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NyRoNet: Optimization of the Receiver Nyquist Rate for Image Distortion Correction of an Underground Imaging Antenna using Matern 5/2

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Abstract: In locating subsurface utilities, one known method is a surveying system towed by trailers employing electrical resistivity tomography (ERT). However, the primary issue with subsurface surveying with towing mechanism is the change in speed caused by unavoidable obstructions and sloping road surfaces since it affects the sampling logging of the system. With that, this study develops a novel technique for fast exploration of extensive transects using optimized receiver sampling rate as a function of velocity, current, power, slope angle, and voltage. Furthermore, regression models such as regression tree (RTree), gaussian process regression (GPR), support vector machine (SVM), and ensemble regression (ER) were used for model optimization. The Nyquist rate optimization network (NyRoNet) will be contemplated as the best-performing prediction model. To avoid data deformation in land surveying, the intended output is a sampling rate that will adapt in slow-down or elevated road conditions. In modeling, the GPR outperforms the RTree, SVM, and ER based on the RSME, SME, MAE, and R^2 values, which were utilized as evaluation metrics in this study. Then, the MSE values of the different models of GPR, such as the rational quadratic (RQ), square exponential (SE), Matern 5/2, exponential, and optimized Gaussian process regression, were identified with $1.938e^{-10}$, $1.735e^{-10}$, $1.663e^{-10}$, $3.785e^{-6}$, and $3.254e^{-10}$ values, respectively. With this, Matern 5/2 regression model was considered as NyRoNet. Other evaluation criteria, such as the MAE and R^2, were also used, demonstrating NyRoNet's efficiency. To further verify the efficiency of NyRoNet, Matplot in MATLAB was utilized and enabled the sampling rate optimization and normalizing of the resistivity map.

Keywords: electrical resistivity tomography, gaussian process regression, image distortion, Nyquist rate, regression optimization

1. Introduction

The Philippines, along with other UN members, have pledged to attaining the 17 Sustainable Development Goals (SDGs) by 2030. These SDGs include an inclusive action plan for a wide spectrum of thematic issues which is also incorporated to the vision and goals of AmBisyon Natin 2040 [1], and to promote the DOST in implementing its 2022–2028 Harmonized National Research and Development Agenda (HNRDA) [2], [3] for long-term planning for infrastructure and resource allocations must continually adapt to the changing digital and technical landscape of the Fourth Industrial Revolution, often known as Industry 4.0. One method for locating underground utilities in road subsurface structures is to use trailers while employing electrical resistivity tomography (ERT) for field surveying. The main issue with electrical resistance tomography is the image reconstruction of ERT. The period of exploration in geophysical prospection can be closely linked to the device's traveling speed by using a high sample rate measurement device. In this instance, most of the measuring methods are towed or, at the absolute least, coupled to mobile equipment. Pulling the device suggests that current approaches must be improved to fit the new measuring method [4], [5]. However, a drawback of utilizing this technology for constant-frequency sampling rate is that the towing mechanism will influence the speed in response to the sloping road surface. A parallax distortion in the produced image may result in the inaccurate location of subsurface artifacts due to distortion, elongation, or an abridged result of the picture. One speed control method that achieved evenly spaced data was adding an odometer to the measuring system or towing vehicle and adding sensor arrays [6]. Road surface anomaly detection performances a crucial role in monitoring the condition of road surfaces [7], [8].

The geoinformation required for investigating underground utilities may be obtained by remote sensing, a crucial technique. Designing a controller that enables tracking arbitrary trajectories is important to keep the trailer electrical resistivity towed array moving at a constant speed [9]. The PID-based controllers used for speed control receive the vehicle's speed error and position data. In that case, underground imaging using intelligent speed control systems may accomplish dynamic surveying and data collection for land resistivity. However, the approach used in [10] was the standard Ziegler-Nichols and Quasi-Newton method for optimizing PID speed controller tuning. The improved control has outstanding performance in the presence of disturbances and is suitable for the proper use of rapid adjusting speed. Interestingly, the multi-objective grey genetic prediction was developed in [11] for the optimization of a high-speed train controller. A grey online correction module was employed to ensure a long and real-time prediction and enhance its effectiveness. Moreover, another optimization of PID parameters was performed in [12], where the Ant Colony algorithm was employed that dynamically selects the best parameters and adjusts the update strategy that caused the system to have better performance. To provide the least integral absolute error of the system in terms of speed demand, simulated results, and response another optimization technique was used with a new Particle Swarm Optimization algorithm [13].

