Modeling stochastic human-driver car following behavior in oscillatory traffic conditions

Final Report

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Abstract (Limit: 250 words)

Accurately modeling the realistic and unstable traffic dynamics of human-driven traffic flow is crucial to being able to understand how traffic dynamics evolve, and how new agents such as autonomous vehicles might influence traffic flow stability. This work is motivated by a recent dataset that allows us to calibrate accurate models, specifically in conditions when traffic waves arise. Three microscopic car-following models are calibrated using a microscopic vehicle trajectory dataset that is collected with the intent of capturing oscillatory driving conditions. For each model, five traffic flow metrics are constructed to compare the flow-level characteristics of the simulated traffic with experimental data.
MODELING STOCHASTIC HUMAN-DRIVER CAR FOLLOWING BEHAVIOR IN OSCILLATORY TRAFFIC CONDITIONS

FINAL REPORT

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FOREWORD

This report summarizes the findings of the project “Modeling stochastic humandriver car following behavior in oscillatory traffic conditions” funded by the Center for Transportation Studies at the University of Minnesota through the Transportation Scholars Program.

This text appeared in manuscript form in the article “Calibrating heterogeneous car-following models for human drivers in oscillatory traffic conditions” presented at the IEEE Forum on Integrated and Sustainable Transport Systems held virtually online by the Technical University of Delft in Delft, Netherlands, November 3-5, 2020 [1].
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CHAPTER 1: INTRODUCTION

Microscopic car-following models have long been used to describe traffic at the level of the individual vehicle. The general microscopic modeling framework is to approximate the acceleration of a following vehicle as a function of the vehicle’s surroundings. Specifically, a common assumption is that the acceleration of the following vehicle is a function of the vehicle immediately in front of the following vehicle referred to as the lead vehicle and takes the general form:

\[ \ddot{x} = f(s, v, \dot{s}), \]

where \( \ddot{x} \) is the acceleration of the following vehicle, \( s \) is the space gap between the lead vehicle and the following vehicle, \( v \) is the speed of the following vehicle, and \( \dot{s} \) is the rate of change of the space gap, which can also be thought of as the relative speed between the lead vehicle and the following vehicle.

The earliest car-following model for traffic dates back to the General Motors model in the 1950s [2]. The researchers used inter-vehicle spacing, relative velocity, and the speed of the following vehicle to approximate the driver response.

Since the introduction of the first car-following model, there have been many improved traffic dynamic models proposed such as Bando’s optimal velocity model [3], the intelligent driver model (IDM) [4], the Gipps model [5], and the Gazis-HermanRothery (GHR) model [6]. These models can effectively capture driver behaviors. For instance, the IDM is constructed with a safety distance which corresponds to the collision precaution of human drivers in reality.

Being able to accurately model and simulate human-piloted traffic that contains realistic traffic oscillations and heterogeneity in driving behavior is a critical step to being able to test autonomous systems in realistic simulations. In order to get realistic car following behavior, calibrated model parameters are often determined using data from a variety of drivers as done in [3,7]. However, this calibration technique makes the implicit assumption that all drivers not only follow the same general car following behavior, but also have the same reaction to a specific stimuli.

Hence, with the goal of producing more realistic microscopic traffic oscillations in simulation, calibration of car following models with heterogeneous driver behavior has been an area of intense research over the past several years. Notably, this includes efforts to capture driver heterogeneity through different parameter values. For example, Kim, et al. [8] use the NGSIM dataset to calibrate a GM-type car following model with varying model coefficients which fluctuate across human drivers. Ossen, et al. [9] identify the Gipps model is the best to capture human driving behavior. Hoogendoorn,

However, the majority of the microscopic model calibration work that has been conducted has been using datasets that are either known to have some degree of inaccuracy, or on datasets that were not explicitly collected to capture oscillatory traffic conditions. For example, Kim, et al. [8] use the NGSIM data and Ossen, et al. [9] adopted Dutch Highway Data. While valuable for understanding traffic flow, these models were not calibrated with the goal of capturing the development of string instabilities in the form of stop-and-go waves.

