; your assistance has been invaluable in the course of earning my degree, and I hope that you enjoy a well-earned retirement. Finally, thank you to my family for supporting my dream of pursuing physics and propping me up when I was in danger of falling down.

Chapter 1

Introduction

Many forms of matter exhibit mechanical hysteresis—a way that the state of a system can depend on its history of deformations. The simplest 'units' of hysteresis we consider are individual 2-state hysteretic subsystems, also known as "hysterons". Hysterons are systems that respond to a scalar field H, and are always in either the "up" or "down" state (sometimes also referred to as "+1" and "-1" states). Which state the subsystem is in at a given time depends primarily on two values, γ^+ and γ^-, thresholds of γ that indicate the energy barriers when a subsystem being driven in the positive or negative directions, respectively, will switch from "-1" to "+1" or vice versa. As a rule, $\gamma^- < \gamma^+$. When $\gamma^+ < \gamma$, the system will always be in the +1 state; when $\gamma < \gamma^-$, the system will be in the -1 state. For $\gamma^- < \gamma < \gamma^+$, the system will retain whatever state it was last in.

When a system is composed of multiple hysterons, a richer memory behavior known as return-point memory (RPM) arises. RPM is the ability for the system to restore its previous state upon the field H returning to a prior value. RPM encodes memories of extrema during driving—in practice, this corresponds to memories not strictly of a given shear amplitude, but of the turning points at $\pm\gamma^o$. If a memory of turning points at $\pm\gamma^o$ is encoded, then while $-\gamma^o < H < \gamma^o$ the state of the hysteron is dependent on its history since the turning points at $\pm\gamma^o$ were last visited. Upon H returning to either $\pm\gamma^o$, the system will again be in its state when it was last at $\pm\gamma^o$. Exceeding $\pm\gamma^o$ will wipe out any history of the system's state prior to returning to $\pm\gamma^o$.

However, memories of multiple pairs of turning points can be encoded if they are nested such that each subsequent memory is of an amplitude smaller than the previous one. This effect is captured by the Preisach model of hysteresis in ferromagnets, where each hysteron represents a magnetic domain coupled to an external magnetic field, with disorder modeled by varying values of the thresholds (in an amorphous solid, γ^+ and γ^-) [1].

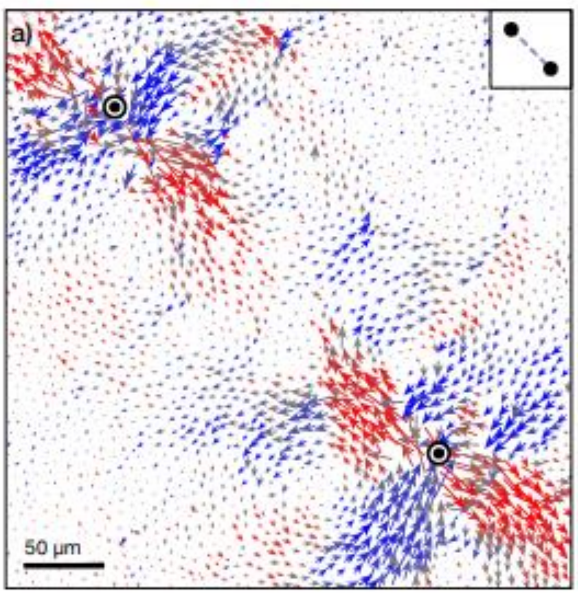

Figure 1: Example of interacting soft spots in a cyclically sheared 2D jammed packing from Keim and Paulsen [5]. Particle displacements around two rearranging soft spots, with centers roughly indicated by concentric circles.

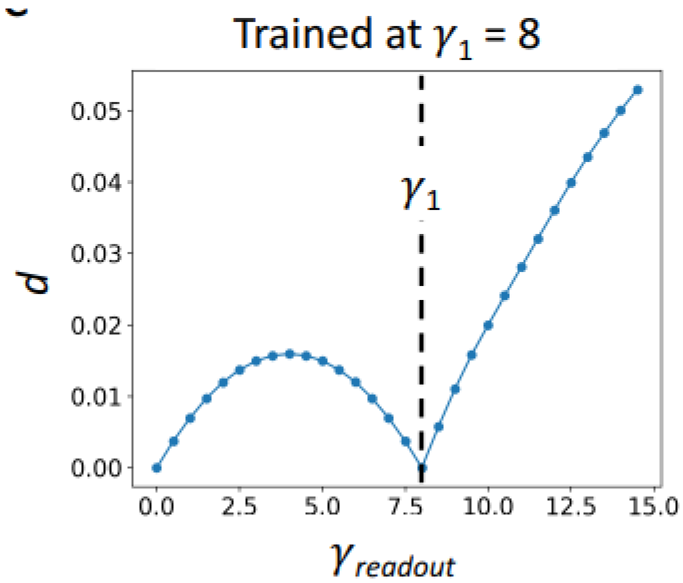

Figure 2: An example of fractional difference in hysteron states versus readout strain from Lindeman and Nagel [6]. The y-axis label 'd' is analogous to 'fdiff' used in later figures. This readout curve is for a non-interacting system of hysterons trained at γ_1 = 8. Because it is a non-interacting system, this is an example of perfect return-point memory—note the non-monotonic readout curve.

Here we are motivated by experiments with jammed packings of particles subject to cyclic quasistatic shear. Memories of shear amplitude are encoded as 'steady states' in which in localized rearranging regions of particles (soft spots) in the jammed packing reorganize in a periodic orbit. The memories can then be retrieved by applying cycles of increasing strain (Figures 3 and 4 below show the encoding and readout protocols for symmetric and asymmetric systems, respectively), with the displacement of particles from their initial state indicating when they are in precisely the original positions as when the training amplitude was first applied [4,14,15]. Figure 1 gives an example of particle displacements around two rearranging soft spots in a cyclically sheared 2D jammed packing.

The Preisach model does not allow for interactions between hysterons within a given system. Despite this, systems can still exhibit RPM in the presence of interactions which are strictly ferromagnetic, or cooperative (a hysteron changing state encourages other hysterons to make the same change) [2]. However, return-point memory is *not* compatible with anti-ferromagnetic (also known as frustrated) interactions. The quadrupolar form of particles' displacement fields, experimental observations like Figure 1, and molecular dynamics simulations [17,18], in which neighboring rearrangements appear to oppose each other, strongly suggest that in jammed packings, hysterons can have anti-ferromagnetic interactions. Previous work by Lindeman and Nagel suggests that including these interactions—an essential feature of other glassy materials such as spin ice [3]—leads to additional higher-order memory capabilities, even as (now imperfect) RPM remains the leading-order contribution [6].