With all the optimization techniques application, resistivity imaging also requires optimization of the system data logging for effective and efficient data processing and interpretation during the surveying. This emphasizes a critical problem since processing inconsistencies can escalate into systematic errors and impact the database's cumulative reliability and performance [14]. In high-speed data acquisition designs, the speed disparity between the front-end data collection unit and the backend data transmission and storage is a performance constraint. Also, obtaining a variable sampling rate in data gathering implies distortion of data and generates a deceptive pattern that leads to misinterpretations and might cause time, cost, and effort to dissipate. The objectives of this study encompass the utilization of correlation analysis, a statistical technique employed to discern relationships between variables, to examine aliasing which is the occurrence of unwanted components in the reconstructed motion, and to optimize the sampling rate's performance on sloping roads in relation to current, power, weight, road slope angle, velocity, and acceleration. Regression models will be used to optimize the sampling rate of the towing system's speed controller, especially regression tree (RTree), support vector machine (SVM), Gaussian process regression (GPR), and ensemble regression (ER) optimization approaches.

Using regression models for optimization evaluation in the context of uncontrolled and optimized controlled towing systems allows for a comprehensive analysis of the sampling rate optimization. They provide interpretable results, capture nonlinear relationships, offer flexibility in modeling approaches, have generalization capabilities, and provide performance metrics for comparison. These characteristics make them a suitable choice for assessing the effectiveness of optimization techniques in towing systems. The models were selected as these are all available in the Regression Learner App of MATLAB, which can train those regression models, data exploration, features selection, validation schemes, and results evaluation to offer significant improvements in terms of prediction accuracy, model flexibility, and optimization capabilities. The selected algorithms produce a sampling rate as their output that determines the appropriate sampling rate as a function of velocity, current, power, and inclination of the road. By comparing the results of sampling rate constructions, the most efficient algorithm was identified as NyRoNet. Using Matplot in MATLAB, resistivity maps sampling datasets with constant velocity, changing velocity, and optimized sampling rate are compared to provide significant considerations concerning the effects of each phase. Thus, this research work has the following contributions: (1) enhancement of depth measurement systems that operate through correcting factor of frequency sampling rate and speed up and down motion; (2) enhancement of accuracy and data distortion avoidance in subsurface surveying; and (3) further development in the data logging system of an underground imaging system.

2. Methodology

To fulfill the research's objective of improving the receiver sampling rate, four critical steps must be taken: (1) modeling of an electrically powered vehicle with a speed controller system; (2) electric vehicle simulation and generation of a dataset using proportional–integral–derivative (PID) controller in MATLAB Simulink; (3) performing regression optimization for the sampling rate using regression learning tool; and (4) simulation and generation of resistivity map using MATLAB Matplot for the validation of the effectiveness of distortion correction actor of the NyRoNet Fig. 1. In this framework, many efforts have been made to identify the most effective methodologies for optimization of sampling rate to gather appropriate and clear visualization of the resistivity map with the function of current, velocity, power, and mass of electric vehicle simulated in MATLAB Simulink including the slope angle and banking of road. The data processing outputs accuracy, survey picture resolution, and overall system performance are determined by the data acquisition subsystem and synchronization mismatch between the backend data transmission and storage's comparatively slow data transfer, and the front-end sampling techniques unit that was quickly accumulating big data.