Both the NGSIM dataset as well as the Dutch highway data were collected with the goal of extracting a broad range of vehicle behavior. As a result, only a small portion of the data contains traffic instabilities, since the dataset was not collected with the primary goal of observing the development of traffic instabilities such as stop-and-go waves. Therefore, there has been a general lack of microscopic traffic flow models calibrated for string unstable traffic flow where oscillations grow, as has been experimentally observed in traffic flow [12]. Here, we consider traffic instabilities to be the propagation of a fluctuation in one vehicle’s motion to the upstream traffic [13], and specifically the amplification of such disturbance through the traffic flow. One important exception is the work by Chen, et al. [14], who develop a new car following model that is capable of producing traffic instabilities using the NGSIM data. With the exception of this significant work though, few studies have focused on the important topic of how to best calibrate microscopic models for realistic simulation of highly oscillatory traffic conditions with heterogeneous drivers.

The contribution of this study is to conduct a calibration analysis on a newly available dataset of experimentally-collected vehicle trajectories in oscillatory driving conditions. Three different models for 20 vehicles in the dataset are calibrated individually and compared based on microscopic properties of the simulated traffic flow. These will allow for more nuanced simulations that will be critical for understanding how these instabilities arise and propagate, and how the presence of a vehicle fleet with increased autonomous capabilities might influence this traffic flow.

The remainder of this article is organized as follows. In Section 2, an introduction of candidate car-following models is presented. Model calibration and simulation methodology is outlined in Section 3. Traffic flow model metrics are introduced in Section 4, and finally, comparison results of different models are shown in Section 5.
CHAPTER 2: MODELING

In this study, three traffic dynamic models are selected to capture human driver behaviors: the optimal velocity-follow the leader (OV-FTL) model [15], the optimal velocity relative velocity model (OVRV) model [16,17], and the IDM [7]. These models are selected because of their prevalence in the literature in the case of the OVRV and IDM, and demonstrated performance in the case of the OV-FTL [18]. The OV-FTL and OVRV are derived from the optimal velocity (OV) model [3], which takes the form

\[ \ddot{x} = \alpha (V(s) - v), \]  

where \(\ddot{x}\) is the acceleration of the following vehicle, which is a function of \(s\), the intervehicle bumper to bumper spacing between the lead vehicle and the following vehicle, \(v\), the following vehicle’s speed; \(V(s)\) is some optimal velocity as a function of \(s\); \(\alpha\) is a parameter value.

We briefly describe each of the considered models below.

### 2.1 OV-FTL MODEL

The OV-FTL was designed based on the optimal velocity model in [3]. It adds a follow-the-leader term which prevents vehicles from colliding. It has been shown that the OV-FTL is capable of producing instabilities by Cui, et al. [15] with the experimental data in [12]. The model takes the form:

\[ \ddot{x} = f(s, \dot{s}, v) = a(V(s) - v) + b \frac{\dot{s}}{s^\nu} \]  

where

\[ V(s) = V_m \frac{\tanh(s/d_o - 2) + \tanh(2)}{1 + \tanh(2)} \]  

is the optimal velocity function with \(s\) defined to be the same as in the OV model and \(\dot{s} = v_l - v_f\) is the relative speed between the lead vehicle and the following vehicle. Parameters \(v_l\) and \(v_f\) are the velocity of the lead vehicle and following vehicle, respectively. Parameters \(a\) and \(b\) are the gains. Parameter \(d_o\) is jam distance, \(V_m\) is the maximum allowable speed, \(\nu\) is a parameter.

### 2.2 OVRV MODEL

The OVRV was designed to take the time-headway relationship into account, while also following the lead vehicle velocity [16,17]. The model takes the form:
\[
\ddot{x} = f(s, v, \dot{s}) = k_1(s - \eta - \tau v) + k_2\dot{s} \cdot . \tag{5}
\]

where \(\ddot{x}, v, s, \dot{s}\) are as defined above. Parameters \(k_1, k_2, \tau,\) and \(\eta\) are the model parameter values that describe the driver behaviors. Specifically, \(k_1\) is the gain on the optimal velocity component, \(\eta\) is the jam spacing (i.e., the inter-vehicle spacing at zero speed), \(\tau\) is the time gap, and \(k_2\) is the gain on the relative velocity.