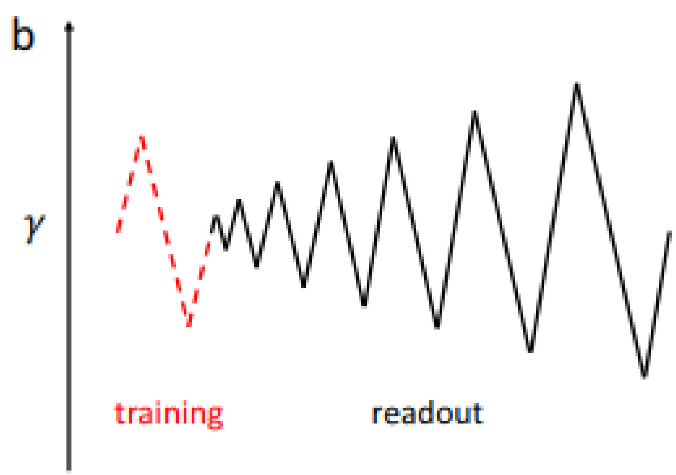

Figure 3: Example of training (dashed red) and readout (solid black) protocol for symmetrically sheared systems from Lindeman and Nagel [6].

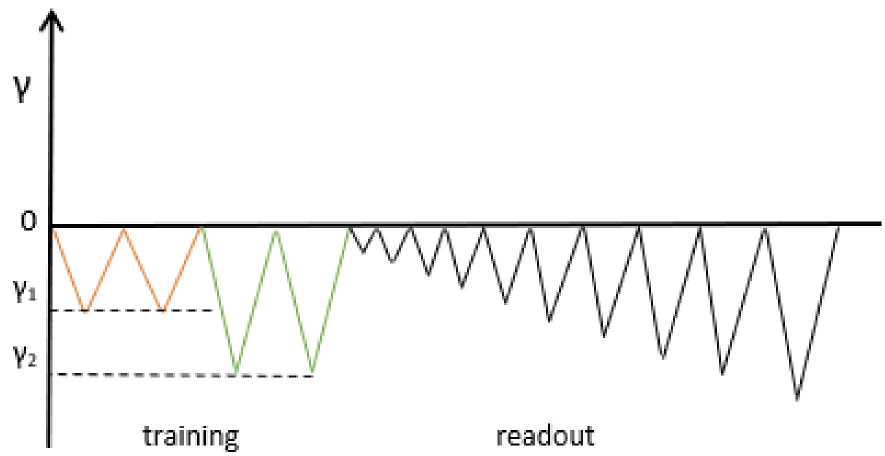

Figure 4: Example of training (red: γ_1, green: γ_2) and readout (black) protocol for negative asymmetrically sheared systems with two training amplitudes where $\gamma_1 < \gamma_2$.

The memories observed in systems of cyclically sheared jammed packings resemble those seen due to RPM, but the presence of anti-ferromagnetic interactions prompts us to dig deeper [5,16]. Here, we further explore the memory capabilities of such systems, shearing only with asymmetric cycles of negative strain amplitude. This prevents the encoding of RPM, removing the leading order effect. Despite this, cusp-like memories of strain amplitude similar to those given by RPM (see Figure 2) are still being encoded in the system. What's more, we find signals of overwritten trained amplitudes in the form of transient memories which would not be present with RPM, which encodes only extremal values and wipes out a systems history after exceeding its previous shear strain. However, this is not the first example of memory that retains traces of training amplitudes that are smaller than those subsequently applied; such behavior has also been investigated in other systems exhibiting multiple transient memories, such as charge-density waves [12,13], non-Brownian suspensions [8,9,10], and the park-bench model [11].

We also explore the impact of the number of training cycles used to encode a memory. In RPM, only a single cycle of writing is needed to encode, but other examples of hysteresis in cyclically driven systems have shown that additional cycles of training can result in stronger memories, or that a single cycle of training is insufficient to encode a memory at all [6].

A feature of the model used here is that the system is prepared with the participating hysterons first all in the same state, either +1 or -1 (up or down). Most simulations were run using systems prepared from hysterons in the -1 state, but a few simulations were also conducted from hysterons in the +1 state. Interestingly, changing the direction of initialization (whether the system is driven to zero from the positive or negative direction, corresponding to all hysterons in the +1 or -1 state) from negative to positive results in readout curves of memories that resemble a different system entirely.

Chapter 2

Methods

My simulations utilize the *hysterons* Python package (https://github.com/nkeim/hysteron) written by Nathan Keim and Joseph Paulsen [5]. Although the package has many functions for exploring 2-state hysteretic subsystems, I primarily utilized evolve_event.

Background

Because the Preisach model of memory is based on the domains of magnetic fields in ferromagnets, the simulation works analogously to the magnetic field. The actual memories the simulations are encoding are of the location of turning points $\pm \gamma^o$, the amplitude to which the system is driven. The value of the field at the location of a given hysteron is given by H_{local}, the sum of the global H field and $H_{interfield}$, where $H_{interfield}$ is the contribution to the field at that hysteron based on the strength of its interactions with the other hysterons in the system.

$$H_{interfield} = \sum_{i=0}^{N} J_{ij} \times S_j \qquad \text{Equation (1)}$$

$$H_{local} = H_{global} + H_{interfield} \qquad \text{Equation (2)}$$

First, a state vector S of length N is created (here, N=9), where each entry represents the local state of a given hysteron, S_i. It starts with each entry equal to -1, a normalized equivalent to a field of negative infinity. This ensures that all hysterons begin in an identical state. To initialize the system, it is driven to $\gamma^o = 0$. Whether the system is driven to $\gamma^o = 0$ from a starting field of positive infinity (all hysterons in the +1 state) or from negative infinity (all hysterons in the -1 state) is referred to as the direction of initialization. Similarly, two additional vectors of length N, γ^+ and γ^-, are made by choosing a pair of values from a uniform distribution with the rule that each entry of γ^+ is greater than the corresponding entry of γ^-. The entries of these vectors indicate the field values at which the corresponding hysteron will flip up or down, changing state.

Next, an NxN interactions matrix is generated. In simulations where interaction between hysterons is prohibited, this matrix is all 0s. When interactions are allowed, as they are here, each entry of this matrix is determined by picking a random floating-point value from a uniform distribution ranging from -1 to 1. This step of randomization, along with the generation of the γ^+ and γ^- vectors, is what makes the outcomes of a given simulation vary. After the field vector $H_{interfield}$ has been calculated, the entries of the state vector S can be populated with each being their respective value of H_{local}. When using parallel readout, many copies of this state vector are made for later use.

Calculating the Field Vector

The *Hysteron* simulation package usually calculates $H_{interfield}$ through direct matrix multiplication of the length N state vector with the NxN interactions matrix, J_{ij}, as in Equation 1. In other words, every hysteron is interacting with every other hysteron, regardless of how far removed they may be from one another. This may be not an issue in small systems, but when simulating a larger system, its more realistic that each hysteron interacts strongest with those immediately around it.

In my simulations, the field vector $H_{interfield}$ is a vector of length N where each entry is the sum of the H field contributions from interactions with only the nearest adjacent hysterons. Periodic boundary conditions are employed so that hysterons located on the "edge" (arranging the vector in 2D space as a 3x3 lattice) of the physical arrangement are still the sum of the nearest eight hysterons, wrapping around to the opposite side or corner as appropriate. Using nearest neighbor interactions is intended to make the results of the simulation more physically realistic when dealing with a larger system in future tests, so that soft spots which are far removed do not have as large an impact on the local field as those nearby.