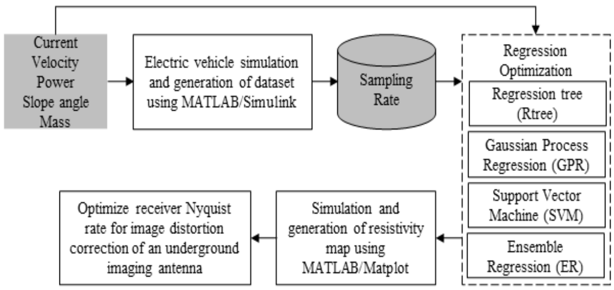

Figure 1. System design architecture for the optimization model of receiver Nyquist rate of an underground imaging antenna.

A. Electrical Vehicle Design

Simulink in MATLAB R2020a was used to model each element of the e-vehicle system. These individual models were then interconnected through block diagrams, forming a comprehensive representation of the entire e-vehicle system. The longitudinal driver, responsible for controlling the vehicle's motion along its axis, was integrated into the model as well. The configuration of the vehicle body structure is presented in Table 1. In contrast, the subsurface imaging system used in this work comprises of an electric vehicle-powered tower, seven body trailers with one transmitter and six receiver antennas as presented in Fig. 2. These antennas played a crucial role in capturing and transmitting relevant information for the underground imaging process.

TABLE I. ELECTRIC VEHICLE BODY, BATTERY, AND DC MOTOR PARAMETERS

Component	Specification
E-vehicle + trailer + weight of driver	250 kg
Gravitational acceleration	9.81 m/s^2
Frontal area	1 m^2
Drag coefficient	0.4
Air density	1.18 kg/m^3
Battery	
Voltage	48 Vdc
Chemical	Lithium-ion
Rated capacity	25 Ah
DC Motor	
Rated load (mechanical power)	750 W
No load speed	3100 rpm
Rated speed	2800 rpm
Rated DC supply voltage	48 V

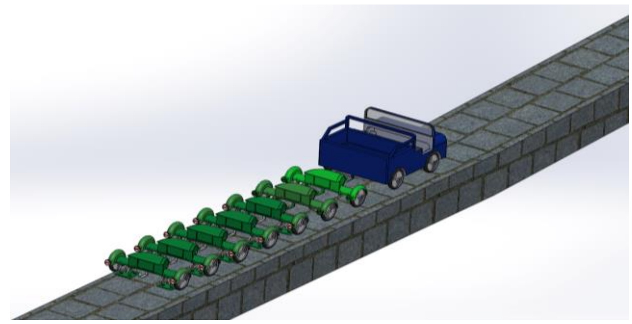

Figure 2. Electric vehicle Simulink model

B. Vehicle Performance and Data Acquisition

Simulink is a widely used selection in control development. Providing a variety of real advantages, including a general decrease in development time, and cost due to the elimination of auxiliary operations, as well as a consistent and repeatable virtual testing environment and development procedures [15,16]. The constant velocity required to produce a quality result is 1.6667 m/s to reduce parallax error during measurement. Several inputs such as the present velocity, current, slope angle, voltage, and power are considered and simulated using Simulink. The designed MATLAB Simulink model was shown in Fig. 3 which illustrates an electric vehicle with towed capacitive imaging trailer array model on an even straight-to-slope road. Then, a method for data sampling was suggested, and velocity readings were continuous and at varying percentages spread over the investigated region.

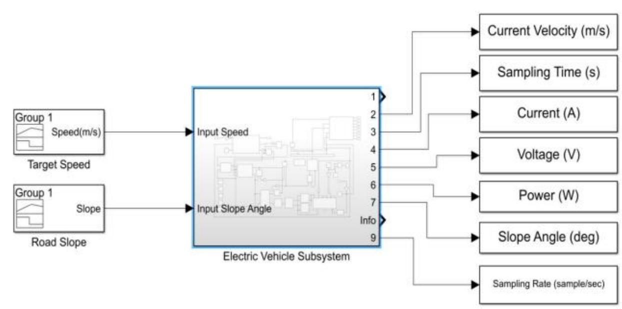

Figure 3. An electric vehicle with towed capacitive imaging trailer array model in even straight-to-slope road