### 2.3 IDM MODEL

The intelligent driver model (IDM) is one of the most widely used microscopic car following models. The model was adopted from Treiber, et al. [7]:

\[
\ddot{x} = a \left(1 - \left(\frac{v}{v_0}\right)^\delta - \left(\frac{\dot{s}(v, \dot{s})}{s}\right)^2\right), \tag{6}
\]

where

\[
\dot{s}(v, \Delta v) = s_0 + \tau v - \frac{v\dot{s}}{2\sqrt{ab}}. \tag{7}
\]

Here \(\ddot{x}, v, s, \dot{s}\) are as defined above, \(v_0\) is the desired speed, which corresponds to the speed limit, \(\tau\) is the time headway, \(a\) and \(b\) are the maximum acceleration and braking rate, respectively, \(\delta\) is the acceleration component, and \(s_0\) is the jam distance.
CHAPTER 3: CALIBRATION AND SIMULATION

3.1 CALIBRATION

Model calibration is conducted using simulation-based optimization where the optimal set of model parameter values $\theta^*$ are found that minimize the error between the experimental data and the simulated results using the model with the best-fit model parameter values. Specifically, the error metric used to compare the model performance with the actual data is the root mean square error (RMSE) of the spacing, which has been found to be the most effective error metric [19]. RMSE is computed as:

$$
\varepsilon = \sqrt{\frac{1}{T} \int_0^T (v_m(t) - v(t))^2 dt},
$$

where $\varepsilon$ is the RMSE spacing error, $T$ is the total time of the simulation, $v_m(t)$ is the measured speed at time $t$ from the data, and $v(t)$ is the simulated speed at time $t$ using the current model parameter values $\theta$.

To find the optimal model parameter values $\theta^*$ that minimize the spacing RMSE between the simulated vehicle trajectories and the experimental data, the space of possible model parameter values is searched to find the minimum RMSE subject to the initial conditions and parameter value constraints shown in Table 1.

Table 1: Calibrated parameter range.

<table>
<thead>
<tr>
<th>Model</th>
<th>Parameter range</th>
</tr>
</thead>
</table>
| OV-FTL | $a \in (0, \infty), b \in (0, \infty),$  
$V_m \in (0,15], d_0 \in (0,15], $  
$\nu \in (0,3]$  |
| OVRV  | $k_1 \in (0, \infty), k_2 \in (0, \infty), \eta \in (0,15], $  
$\tau \in (0,15]$  |
| IDM   | $v_0 \in (0,35], \tau \in (0,15], a \in (0, \infty), $  
$b \in (0, \infty), \delta \in (0,5], s_0 \in (0,15]$ |
The simulation process is built on a closed-loop circular road where the length is \( L \) and \( N \) vehicles are on the ring road. See Table 2 for specific values used in simulation. This setup is similar to the one used to collect the experimental data by Wu, et al. [20]. The simulated acceleration, velocity and spacing function take the form as follows respectively.

\[
\ddot{x}(t) = f(s(t), \dot{s}(t), v(t)) \tag{10}
\]

\[
v(t + \Delta t) = v(t) + \ddot{x}(t)\Delta t \tag{11}
\]

\[
s(t + \Delta t) = s(t) + \dot{s}(t)\Delta t \tag{12}
\]

where \( \ddot{x}(t), v(t), s(t), \dot{s}(t) \) are the simulated acceleration, velocity, spacing, and relative speed respectively at time \( t \), \( \Delta t \) is a short time interval after time \( t \). The acceleration is calculated from the car-following models introduced in Section 2.

Table 2: Physical parameter values used for simulation.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Length of Road</td>
<td>260</td>
<td>m</td>
</tr>
<tr>
<td>Number of Vehicles</td>
<td>20</td>
<td>-</td>
</tr>
<tr>
<td>Average car length</td>
<td>5.1</td>
<td>m</td>
</tr>
<tr>
<td>Equilibrium spacing</td>
<td>7.9</td>
<td>m</td>
</tr>
</tbody>
</table>
Also note that a random noise shown in (13) is applied in the velocity simulation process. The purpose of including such noise is to perturb the vehicles from the equilibrium state. The noise is applied every 1 second. It takes the form:

\[ v(t) = v(t) + \epsilon \]

where \( \epsilon \) is a random value from Gaussian distribution \( \epsilon \sim N(0, \sigma) \). For consistency, \( \sigma = 0.05 \text{ m/s} \) in all model simulations in Section 3.4.