Encoding Protocol

Once the system has been initialized and the field, state vectors prepared, the system can then be driven with cyclic shear to encode memories. We are focusing systems of hysterons where two distinct amplitudes are encoded, with the first encoded being the smaller memory (γ_1) and the second encoded being the larger memory (γ_2), unless otherwise stated. Since the prepared system starts at an amplitude of zero, we start by driving from 0 down to - γ_1, then back up to 0 ($0 \rightarrow -\gamma_1 \rightarrow 0$). Depending on the test being run, this cycle may be repeated. Once the first memory has been encoded, we drive down from 0 to - γ_2, then back up to 0 ($0 \rightarrow -\gamma_2 \rightarrow 0$). Again, depending on the test being run, this may be repeated more than once.

Readout Protocol

A parallel readout protocol is used. With parallel readout, an interactions matrix is randomly generated and the field vector of the hysterons is prepared as usual. Memories of the desired shear strain are then encoded by driving the system with negative asymmetric shear (see Figure 4) for each cycle of writing. Once encoded, many copies of the system are made. To read the memories, each copy is driven to strains $\gamma = 0 \rightarrow -\gamma^o \rightarrow 0$, at a different, increasing shear strain amplitude γ^o (the first at $\gamma^o = 0$, second at $\gamma^o = 0.002$, third at $\gamma^o = 0.004$…).

After each readout cycle, the state of each hysteron is compared to its value in the initial state of the system, $S_{trained}$. The number of hysterons in different states i is divided by the total number of hysterons N and this value contributes to an average over all trials of the system for each strain amplitude in the readout. This gives the average fractional difference in hysteron states at each point, which is then plotted against $\gamma_{readout}$. This process is repeated millions of times, creating an ensemble where each shear strain visited in $\gamma_{readout}$ has a corresponding fractional difference in hysteron states calculated with millions of different sets of interaction strengths.

Chapter 3

Results

Impact of Interactions Between Hysterons

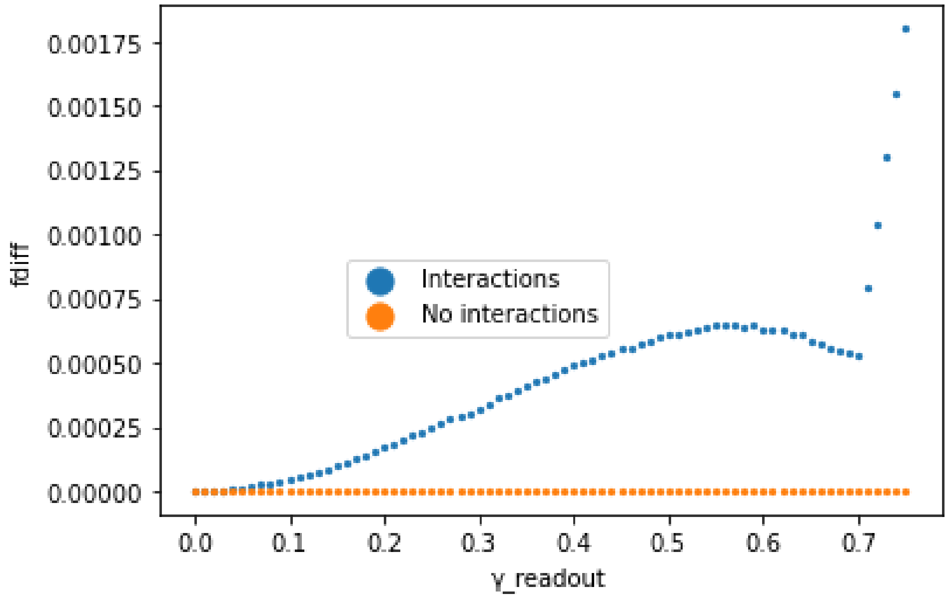

Figure 5: Readout curves of single memories encoded with asymmetric negative shear at |γ|=0.7, with interactions allowed (blue) and prohibited, as in the Preisach model (orange).

Modifying the Preisach model to permit interactions between hysterons within the system expands its memory capabilities of the system significantly [5,6]. In the Preisach model, driving with negative asymmetric shear strain would not encode a memory at all, as demonstrated in Figure 5. However, allowing interactions gives rise to nonmonotonic cusp-like memories similar to those seen from RPM.

Although much work based on hysteretic models has looked at RPM as the only result of cyclically sheared jammed solids, in reality it is just the leading order effect. Just as in the simulations performed by Lindenman and Nagel [6], permitting interactions for a system trained first with multiple cycles of γ_1 and then a single cycle at γ_2, $\gamma_1 < \gamma_2$, allows the encoding of a transient memory of the smaller amplitude γ_1. In the absence of interactions (the Preisach model), a single cycle of γ_2 would be all that is necessary to erase the system's history and any trace of encoding at a previous shear strain.

However, unlike in Lindenman and Nagel, these memories are all encoded and read out using asymmetric shear only, which explicitly prevents the encoding of RPM. The fact that memories are still being encoded by asymmetric shear shows that RPM is not the only memory mechanism to be examined here, and what we are looking at is something distinct entirely.

Impact of Direction of Initialization

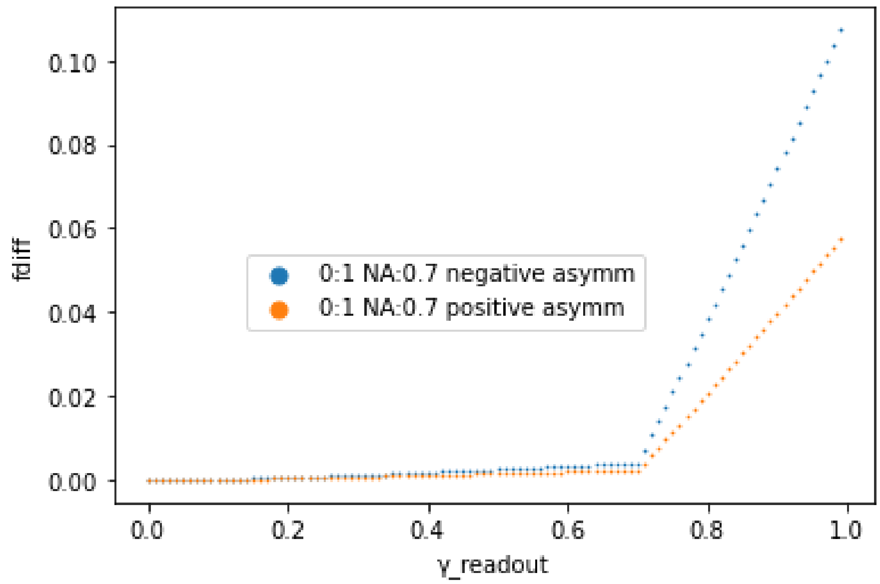

Figure 6: Readout curves of single memories with negative asymmetric encoding and readout and positive asymmetric encoding and readout for a system initialized from the positive direction (all hysterons starting in the +1 state). The legend indicates how the systems for the readout curves were prepared, and is read in the following way: "cycles of γ_1:cycles of γ_2, γ_1: γ_2".

