Online Soil Classification Using a UAS Sensor Emplacement System*

Adam Plowcha, Jacob Hogberg, Carrick Detweiler, and Justin Bradley

Department of Computer Science and Engineering
University of Nebraska-Lincoln, Lincoln NE 68588, USA,
adam.plowcha@huskers.unl.edu, jhogberg@unl.edu, carrick@cse.unl.edu,
jbradley@unl.edu

Abstract. Deployment of sensors in hard-to-access locations can improve data gathering for scientific studies. We have developed a sensor emplacement system that can be mounted to unmanned aircraft systems with vertical takeoff and landing capabilities to autonomously auger a sensor into the ground. Various techniques can be chosen to enhance the augering process when certain characteristics of the soil are known. Moisture content and compressive strength are the soil characteristics that most impact the augering process, yet directly measuring them would require additional sensors to an already-burdened airframe. We address this through a novel means of predicting these soil characteristics within the first 30 seconds of an average 85 second augering evolution using onboard sensors and a Gaussian process regression scheme that predicts the soil moisture content and compressive strength with accuracy of 86.53% and 90.53% of the respective measured values.

Keywords: soil classification, field robotics, machine learning

1 Motivation and Problem Statement

Remote deployment of sensors in hard-to-access locations can enable improved data gathering for scientific study. Some sensors, such as seismic or soil moisture sensors, function best when placed into the soil. We have developed an in-ground sensor emplacement system for an unmanned aircraft system (UAS) capable of remotely augering these types of sensors into the soil (Figure 1).

Fig. 1: Sensor emplacement system.
a) Augering b) Emplaced sensor

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The general concept of operations for our system is as follows. The UAS arrives in the area where the sensor is to be placed and lands. It then uses a custom augering mechanism to drill a sensor into the ground [8, 13]. If the system cannot successfully emplace the sensor into the ground, then it relocates to a new location and tries again. If sensor emplacement is successful, then the UAS departs the area.

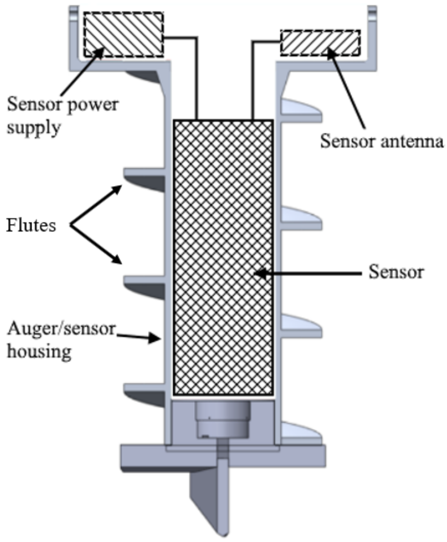


Fig. 2: Auger with internal sensor

The sensor is housed inside the body of the auger which is left behind at the completion of the emplacement sequence. The sensor can be any sort of generic device that can fit inside the 100 mm long by 35 mm diameter hollow section of the auger body (see Figure 2). The emplacement system is mechanically robust and allows for fine control of the downforce delivered on bit as well as the revolutionary speed of the auger itself. The auger's vertical position in the soil column and the downforce on bit is controlled by an advanced elevator platform that allows for rapid up and down movement enabling us to employ a technique known as "pecking" [4, 6]. The upward movement of the pecking motion allows soil that has been broken up and potentially clogging the lower portions of the auger flutes to be transported up and out of the hole. This creates space for the soil in the bottom of the hole to move into the newly vacant flute areas when the auger is pushed back down into the hole. Soil parameters determine the choice of an effective pecking profile, i.e. the speed and distance of the peck.

Augering and, if necessary, relocating to a new location place considerable demand on the available energy stored in the system's batteries. Therefore, efficiently emplacing the sensor or rapidly determining that a new a location must be tried are two key factors in the overall success of our system. Emplacing the sensor as fast as possible and with the greatest chance of success requires continuous adjustment of the auger's rotational speed, downward force, and pecking motions but is highly dependent upon key soil parameters (e.g., water content). As a result, knowledge of soil parameters, especially during augering activities, greatly increases the chance of a fast and successful sensor emplacement or determination of imminent failure.