### 3.3 EXPERIMENTAL DATA

The experimental data used in this study was taken from Experiment A and B of the eight car-following datasets of experiments and published by Wu, et al. [20]. The data was collected on an experimental track in the absence of external bottlenecks or geometric factors that may be a trigger for traffic waves. Therefore, this data shows the development of traffic instabilities due to human driving behavior alone. To the best of our knowledge, this is the most comprehensive microscopic car following trajectory dataset to consider exclusively oscillatory traffic conditions in a controlled environment.

The data contains vehicle trajectories from twenty unique drivers and vehicles over two days of testing with differing vehicle order. Therefore, the data contains a wide range of driver behaviors. As seen in Figure 1 and 2, the vehicle trajectories show that the human driver behavior was sufficient to induce instabilities in the form of traffic oscillations. In total, the data represents roughly 20 vehicle hours of closely controlled experiments to study the development and growth of traffic waves due to human driving behavior.

There are two different datasets used in this work. Data from Experiment B is presented in Figure 2 and is used for calibrating the model parameter values, while data from Experiment A shown in Figure 1 is used to test the calibrated models and used for additional simulations.

### 3.4 CALIBRATION AND SIMULATION RESULTS

In this section, the calibrated parameter results for 20 vehicles across four car following models are presented.

#### 3.4.1 Simulation results for OV-FTL

Recall that in the OV-FTL (3) in Section 2, there are 5 parameters in the model \( a, b, d_0, V_m, \text{ and } v \) where are different from driver to driver as seen in Figure 6a, where each point represents the best-fit model parameter values for one driver. The calibration results show parameter \( a \) ranges from 0 to 0.6/s.
Parameter $b$ ranges from 0 to 700 $m^2/s$. The maximum allowable speed $V_m$ ranges from 2 to 15 $m/s$. The reference distance $d_0$ ranges from 0 to 15 m. The magnitude $v$ ranges from 0 to 3.

Figure 3 shows the velocity, trajectory, and spacing oscillation which are simulated with the calibrated parameters and the constant parameters in Table 2. Note that the equilibrium spacing is considered as an input spacing which evenly divides the loop length by number of vehicles. The simulation starts with vehicle speed of zero.

Figure 1: The traffic velocity, trajectory, and spacing of the experimental dataset A, used as a hold-out test set.
Figure 2: The traffic velocity, trajectory, and spacing of the experimental dataset B used as training data to
Figure 3: The traffic velocity, trajectory, and spacing of the OV-FTL.
Figure 4: The traffic velocity, trajectory, and spacing of the OVRV.

3.4.2 Simulation results for the OVRV

For the OVRV, there are four parameters to be calibrated: $k_1, k_2, \tau, \eta$. The calibrated values differ from driver to driver shown in Figure 6b, where each point represents the calibrated value for one driver. Velocity gain $k_1$ ranges from 0 to $20 \, \text{s}^{-2}$; the speed difference gain $k_2$ ranges from 0 to $25 \, \text{s}^{-1}$; the time gap $\tau$ ranges from 0 to 4.5 s; the jam distance $\eta$ ranges from 0 to 12 m.

Figure 4 shows the velocity, trajectory, and spacing oscillation which are simulated with the calibrated parameters and the constant parameters in Table 2. The simulation starts with vehicle speed of zero.
3.4.3 Simulation results for the IDM

As before, the IDM (6) in Section 2 is calibrated using 6 parameters $v_0, \tau, a, b, \delta, s_0$ shown in Figure 6c, which result in the desired velocity $v_0$ ranges from 0 to 30 $m/s$; the safe time headway $\tau$ ranges from 0 to 2 $s$; the maximum acceleration $a$ ranges from 0 to 14 $m/s^2$; the desired deceleration $b$ ranges from 0 to 2 $m/s^2$; the acceleration exponent $\delta$ ranges from 1 to 3.5; the jam distance $s_0$ ranges from 0 to 7 $m$.

In simulation, Figure 5 shows the velocity, trajectory, and spacing oscillation which are simulated with the calibrated parameter values and the constant parameters in Table 2. The simulation starts with vehicle speed of zero.
(a) OV-FTL parameter (b) OVRV parameter values (c) IDM parameter values.