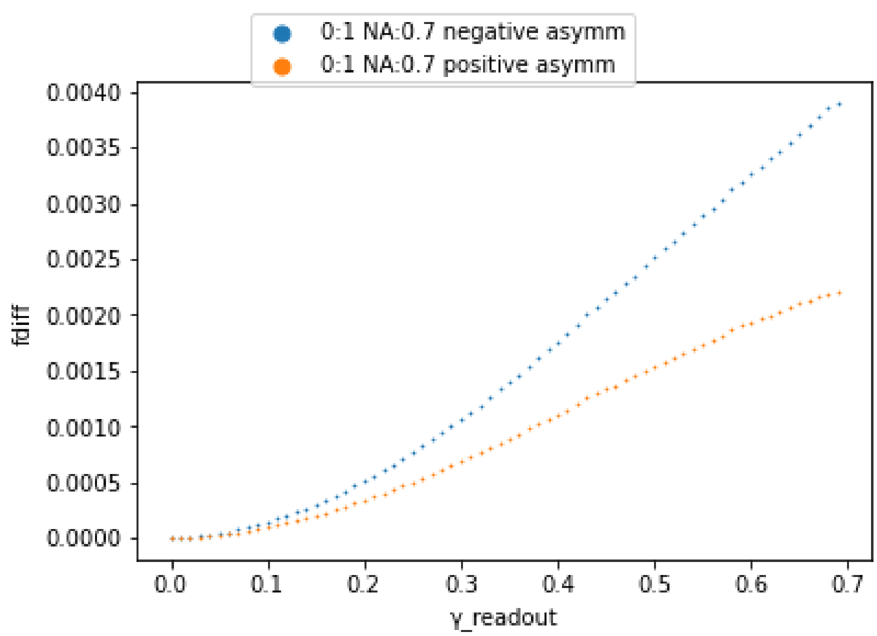

Figure 7: Zoomed-in version of the previous figure, showing the readout curves in more detail. Unlike systems initialized from the negative direction, the readout curves here are monotonically increasing.

Interestingly, initializing the system from the positive direction (field starts at positive infinity, with all hysterons in the +1 state) gives an entirely different shape of readout curve. Rather than the nonmonotonic cusped memories reminiscent of RPM seen in negatively initialized systems, as in Figure 9 below, the readout curves here are monotonic increasing.

Impact of Location of "Overwritten" Memory

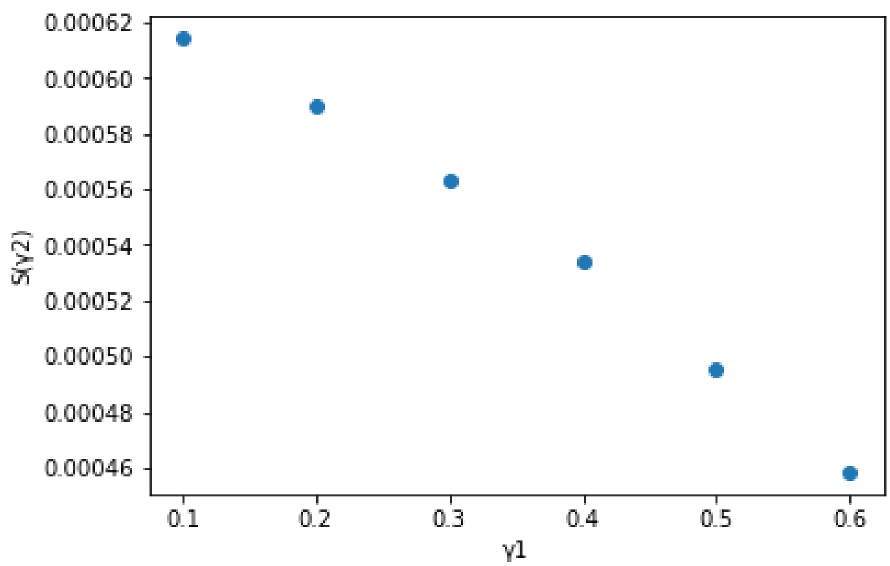

Figure 8: Magnitude of fdiff at γ_2 as a function of γ_1. Data for this graph was pulled from the readout curves of Figure 9 below.

For systems encoded with $\gamma_1 < \gamma_2$, there is a roughly linear negative relationship between the magnitude of fdiff at γ_2 and the location of γ_1, shown in Figure 5. As γ_1 approaches γ_2, fractional difference in hysteron states in the system at γ_2 decreases steadily.

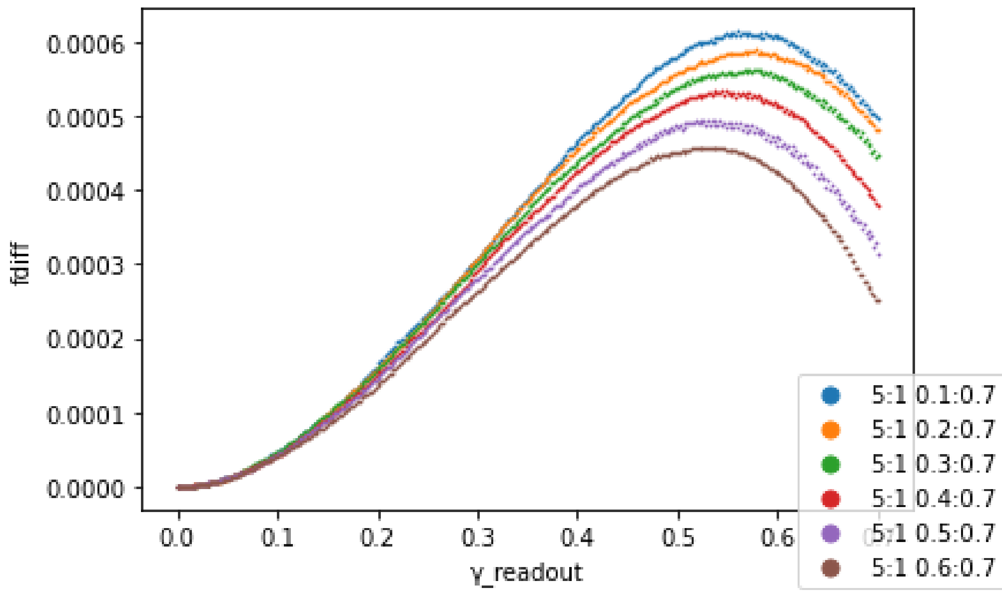

Figure 9: Readout curves for interacting systems encoded and read with negative asymmetric shear. 5 cycles of training are performed for each γ1, with a single cycle of encoding for γ2. Tails have been cut off here to better show detail between curves.