In this paper, we describe a novel, online soil classification strategy that takes information from the on-board sensor suite and determines key soil parameters, enabling us to adjust our augering strategy in real time or quickly determine that a new location must be tried. Previous work has estimated the relative hardness of a surface with a UAS [2, 3, 11], although these methods did not leverage an in-ground emplacement augering system that makes direct contact with lower layers of the soil. This capability, including direct interaction with the soil, provides a rich dataset from which an online classifier can be trained.

Soil classification covers a wide range of parameters [1], however, for the purposes of in-ground sensor emplacement to 150 mm, we have found water content and soil compressive strength are the characteristics that most greatly impact the chance of successful emplacement. These key characteristics help us determine how much downforce, torque, and speed to apply, whether or not to engage higher level augering strategies (e.g., pecking), and predict whether or not the current digging effort will be successful. However, direct measurement of these parameters is difficult and would require additional equipment to be mounted to the UAS, which cannot be done with current size, weight, and power restrictions. As a result, we leverage auger RPM, motor current use, downward force on the auger, and system vibration levels on the UAS, alongside a custom classifier to determine the water content and compressive strength of the soil.

Rocks, tree roots, or other impediments can prevent emplacement of the sensor. However, the highly stochastic nature of their locations in soil make prediction especially difficult. Here, we focus on regularly predictable soil parameters that impact emplacement in the absence of significant halting impediments. This paper makes the following contributions:

- A novel classifier for soil water content and compressive strength through indirect means
- A comparison of various machine learning technique in their application to classifying soil water content and compressive strength
- A large, expansive data set of 2.8 million points of data over 150 augering evolutions

The on-board sensors used to classify a soil in terms of its water content and compressive strength are not the respective purpose-built moisture sensors and penetrometers, but rather the sensors used for monitoring the system performance of the auger mechanism: auger motor RPM, auger motor current use, weight on auger bit, system vibration (via accelerometers), and time. The data from these sensors is analyzed using machine learning techniques such as decision trees, linear discriminant analysis, naive Bayesian analysis, k-nearest neighbor (knn) analysis, and Gaussian process regression. We also examine the effectiveness of each technique in assessing the soil composition within the first *30 seconds* of an emplacement operation. Barring any stoppages of the emplacement process, it takes a minimum of 60 seconds to emplace a sensor. This minimum time is increases with an increase in sensor (and subsequent auger) size. We show that Gaussian process regression outperforms the other methods at the 30 second mark with an overall average predictive accuracy of 86.53% when determining moisture content and 90.53% when determining soil compressive strength.

2 Related Work

Machine learning can be used to classify or predict new data based on previously observed values. Our work examines the effectiveness of decision trees, linear discriminant analysis, naive Bayes prediction, k-nearest neighbor, and Gaussian process regression to predict the current values of moisture and soil compressive strength based on the sensor data available to our sensor emplacement system while engaged in an augering evolution. These particular algorithms have been previously employed in the analysis of soil composition.

Pekel examined the use of decision trees to predict soil moisture using atmospheric measurements obtained from stationary HOBO U30 weather data loggers as predictors [7]. The loggers are left in the field and gather data over several days. Suthar used eight soil-specific predictors, to include moisture content and the amoung of lime sludge present, to predict the compressive strength of stabilized pond ash [14]. Gathering these parameters from a given soil sample required transport of the sample to a lab and upwards of seven days of curing. Valaee et al. have used linear discriminant analysis and the magnetic properties of soil measured by external instruments such as Kappameters to predict its moisture content [15]. Yamaç et al. predicted moisture content of soil using k-nearest neighbor analysis with lime content, organic matter, soil particle size, and bulk density as predictors [16]. Rajeswari and Arunesh used naive Bayesian analysis to classify soil in terms of iron content versus organic content [9]. For these last two, organic content was analyzed using a LECO CN-2000 combustion oven that was not located at the sample site.