Figure 6: Calibrated parameter values for OV-FTL (a), OVRV (b), and IDM (c).
CHAPTER 4: TRAFFIC FLOW METRICS CHARACTERISTICS

In order to properly and accurately compare the simulation from different traffic models, it is
important to define relevant traffic flow metrics that can be used to describe the simulated traffic flow.
We briefly introduce and apply these metrics to the simulated vehicle trajectories from each model.

4.1 VEHICLE MEAN VELOCITY (OR SPACING) STANDARD DEVIATION

First, the speed and spacing standard deviation of each vehicle during the entire simulation period are
calculated and averaged across all vehicles to get the mean speed and standard deviation. The result is
called Vehicle Mean Velocity (or Spacing) Standard Deviation $\delta_{vn}$ (or $\delta_{sn}$):

$$\bar{\delta}_{vn} = \frac{\sum \delta_{vn}(n)}{n} \quad \text{or} \quad \bar{\delta}_{sn} = \frac{\sum \delta_{sn}(n)}{n}$$

(14)

where $\delta_{vn}$ is the speed standard deviation; $n$ is the number of vehicles; $\delta_{vn}$ is the vehicle mean
velocity standard deviation; $\delta_{sn}$ is the vehicle spacing standard deviation.

4.2 TIME MEAN VELOCITY (OR SPACING) STANDARD DEVIATION

The time mean velocity (or spacing) standard deviation $\bar{\delta}_{vt}$ (or $\bar{\delta}_{st}$) is different from the metric
introduced in Section 4.1. This is calculated based on the temporal velocity (or spacing) standard
deviation of all vehicles at one time, and average that through the entire simulation period:

$$\bar{\delta}_{vt} = \frac{\sum \delta_{vt}(t)}{T} \quad \text{or} \quad \bar{\delta}_{st} = \frac{\sum \delta_{st}(t)}{T}.$$ (15)

Here $\delta_{vt}$ is the time velocity standard deviation for all vehicles at time $t$; $T$ is the time duration; $\bar{\delta}_{vt}$ is the
time mean velocity standard deviation; $\delta_{st}$ is the time spacing standard deviation for all vehicles at time
$t$; $\bar{\delta}_{st}$ is the time mean spacing standard deviation.

4.3 WAVE START TIME

The wave starts at $t_s$ when the time speed standard deviation $\delta_{vt}$ of all vehicles first reaches $\lambda$ times the
time mean velocity standard deviation $\bar{\delta}_{vt}$ which takes the form:

$$\delta_{vt}(t) \geq (1 + \lambda) \cdot \bar{\delta}_{vt}$$ (16)
The threshold coefficient $\lambda$ is introduced to exclude the oscillations caused by velocity change at the start of simulation. Similar to the system settling time definition [21], $\lambda$ is selected as 5%, which means the wave starts when the $\delta\nu$ is larger than 5% of the $\bar{\delta\nu}$. 
CHAPTER 5: DISCUSSION AND RESULTS

Based on the metrics computed in Section 4, Table 3 shows the computed metric values for each simulation. The bold values represent the model simulation results that are closest to the experimental testing dataset. We discuss the findings for each of the considered traffic flow metrics below.

The experimental test data has a vehicle mean speed standard deviation $\bar{\delta}_v$ of 0.95 m/s. For the OVRV, $\bar{\delta}_v$ is 0.61 m/s, 0.57 m/s for the OV-FTL, and 0.31 m/s for the IDM. Comparing to experimental data, the OV-FTL and OVRV speed fluctuations are both closer to the experiment than the IDM, which is less oscillatory.

The experimental dataset has a mean spacing standard deviation $\bar{\delta}_s$ of 2.19 m. In comparison, the OV-FTL has a standard deviation of 1.81 m, the OVRV produces data with a standard deviation of 1.40 m, and the IDM produces simulation results with a standard deviation of 0.64 m. The OV-FTL simulation results are the most similar to the experimental data for this traffic flow metric.

The experimental dataset has a time mean speed standard deviation $\bar{\delta}_t$ of 0.71 m/s.