Figures 9 displays the data used to make Figure 8. Together, they show how the location of the "overwritten" memory (γ_1 for $\gamma_1 < \gamma_2$) influences the shape of the readout curve, suppressing the fractional difference in hysteron states more and more as γ_1 approaches γ_2. Interestingly, the location of the peak shifts backwards as γ_1 increases, and the size of Δfdiff measured from a curves peak to its value at $\gamma_{readout} = 0.7$ increases in magnitude, resulting in a 'sharper' memory.

Impact of Multiple Training Cycles

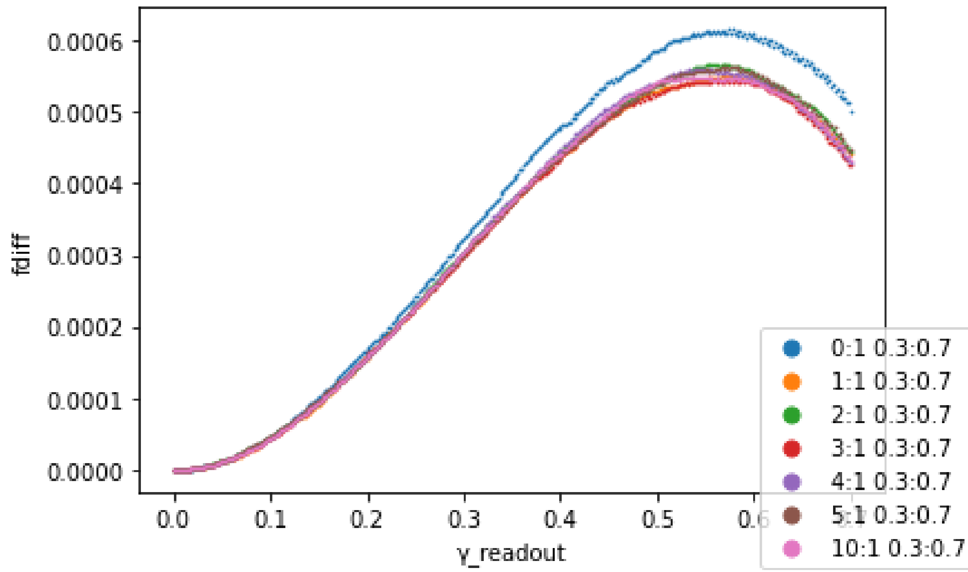

Figure 10: Readout curves of fractional difference in hysteron states for memories γ_1=0.3, γ_2=0.7, γ_1 encoded before γ_2, with increasing numbers of training cycles for γ_1.

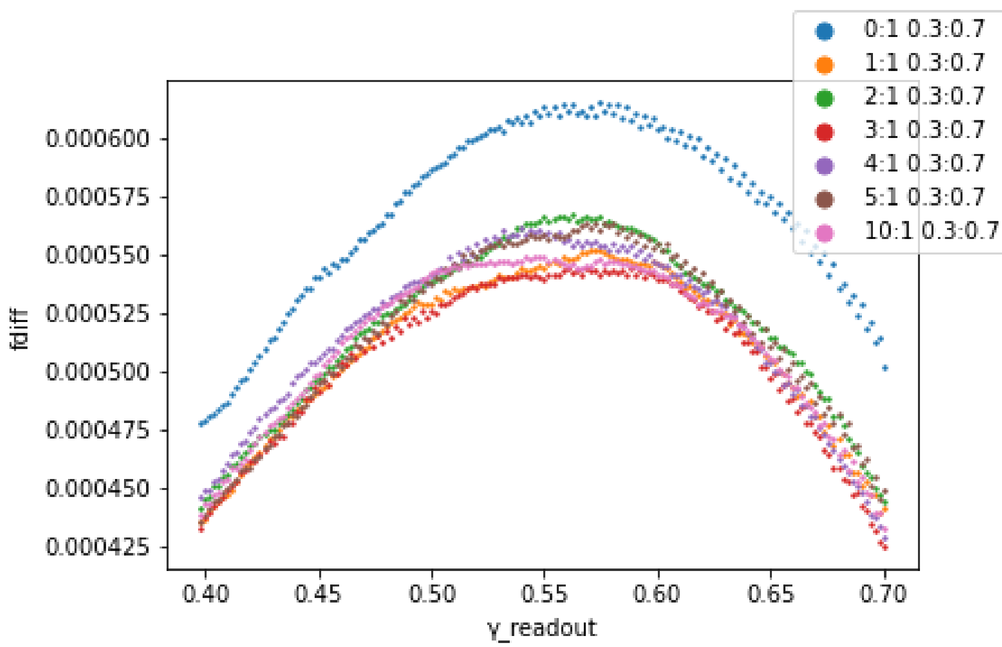

Figure 11: A zoomed-in version of the previous figure, centered on the apex of the readout curves. The state of hysterons (measured by fdiff) in systems trained at both γ_1 and γ_2, $\gamma_1 < \gamma_2$ do not appear to have a clear relationship with the number of training cycles performed to encode γ_1.

Previous work on systems of hysterons has shown that the number of cycles of writing used when preparing a sample has an impact on the 'strength' of the memory [11]. Here, Figure 11 suggests that a single cycle of training at γ_1 is all that is necessary to encode a memory of it, which is retained despite the prediction of RPM that it should be erased by the subsequent γ_2. Varying the number of training cycles used for encoding the γ_1 (Figures 10, 11) had unusual effects. I expected that the number of training cycles of γ_1 would have a more easily discernable impact, but there doesn't seem to be a relationship between the shape of the readout curves and the number of cycles used to encode the memory. Although encoding the first memory does have an influence on the readout of the system, the number of training cycles of the first memory does not seem to have an impact. Further analysis could include comparing the state between cycles of training, for example comparing the state after two training cycles to the state it was in after the first.

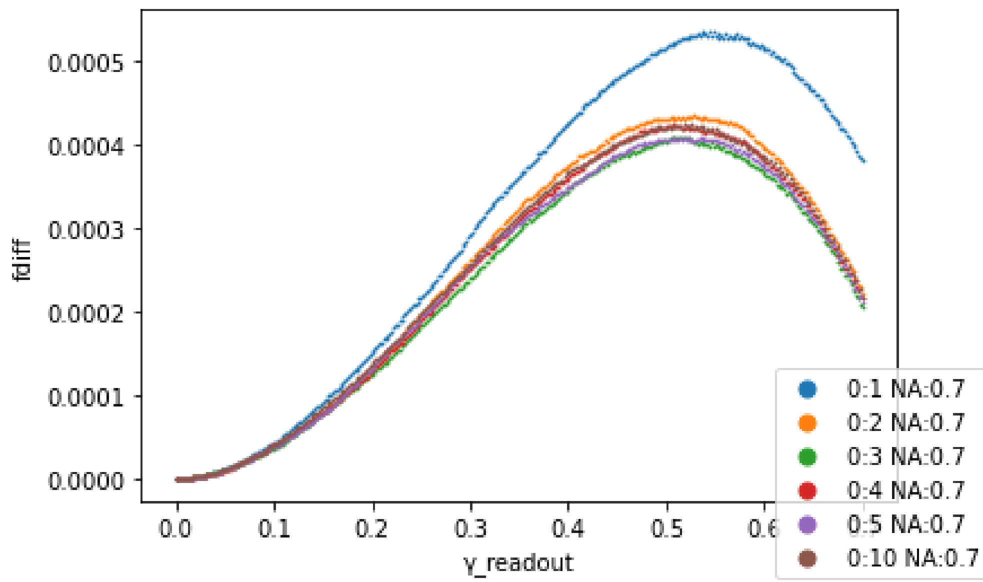

Figure 12: For a single memory, multiple training cycles at a given strain γ results in a smaller fractional difference readout curve than that of a memory of γ encoded with a single cycle of training.