In all of the aforementioned works, measuring the parameters to be used in the prediction schemes required either equipment or facilities not available for a UAS-sized platform. Additionally, these methods often require the sampling and removal of material from the environment. The material must be analyzed external to the device using the predictive policy in order to provide inputs for that policy [14, 16, 9]. This is where our approach differs from the above. While, like the other approaches, we generate our policy offline, our system is able to gather the required data in situ and use it in our predictive policy as it is being gathered. Our approach to analyzing soil moisture and compressive strength is unique in that we use the sensors internal to our emplacement system during the physical act of drilling into the soil to determine our predictions.

3 Technical Approach

3.1 Description of the Emplacement System

The sensor emplacement system is a modular design that can be mounted to the underside of unmanned aircraft systems that have vertical takeoff and landing capability. The system is housed in an aluminum chassis that can be adapted to fit on any applicable air frame capable of operating with a 2.7 kg payload and supplying the system with 24 volts DC.

The emplacement system (Figure 3) consists of an auger with a 150 mm long shaft and diameter of 75 mm. It is attached to a T-Motor A80-6 24 volt brushless

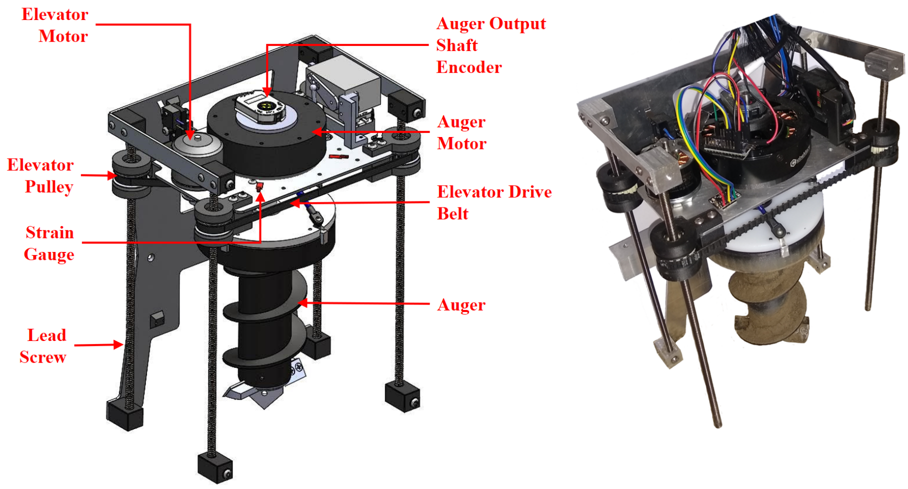


Fig. 3: Emplacement mechanism: model (left) and system (right)

motor with an integral planetary gear transmission and rotary encoder used for measuring auger RPM. During augering operations, a proportional control law is used to maintain auger rotational speed at 200 RPM. In difficult soil conditions where maintaining 200 RPM causes excessive current draw, auger RPM is allowed to decrease in order to maintain safe operating conditions for the auger motor. The auger motor is capable of outputting continuous 6 Nm of torque under a 12 A load. The motor/auger combination is mounted to an aluminum plate that advances downward at a rate of 0.1375 cm/s during augering operations. Strain gauges mounted to the elevator plate measure vertical force applied during augering. An inertial measurement unit (IMU) mounted to the aluminum plate provides data for vibration analysis. The elevator consists of a smaller T-Motor MN3520 brushless motor, driving a belt connected to pulleys on each corner of the aluminum plate to raise or lower the aluminum platform on four lead screws. A rotary encoder is calibrated to measure the vertical distance the platform travels. An Odrive Robotics motor controller is used to control the auger and elevator motors, while an ATMega-based microcontroller is used as the primary computing device that manages communications with the Odrive controller and outputs the various measured parameters via serial connection.

For this work, the emplacement system is mounted to an aluminum frame for ease of testing, although normally the system is attached to an unmanned aircraft as shown in Figure 1.

3.2 Measured Parameters

The following parameters are continuously monitored by the emplacement system and output to a serial communications line at a rate of 10 Hz. Their values provide quantitative insight into the augering process and are aggregated to classify the type of soil.

