PREDICTIVE MODELING OF MAMMAL FIBER DEFLECTION IN LAMINAR FLOW

ALEXANDRIA CARTER
DEPT. OF BIOMEDICAL ENGINEERING
UNIVERSITY OF TENNESSEE KNOXVILLE

DOUGLAS SHU
DEPT. OF COMPUTER SCIENCE AND ENGINEERING
UNIVERSITY OF FLORIDA

MILOS KRSMANOVIC
DEPT. OF MECHANICAL AND AEROSPACE ENGINEERING
UNIVERSITY OF CENTRAL FLORIDA

FURKAN CIMEN
DEPT. OF COMPUTER SCIENCE
UNIVERSITY OF CENTRAL FLORIDA

DAMLA TURGUT
DEPT. OF COMPUTER SCIENCE
UNIVERSITY OF CENTRAL FLORIDA

ANDREW DICKERSON
DEPT. OF MECHANICAL ENGINEERING
UNIVERSITY OF TENNESSEE KNOXVILLE

ABSTRACT

This study explores the use of machine learning in combination with fluid dynamics to predict the biomechanical behaviors of different mammal furs in a variety of flow states. As these states vary, the drag upon furs can be modeled similar to the nonuniform loading of a beam containing complex static and mechanical relationships inspiring the use of machine learning.

INTRODUCTION

- Biomechanics can teach about:
  - **efficiency potential in fluid mechanics**
  - biomechanical properties like **hydrophobicity and anti-fouling capabilities**
- Highly nonlinear deflection of fibers exposed to flow yield nonuniform forces along fiber
- Machine Learning (ML) can take experimental knowledge to new heights

METHODS

- Fluid passes over fur to create **laminar flow with vortex shedding** inside fur-containing flow cell
- Camera set to 576 x 602 resolution, 500 frames per second, and exposure set to capture only fur (darkest feature)

RESULTS AND ANALYSIS

99.1 Gradient Boosting Accuracy

98.1 Support Vector Accuracy

98.1 Random Forest Accuracy

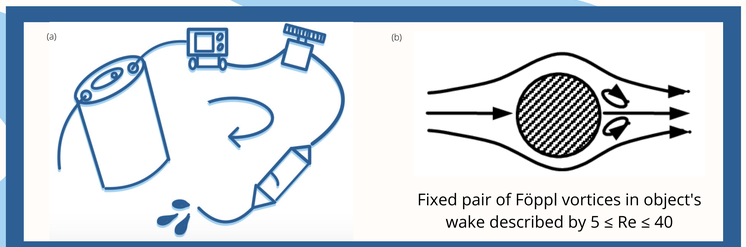

Figure 2: System design and motivation for such seen by (a) physical system used during experimentation in coordination with high speed camera for video capture and (b) the fluid mechanical reason for choosing design seen in Figure 1 to accomodate appropriate Reynold's number for laminar flow with minimal vortex shedding

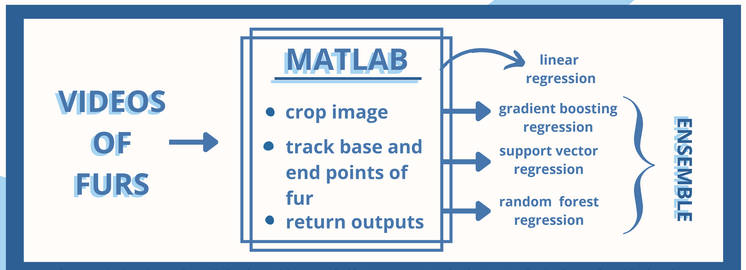

Figure 3: Code schematic outlining how videos are fed into MATLAB to obtain outputs in the form of usable data from independent variables controlled during experimentation. These variables are then processed by a machine learning script containing linear regression and a stand-alone ensemble yielding accuracy scores as data in trained and tested

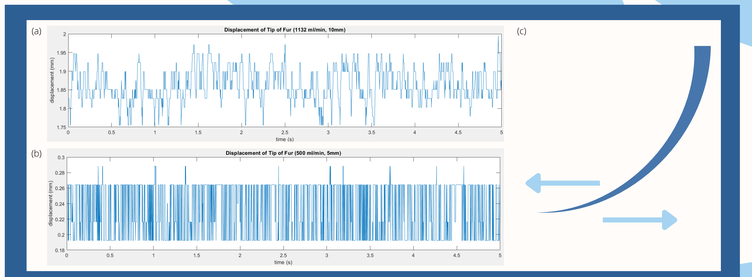

Figure 4: Fur motion described by (a) plot of displacement v. time of 10 mm coyote fur at flow rate 1132ml/min, (b) plot of displacement v. time of 5 mm coyote fur at flow rate 500ml/min and (c) the motion of fur being described in each plot with a fixed end inside laminarizing flow cell

Table 1: Describing all variables which outline up-to-date experimentation thus far. There exist five flow rate group split into 25 unique flow rates per group. There were three fibers and animals furs used during experimentation as well as three lengths used. These lengths are represented by numbers 5, 10, and 15 represnting the fur length in millimeters

	Type of Fur/Fiber								
Flow Rate mL/min	Nylon			Coyote			Beaver		
400-700	5	10	15	5	10	15	5	10	15
700-1000	5	10	15	5	10	15	5	10	15
1000-1300	5	10	15	5	10	15	5	10	15
1300-1600	5	10	15	5	10	15	5	10	15
1600-1900	5	10	15	5	10	15	5	10	15

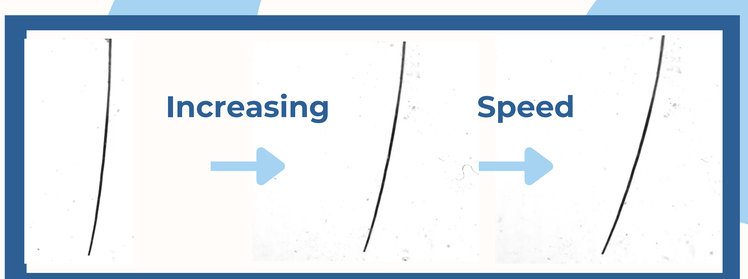

Figure 5: Fur motion and curvature in order (a) 10 mm coyote fur curved due to 546 mL/min flow rate, (b) 10 mm coyote fur curved due to 1300 mL/min flow rate, and finally, (c) 10 mm coyote fur curved due to 1896 mL/min flow rate

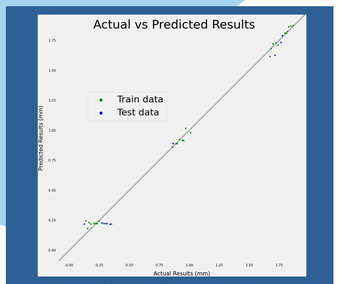

Figure 6: Describes results of ML ensemble and its accuracy in predicting outputs based on fed input

CONCLUSIONS

- Inputs **fur length and flow rate** yield outputs like **mean curvature of fur** as well as **average and maximum displacement**
- Accuracy of 98.9% is produced from **linear regression model**
- Ensemble outputs **99.5% accuracy**
- Small data sets still yielded significant training and accurate testing

FUTURE WORK

- Optimize ML ensemble to create **efficient, accurate, and precise model** to predict variable outputs consistently
- Continue data collection with varying fluids to add additional variable into machine learning ensemble
  - **more inputs than outputs yields increased optimization**

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References