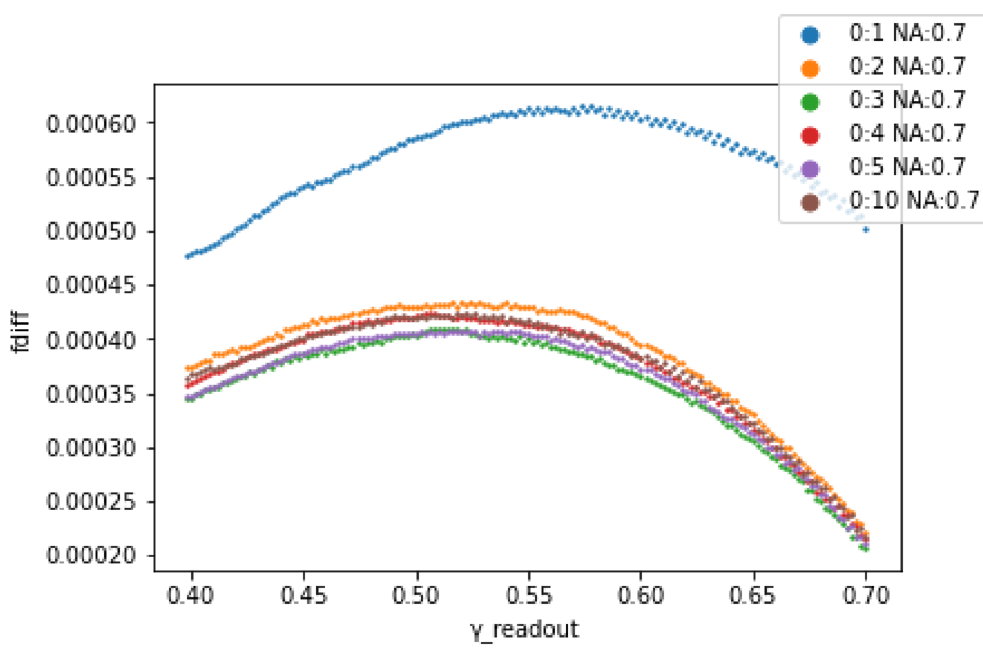

Figure 13: A zoomed-in version of the previous figure, focusing on the apex of the readout curves. Despite being encoded with the most cycles of training, the purple readout curve is consistently greater than those encoded with 3, 4, or 5 cycles of training when encoding γ.

In the case of a single memory γ, shown in Figures 12 and 13 above, encoding a memory of a shear strain using more than one training cycle clearly impacts the shape of the readout curve relative to a system prepared with a single cycle of training. However, there does not seem to be a relationship between the number of additional cycles and the magnitude of the fractional difference in hysteron states of the system.

Impact of Encoding Protocol

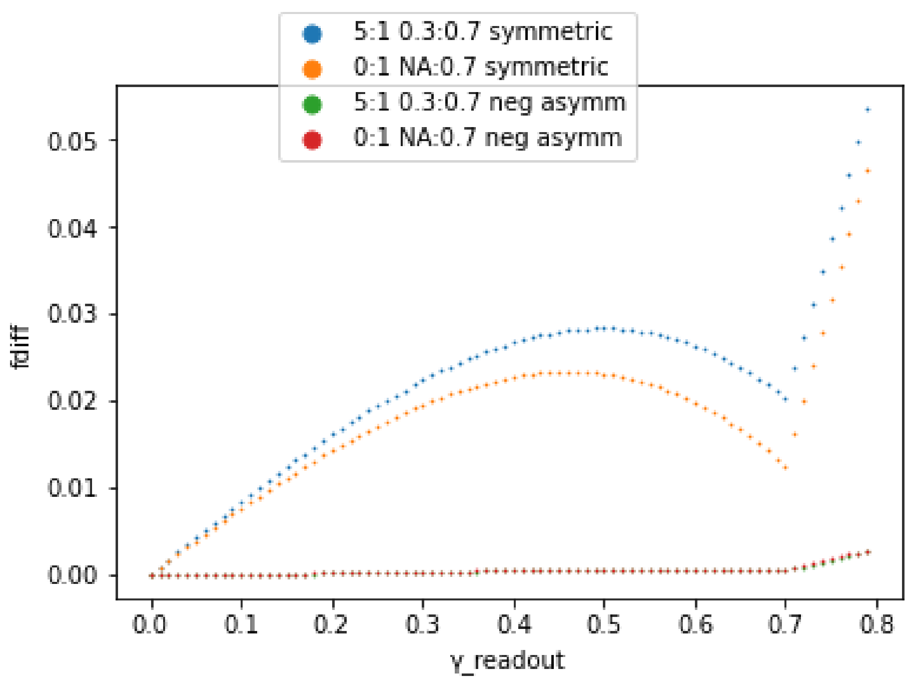

Figure 14: Comparing readout curves made with symmetric shear strain to those made with negative asymmetric shear strain.

The most important distinction that can be drawn is that between systems encoded and read with symmetric shear strain and systems encoded and read with negative asymmetric shear strain. Figure 14 shows that the disorder displayed in the readout curve of a symmetric system is orders of magnitude larger than that of an asymmetrically sheared system. Also of interest is that for symmetric systems, encoding a γ_1 before γ_2, $\gamma_1 < \gamma_2$, results in a readout curve with a greater fdiff than that of a system trained with a single shear strain γ. This result is opposite the case of systems prepared with negative asymmetric shear strain, seen in Figure 10.

Chapter 4

Discussion

By driving only with asymmetric shear, the impact of the leading order effect, RPM, is eliminated—we propose that what remains is something else entirely, due to an aspect of the system's physics that is incompatible with RPM: anti-ferromagnetic interactions between hysterons. Furthermore, this alternate type of memory can retain memories that would always be wiped out in a system with pure RPM: the memory of driving with a smaller amplitude γ_1 survives the application of a larger amplitude γ_2, while in RPM it would not. It is difficult to quantify this memory of small strain amplitude γ_1, since there is no local feature in the readout graph at γ_1. However, there is no denying that it has a measurable impact on the expression of the larger memory; this is seen in Figure 11, where it is shown that encoding an additional smaller memory γ_1 before γ_2 suppresses the disorder (fractional difference in hysteron states) shown in the readout curve. In this way, the training at γ_1 leaves a vestige of its presence, encoding a memory of its own.