- Revolutions per minute of the auger motor - measured in RPM
- Current draw of the auger motor - measured in Amps
- Weight on auger bit (WOB) - measured by the strain gauges in kg
- Elevator position relative to top - measured in cm
- Acceleration in the X, Y, and Z axes - measured in m/s^2
- Time - each line of logged output is timestamped in seconds

3.3 Soil Parameters of Interest

Soil can be described by various parameters ranging from its particle sizes to its organic material content [1]. In our case, we are concerned with the physical properties that have the most impact on successfully augering into the soil. In our previous work, we have have determined that higher moisture content and/or higher compressive strength coincide with a reduced chance of success for an augering evolution [8, 13]. An increase in moisture leads to an increase in friction between the soil and the auger surfaces. Higher compressive strength means the soil is more compact and requires that more force be applied in order to loosen the soil for transport up the auger's flutes.

4 Experimental Setup

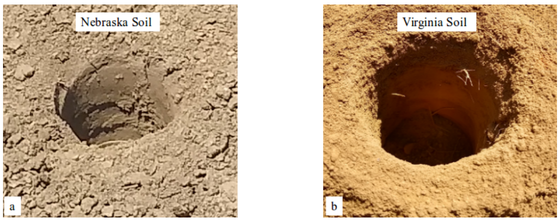


Fig. 4: Representative soil types - a) shows the higher clay content of the Nebraska testing area (with Pennsylvania being similar), and b) shows the relatively more sandy soil of the Virginia testing area (with Kentucky being similar)

We conducted 150 trials of our emplacement system in order to gather the required data for our analysis. 110 trials were conducted in the silty clay soil commonly found in eastern Nebraska with an additional 40 trials conducted between north central Pennsylvania, western Virginia, and north central Kentucky. The soils in Nebraska and Pennsylvania exhibited similar characteristics to each other, with each having a higher clay content than the soils in Virginia and Kentucky. Figure 4 shows the relative differences in the soils.

To obtain truth data, we manually measured the soil moisture content and soil compressive strength with tools and techniques accepted in the pedology community: a capacitive moisture sensor, volumetric analysis, and pocket penetrometer [1, 10, 12]. Specifically, the percentage of soil moisture was measured with a capacitive device for each trial, with every tenth trial verifying the moisture content by volumetric means (i.e., weighing the soil before and after baking the moisture out in an oven). The moisture values over the 150 trials ranged from

5% to 80%. Measurements were taken in the upper, middle, and lower thirds of the soil column at the completion each augering operation (see Figure 5).

The unconfined compressive strength of soil is defined as the amount of force required to crush or displace the soil within a given area [10, 12] and is measured in kg/cm^2. The soil in our trials was measured with a pocket penetrometer by probing the side wall of the resultant hole left by the auger. Measurements were taken near the surface, in the middle third of hole, and at the bottom (Figure 5). The compressive strength values over the 150 trials ranged from 0.5 kg/cm^2 to 4.6 kg/cm^2. Figure 6 shows the distribution of these measurements.

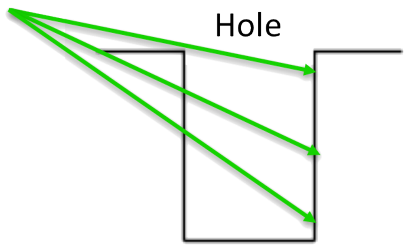


Fig. 5: Soil measurement locations in the upper, middle, and lower thirds of an excavated soil column

The initial 4 trials were conducted indoors using an 18 liter bucket filled with soil that was compressed to the desired soil strength using a hydraulic press. The remaining 146 trials were conducted outdoors in areas where soil moisture content and compressive strength varied in order to gather data over a range of soil conditions. Figure 7 shows the indoor testing area and a representative outdoor testing area.