The simulation results for the OV-FTL have a standard deviation of 0.42 m/s, the OVRV a standard deviation of 0.40 m/s, and the simulation results for the IDM have a standard deviation of 0.25 m/s. The OV-FTL and OVRV have subtle difference in speed velocity fluctuation across the simulation time, yet they are both closer to the experimental data than the IDM.

The time mean spacing standard deviation $\bar{\delta}_st$ of the experimental data is 3.02 m, while the simulated data from the OV-FTL has a standard deviation of 4.19 m, the OVRV simulated data has a standard deviation of 3.71 m, and the IDM simulated data has a standard deviation of 2.58 m. The time spacing fluctuations for the OVFTL and the OVRV are larger than the experimental data, but the IDM is closer to the experimental data.

The wave start time ($t_s$) is marked in Figure 7, the red line indicates when the wave has been detected. The wave starts at 10.10 s in the experimental testing data. In contrast, the OV-FTL wave starts around 8 s, and the OVRV wave starts around 7.03 s. It reveals the OV-FTL and the OVRV have subtle differences in wave start time which is around 2 to 3 seconds before the experimental data. The IDM is not in the comparison, because Figure 5 shows that under the simulated conditions, the IDM does not have consecutive oscillatory waves.

For the IDM, although the metrics in Table 3 show this model does not capture the full extent of the oscillatory traffic conditions observed in the experimental data. However, it is important to note that the IDM is a realistic model that, with sufficient stimulation noise applied, is capable of producing
realistic oscillatory traffic simulations. For example, using $\epsilon \sim N(0,0.4)$ as shown in the simulation results in Figure 8. The traffic flow metrics for this simulation are $\bar{\delta}_v = 0.83 \text{ m/s}$, $\bar{\delta}_s = 2.05 \text{ m}$, $\bar{\delta}_t = 0.77 \text{ m/s}$, $\bar{\delta}_s = 3.54 \text{ m}$, the wave start time is 0.8 s. Comparing with the experimental data in Table 3, four metrics simulated using this noise show closeness to the experimental test data. However, the wave start time is much earlier than the experimental data due to the high magnitude of noise. Since the OV-FTL and OVRV show similar simulation results, we believe the OVRV and the OV-FTL can both be used to simulate the development of oscillatory traffic.

Table 3: Comparison of traffic flow metrics for each model.

<table>
<thead>
<tr>
<th></th>
<th>Exp. A (test)</th>
<th>Exp. B (train)</th>
<th>OV-FTL</th>
<th>OVRV</th>
<th>IDM</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\bar{\delta}_v$</td>
<td>0.95</td>
<td>0.81</td>
<td>0.57</td>
<td><strong>0.61</strong></td>
<td>0.31</td>
</tr>
<tr>
<td>$\bar{\delta}_s$</td>
<td>2.19</td>
<td>2.17</td>
<td><strong>1.81</strong></td>
<td>1.40</td>
<td>0.64</td>
</tr>
<tr>
<td>$\bar{\delta}_t$</td>
<td>0.71</td>
<td>0.61</td>
<td><strong>0.42</strong></td>
<td>0.40</td>
<td>0.25</td>
</tr>
<tr>
<td>$\bar{\delta}_s$</td>
<td>3.02</td>
<td>3.53</td>
<td>4.19</td>
<td>3.71</td>
<td><strong>2.58</strong></td>
</tr>
<tr>
<td>$t_s$</td>
<td>10.10</td>
<td>10.63</td>
<td><strong>8.00</strong></td>
<td>7.03</td>
<td>-</td>
</tr>
</tbody>
</table>
CHAPTER 6: CONCLUSIONS

In conclusion, three car-following models are calibrated and simulated for each individual driver using a comprehensive microscopic car following trajectory dataset. The calibrated parameter values show the variability of individual driver behavior. By testing with five traffic flow metrics, the results show that OV-FTL and OVRV have similar ability to reproduce oscillations, while the IDM does not exhibit traffic waves when simulated under the same noise. These calibrated models can be used in further microscopic traffic simulations to understand the impacts of heterogeneous traffic flow with other agents such as autonomous vehicles.

Figure 7: Wave start time for each model simulation.
Figure 8: IDM velocity, trajectories, and spacing with an elevated noise of $\epsilon \sim N(0, 0.4)$ added to the velocity to introduce sufficient perturbations.
REFERENCES