While it remains an open question how best to measure the impact of frustrated interactions on a system of hysterons, it is clear that we are only just beginning to scratch the surface of understanding their role in hysteretic systems. Other papers examining hysteretic systems have utilized asymmetric driving in the past, but they rarely discuss the reasoning behind their choice and its theoretical implications. This is an underappreciated question, especially in systems which exhibit memory behavior when driven both symmetrically and asymmetrically, but have only been investigated in depth for one protocol or the other.

Figure 5 shows the fundamental result of this work; without frustrated interactions, there are no observable memories in a system encoded and subsequently read out using negative asymmetric shear. In the presence of frustrated interactions, negative asymmetric shear successfully encodes and reads out memories of a system's history of deformation. This unambiguously demonstrates the impact of frustration on memory formation, providing a new stratagem for observing these otherwise elusive interactions.

Figure 14 further highlights the importance of the choice of protocol; encoding and reading out memories using only negative asymmetric shear nullifies the influence of leading-order effects such as return-point memory. This is plainly seen by the difference in order of magnitude between the readout curves for symmetrically driven systems and those for (negative) asymmetrically driven systems.

Chapter 5

Future Work

Possible Experiments

These simulations were inspired by work on cyclically sheared jammed packings [4,5] in which a 2D layer of jammed PS microparticles is driven with symmetric shear strain. It was my hope to perform an analogous experiment examining asymmetric shear strain, as I did in the simulations described here, but it was not permitted by time. Another possible way to realize an experimental test of the ideas here would be to devise a system where driving is not by direction, and the system is instead compressed from one side. Simulations of similar systems have been performed, and indicate that memories of both translational and rotational displacements are present—but those studies did not compare different driving protocols and explore the role of interactions, as I have done here [7].

More Simulations

Both simulation and experiment have shown that an amorphous solids response to cyclic driving can change drastically based on the regime of strain used to encode and read the memories [7]. Here I have only explored rather large values of strain which were chosen arbitrarily; this very well may have limited the scope of my findings. Further simulations of systems trained with cyclic asymmetric shear strain of smaller regimes ($\gamma^{o} < 0.1$) are needed to shed light on whether this lightweight model will also produce systems which reflect the changes in plasticity seen in other cyclically driven hysteretic systems [7,17].

Also of interest would be testing specific arrangements of cooperative and frustrated interactions, for example so that hysterons at (2n+1) *45° angles from one another are anti-ferromagnetic/frustrated and those at n*90° angles are ferromagnetic/cooperative, as has been observed experimentally in cyclically sheared 2D solids [5]. An example of this is shown in Figure 1. Studying systems with fixed geometries, for example in which all interactions are strictly anti-ferromagnetic/frustrated, also would have been good to simulate to further explore the role of frustrated interactions in the robustness of a systems memory capabilities.

Appendix A: Code

Calculating the Field Vector (inter_field in hysteron.py)

```
def lookup_index(e, f, system_width):  # calculates the index of interest from the state vector
    return f * system_width + e
  interaction = np.zeros((9))  # empty vector, entries are sums of interactions with neighbors
  system_width = 3  # no. columns
  system_height = 3  # no. rows
  for e in range(system_width):
    for f in range(system_height):
      k = lookup_index(e, f, system_width)  # entry of the state vector being constructed AKA "11"
      north = (f - 1) % system_height  # used to calculate the indices of the neighbors as they are cycled
      south = (f + 1) % system_height
      east = (e + 1) % system_width
      west = (e - 1) % system_width
      l = lookup_index(west, north, system_width)  # 00
      interaction[k] += state[l] * interactions[l, k]
      l = lookup_index(e, north, system_width)  # 01
      interaction[k] += state[l] * interactions[l, k]
      l = lookup_index(east, north, system_width)  # 02
      interaction[k] += state[l] * interactions[l, k]
      l = lookup_index(west, f, system_width)  # 10
      interaction[k] += state[l] * interactions[l, k]
      l = lookup_index(east, f, system_width)  # 12
      interaction[k] += state[l] * interactions[l, k]
      l = lookup_index(west, south, system_width)  # 20
      interaction[k] += state[l] * interactions[l, k]
      l = lookup_index(e, south, system_width)  # 21
      interaction[k] += state[l] * interactions[l, k]
      l = lookup_index(east, south, system_width)  # 22
      interaction[k] += state[l] * interactions[l, k]
  inter_field = interaction
```

Simulation Code

```
import numpy as np

import hysteron as hyst

def encode(state, amp1, amp2): #writes the memories

   s = state.copy() #working copy of the state vector--changes to it are persistent

   amp1_cycles = 0

   while amp1_cycles < 5: #Performs training cycles of gamma1

      hyst.evolve_event(s, -amp1, 0, interactions, Hon, Hoff, rec)

      #hyst.evolve_event(s, amp1, 1, interactions, Hon, Hoff, rec) #commented out because we are
encoding asymmetrically

      hyst.evolve_event(s, 0, 1, interactions, Hon, Hoff, rec)

      amp1_cycles += 1

   amp2_cycles = 0

   while amp2_cycles < 1: #Performs training cycles of gamma2

      hyst.evolve_event(s, -amp2, 0, interactions, Hon, Hoff, rec)

      #hyst.evolve_event(s, amp2, 1, interactions, Hon, Hoff, rec) #commented out because we are
encoding asymmetrically

      hyst.evolve_event(s, 0, 1, interactions, Hon, Hoff, rec)

      amp2_cycles += 1

   return s

def fdiff(state, s): # calculates fdiff, fraction of hysterons that have changed state

   i = 0 # similar to y axis of fig 4f in 'global memory from local hysteresis'

   k = 0

   for k in range(len(state)):

      if (s[k] - state[k]) != 0: #checks for a difference between current state of hysterons and previous
states

         i += 1

      else:

         pass

   return float(i / N) #fractional difference in hysteron states
```

```
N = 9
b = 0
i = 0
j = 0
for b in range(4000000):
  try:
    interactions = np.random.uniform(-1, 1, (N,N)) #generates random J_ij matrix of interaction strengths between hysterons. This is then used to calculate the field vector
    for i in range(N-1): #Here we impose the restriction that transpose entries must be of like sign
      if np.sign(interactions[i,j]) != np.sign(interactions[j,i]):
        interactions[j,i] *= -1
        i += 1
      else:
        i += 1
      for j in range(N-1):
        if np.sign(interactions[i,j]) != np.sign(interactions[j,i]):
          interactions[j,i] *= -1
          j +=1
        else:
          j += 1

    rnd = np.random.random((N, 2)) * 2 – 1 #Other parameters needed for evolve_event are made here
    Hon = np.max(rnd, axis=1) #Hon and Hoff are the threshold values which determine when hysterons flip
    Hoff = np.min(rnd, axis=1)

    state0 = np.ones(N) * -1 #system starts with all hysterons in the -1 state ~ at a field of -infinity
    hyst.evolve_event(state0, 0, 1, interactions, Hon, Hoff, rec) # Bring field from -infinity to 0
```

```
        state = state0.copy() #initialized state vector
        s = encode(state, 0.5, 0.7)


        fdif = []
        fdif.clear()
        #u = s.copy() #If reading out in parallel, this line is uncommented and the one below is struck
        for m in np.arange(0, 0.8, 0.002): #readout sequence
            u = s.copy()
            hyst.evolve_event(s, -m, 0, interactions, Hon, Hoff, rec)
            #hyst.evolve_event(s, m, 1, interactions, Hon, Hoff, rec) #commented because we are reading out asymmetrically
            hyst.evolve_event(s, 0, 1, interactions, Hon, Hoff, rec)
            l = fdiff(s, u) #calculates difference in hysteron states after each strain amplitude is applied
            fdif.append(l) #this is the list of differences which will be averaged over all trials and then plotted against gamma
        addtl.append(fdif)
        count += 1
        pass


    except RuntimeError:
        continue
```

Bibliography

[1] Preisach, F. Über die magnetische Nachwirkung. *Z. Physik* **94,** 277–302 (1935).