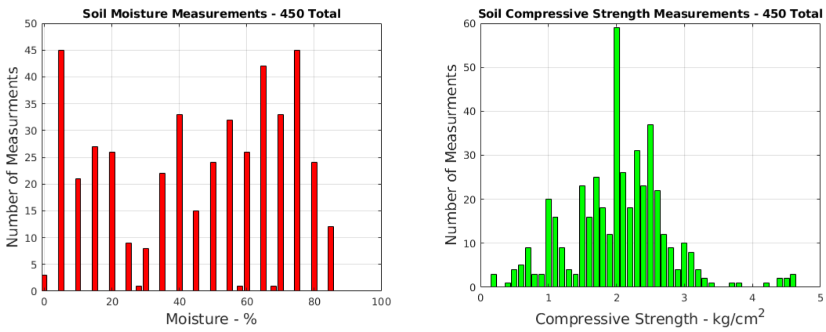
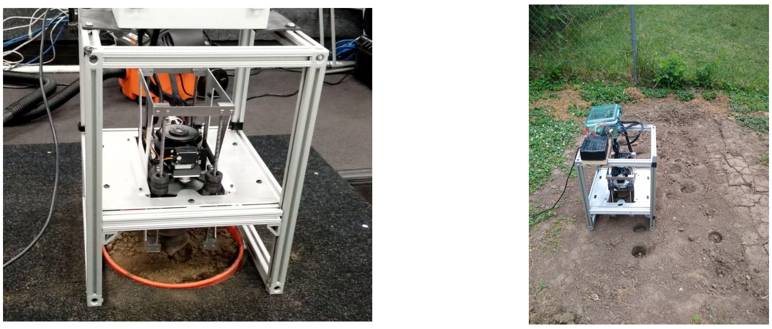


Fig. 6: Distribution of soil measurements taken over the 150 trials

Auger RPM, auger current, auger depth, weight on bit, and acceleration values were logged at a rate of 10 Hz during each augering evolution. These parameters were then used as predictors in the following machine learning algorithms:

- Decision tree
- Linear discriminant
- Naive Bayes
- K-Nearest neighbor
- Gaussian process



(a) Indoor testing

(b) Outdoor testing

Fig. 7: Testing areas

5 Experimental Results

Figure 8 shows a representative plot of the parameters we monitored during each trial of our system: auger RPM, auger motor current, weight on bit, depth, acceleration, and time. These parameters are used as the predictor variables in following survey of classification/regression schemes: decision tree, linear discriminant, naive Bayes, k-nearest neighbor, and Gaussian process regression. The responses in these schemes are our desired soil moisture content and soil compressive strength. We use Matlab®'s "fitctree()," "fitcdiscr()," "fitcnb()," "fitcknn()," and "fitrgp()" methods to generate our predictive models [5]. We randomly chose 50 of our trials to provide the training data for our classification schemes. We then simulated our predictive models against the data from our remaining 100 trials.

As one of our main goals is to determine the soil moisture content and compressive strength as quickly as possible, we examine the predictive accuracy of our models at 5, 10, 20, and 30 seconds into an augering evolution. We define predictive accuracy as how closely a model calculates the soil moisture content or compressive strength compared to the actual measured value for that trial at the auger depth for the given point in time. Table 1 shows the results of our simulations. Gaussian process regression was the most accurate prediction method during all phases of an augering evolution.

Additionally, we examine how the choice of predictors can influence the accuracy of the chosen classification/regression schemes. In our previous work we used auger RPM, auger motor current, auger depth, and time to predict whether an augering evolution would succeed or not [8]. For that work, we were limited to those four parameters as a function of the system design. Our current emplacement system is a complete redesign of our initial system and allows for the addition of recording weight on bit and acceleration values. Table 2 shows an increase in predictive accuracy for our Gaussian process regression when incorporating weight on bit and x, y, and z axis acceleration values.

Accuracy		**Decision Tree**	**Linear Discriminant**	**Naive Bayes**	**k-Nearest Neighbor**	**Gaussian Process**
5 Second	Moisture Content	82.29%	83.54%	84.66%	84.85%	**86.86%**
	Soil Strength	86.34%	89.59%	85.25%	87.44%	**89.92%**
10 Second	Moisture Content	86.34%	84.44%	86.40%	85.81%	**88.86%**
	Soil Strength	88.03%	86.57%	84.58%	87.40%	**90.02%**
20 Second	Moisture Content	85.96%	82.07%	84.98%	85.83%	**87.90%**
	Soil Strength	88.63%	85.11%	88.00%	87.36%	**90.65%**
30 Second	Moisture Content	76.36%	70.99%	80.59%	76.85%	**82.51%**
	Soil Strength	88.18%	90.02%	90.70%	87.38%	**91.51%**
Average	Moisture Content	82.74%	80.26%	84.16%	83.34%	**86.53%**
	Soil Strength	87.79%	87.82%	87.15%	87.39%	**90.53%**

Table 1: Prediction scheme accuracy

Accuracy		**RPM, Current, Depth, Time**	**RPM, Current, Depth, Time, WOB, Acceleration**
5 Second	Moisture Content	84.29%	**86.86%**
	Soil Strength	89.11%	**89.92%**
10 Second	Moisture Content	86.07%	**88.86%**
	Soil Strength	89.60%	**90.02%**
20 Second	Moisture Content	87.34%	**87.90**%
	Soil Strength	**90.96**%	90.65%
30 Second	Moisture Content	82.20%	**82.51%**
	Soil Strength	91.31%	**91.51%**
Average	Moisture Content	84.98%	**86.53%**
	Soil Strength	90.24%	**90.53%**

Table 2: Prediction accuracy with original system parameters (3^{rd} column), compared with new system parameters (4^{th} column).

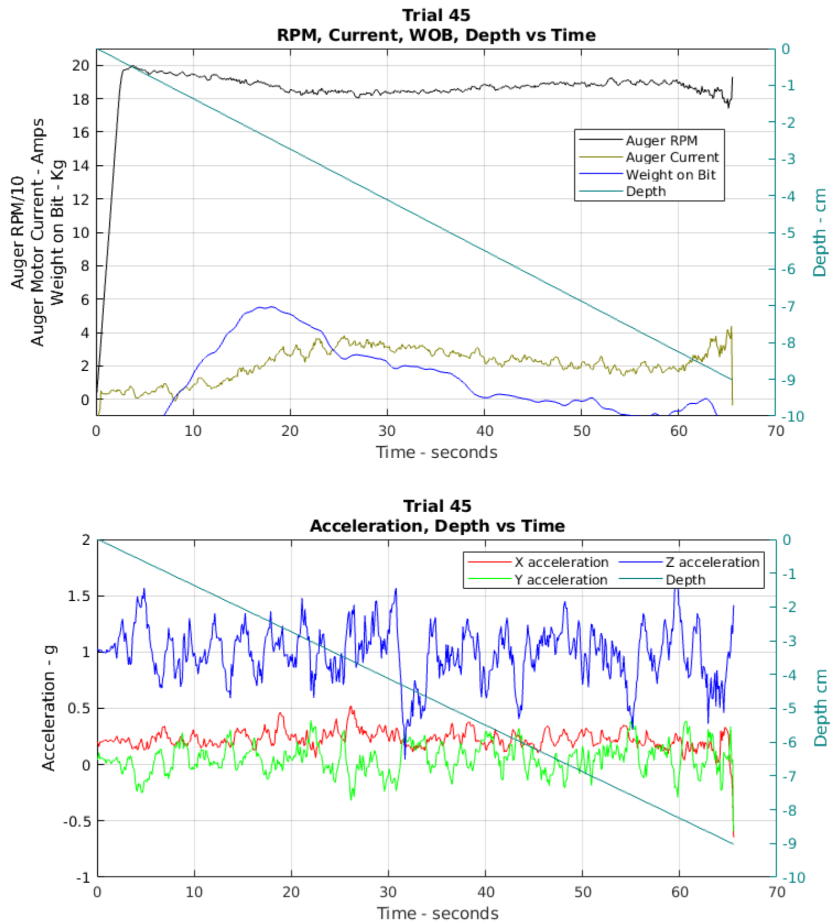


Fig. 8: Example of parameters gathered during system trials. The top graph shows auger RPM, motor current, weight on bit, and depth over time. The bottom graph show accelerations in the x, y, and z axes and depth over time

6 Conclusion and Future Work

We show that it is possible to predict soil moisture content and compressive strength using the available sensor that provide auger RPM, auger motor current, auger depth, weight on bit, and acceleration data. Gaussian process regression generates the most accurate policy of the schemes that were tested. It can predict within the first 30 seconds of an average 85 second augering evolution the soil moisture content within 86.53% of the actual value and soil compressive strength within 90.53% of the actual value.

Encoding this policy on the hardware that controls the augering mechanism is the next step in our research. Additionally, this will allow us to use the real-time predicted soil composition to adjust our augering technique in order to optimally drill our sensor into the soil.

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