[2] J. P. Sethna, K. Dahmen, S. Kartha, J. A. Krumhansl, B. W. Roberts, and J. D. Shore, Hysteresis and Hierarchies: Dynamics of Disorder-Driven First-Order Phase Transformations, Phys. Rev. Lett. 70, 3347 (1993).

[3] G. M. Wysin, W. A. Moura-Melo, L. A. S. Mól, and A. R. Pereira, Dynamics and Hysteresis in Square Lattice Artificial Spin Ice, New J. Phys. 15, 045029 (2013).

[4] N. C. Keim, J. Hass, B. Kroger, and D. Wieker, Global Memory from Local Hysteresis in an Amorphous Solid, Phys. Rev. Research 2, (2020).

[5] N. C. Keim and J. D. Paulsen, Multiperiodic Orbits from Interacting Soft Spots in Cyclically Sheared Amorphous Solids, Sci. Adv. 7, (2021).

[6] C. W. Lindeman and S. R. Nagel, Multiple Memory Formation in Glassy Landscapes, Sci. Adv. 7, (2021).

[7] Z. A. Benson, A. Peshkov, D. C. Richardson, and W. Losert, Memory in Three-Dimensional Cyclically Driven Granular Material, Phys. Rev. E 103, (2021).

[8] N. C. Keim, J. D. Paulsen, and S. R. Nagel, Multiple Transient Memories in Sheared Suspensions: Robustness, Structure, and Routes to Plasticity, Phys. Rev. E 88, (2013).

[9] J. D. Paulsen, N. C. Keim, and S. R. Nagel, Multiple Transient Memories in Experiments on Sheared Non-Brownian Suspensions, Phys. Rev. Lett. 113, (2014).

[10] N. C. Keim and S. R. Nagel, Generic Transient Memory Formation in Disordered Systems with Noise, Phys. Rev. Lett. 107, (2011).

[11] N. C. Keim, J. D. Paulsen, Z. Zeravcic, S. Sastry, and S. R. Nagel, Memory Formation in Matter, Rev. Mod. Phys. 91, (2019).

[12] S. N. Coppersmith, T. C. Jones, L. P. Kadanoff, A. Levine, J. P. McCarten, S. R. Nagel, S. C. Venkataramani, and X. Wu, Self-Organized Short-Term Memories, Phys. Rev. Lett. 78, 3983 (1997).

[13] M. L. Povinelli, S. N. Coppersmith, L. P. Kadanoff, S. R. Nagel, and S. C. Venkataramani, Noise Stabilization of Self-Organized Memories, Phys. Rev. E 59, 4970 (1999).

[14] D. Fiocco, G. Foffi, and S. Sastry, Encoding of Memory in Sheared Amorphous Solids, Phys. Rev. Lett. 112, (2014).

[15] Adhikari, M., Sastry, S. Memory formation in cyclically deformed amorphous solids and sphere assemblies. Eur. Phys. J. E 41, 105 (2018).

[16] M. Mungan, S. Sastry, K. Dahmen, and I. Regev, Networks and Hierarchies: How Amorphous Materials Learn to Remember, Phys. Rev. Lett. 123, (2019).

[17] M. Adhikari, M. Mungan, and S. Sastry, Yielding Behavior of Glasses under Asymmetric Cyclic Deformation, preprint, (2022).

[18] A. Szulc, M. Mungan, and I. Regev, Cooperative Effects Driving the Multi-Periodic Dynamics of Cyclically Sheared Amorphous Solids, preprint, (2021).

ACADEMIC VITA

EDUCATION

The Pennsylvania State University Schreyer Honors College — **University Park, PA**
Eberly College of Science | B.S. in Mathematics, B.S. in Physics with Honors — *Class of 2022*

ACADEMIC EXPERIENCE

Pennsylvania State University Department of Physics — **University Park, PA**
Keim Lab | Undergraduate Research Assistant — *June 2021 – Present*

- Discovered novel memory behaviors in disordered amorphous solids…*
- Managed troubleshooting and repair of critical servo module, interfacing directly with part manufacturer and Physics Department administration
- Programmed simulations of interacting hysteretic elements in Python using scientific packages such as numpy, trackpy, and pandas

Pennsylvania State University Department of Physics — **University Park, PA**
Learning Assistant | Physics 211, Classical Mechanics — *Spring 2020*

- Engaged students to foster a positive and inclusive classroom environment
- Facilitated collaborative active learning exercises in-class and during independent out-of-class problem solving sessions

The Perkiomen School Peer Tutoring Program — **Pennsburg, PA**
Co-Founder | Tutor — *Sep 2016 - May 2018*

- Co-founded and administrated school's first student-led peer tutoring program
- Oversaw scheduling tutoring sessions and crafted personalized worksheets to supplement students' existing study routines, catered to their unique style of learning
- Instructed fellow students in one-on-one and group settings on Spanish, calculus, chemistry, and physics for two hours after school every Monday, Wednesday, and Friday

RELEVANT COURSEWORK

- Thermal Physics/Statistical Mechanics
- Intro. to Quantum Mechanics I, II
- Intermediate Electricity and Magnetism
- Experimental Physics
- Classical Analysis
- Linear Algebra
- Theoretical Mechanics
- Special and General Relativity
- Electronic Physics Lab

SKILLS, HONORS, AND INTERESTS

Skills: Conversational Spanish, Python, Ubuntu, Adobe and Microsoft applications, electronics soldering, laboratory safety and ethics training, woodworking, conflict resolution
Honors: Lindquist Trustee Scholarship, John Ramsey Scholarship, Chapman Trustee Scholarship, Dean's List (7/8 semesters), AP Scholar with Distinction, Schreyer Academic Excellence Scholarship, The President's Freshman Award, Bausch & Lomb Honorary Science Award, M. Dean and Jean L. Underwood Scholarship in Physics, Elsbach Physics Scholarship, John and Elizabeth Teas Scholarship in Science
Interests: Chess, Billiards, Kayaking, Backpacking, Acoustic Guitar, *The Feynman Lectures on Physics*