C. Correlation of the Variables of NyroNet

Minitab 20 software was used to create a correlogram with the given correlation coefficients determined by sampling rate, velocity, current, power, slope angle, and voltage. A biplot of principle components (PC) based on correlation was also created using the same platform. The Pearson correlation gauges the linear connection between continuous variables. The coefficient of correlation is a useful indicator of the extent of the relationship between the variables. Minitab, statistical software is used to generate relationships among the process variables from the current, velocity, power, and mass of the electric vehicle. The Pearson product-moment correlation is employed to analyze the degree and trend of the relationship between two linearly related continuous variables. The coefficient of the relationship, r, which ranges from -1 for a perfect negative linear relationship to +1, indicates the relationship's strength and direction. No correlation exists between the two variables if the value is zero.

D. Regression Modeling of Sampling Rate

Regression analysis is a statistical procedure employed to predict the future functionality of a phenomenon or dataset [17]. Relatedly, regression modeling is the process to develop and determine a model that best fits with the given data set to perform future predictions [18]. The study population was made up of the following variables: sampling rate, predicted output fs, β0 is the y-intercept of the best-fit regression line, β coefficients represent the change in outcome compared to its x, v, I, P, m, and V values represents the predictors namely, velocity, current, power, slope angle, and voltage which is shown in Eq. 1. 36,050 datasets were sampled for 70% training, 20% validation, and 10% testing in fitness modeling. The Supervised Machine Learning Regression Learner Application in MATLAB R2022a and the NVIDIA GeForce RTX 2060 GPU were both employed to validate each model. The automatic, adaptive, and flexible modeling is strongly connected to these cross-validation methods, whereas the cross-validation manifold is 10 as set for all regression models. Model functions were characterized based on the regression learner using mean square error (MSE) in Eq. 2, mean absolute error (MAE) in Eq. 3, and coefficient of determination (R^2). Mean square error (MSE) in Eq (2), the mean absolute error (MAE) in Eq (3), as well as the coefficient of determination (R^2) were all used to characterize model functions based on the regression learner.

$$f(fs) = \frac{\beta 0}{\beta}(\mathrm{I}, \mathrm{v}, \mathrm{V}, \mathrm{P}, \mathrm{m}) \tag{1}$$

$$MSE = f(N_1, N_2, N_3) = \alpha - \beta N_1 - \gamma N_2 + \delta N_3 \tag{2}$$

$$MAE = \left(\frac{1}{N}\right)\sum\frac{N_{pred.}-N_{experiment}}{N_{experiment}}x100\% \tag{3}$$

Regression models are trained using MATLAB's Regression Learner tool, which may be accessed via the APPS ribbon. It can analyze the data of train models and interpret the data with this application. Users apply ensembles of regression trees, Gaussian process regression models, support vector machines, and linear regression models to carry out automated training to select the best regression model [19]. Regression tree models are one of the most widely used models due to the simplicity of the condition-action or if-else rules that can be represented by a tree. Regression tree models are created by repeatedly partitioning the data set and fitting a straight prediction model for every partition [20], [21]. The regression tree compromise of the fine tree, medium tree, coarse tree, and optimized tree.

$$f(fs) = \beta 0 + \beta^T(\mathrm{I}, \mathrm{v}, \mathrm{V}, \mathrm{P}, \mathrm{m}) + \dot{\epsilon} \tag{4}$$

The hyperparameters can be seen in Table 2 and the principal component analysis (PCA) was unused in all models. The recursive partition is represented by a tree in prediction trees. A simple model Eq.4 that only applies to that cell is attached to each of the terminal nodes, or leaves, of the tree, which each represent a cell of the partition. The points (I, v, V, P, m) are a leaf if it is in the partition of the corresponding cell. An important criterion for stopping is to stop expanding the tree when additional splits only add a small amount of additional information. Thus, a more effective way for identifying regression trees is by splitting the data into a training set, cross-validation set, and testing set at random from the previous run.

TABLE II. HYPERPARAMETERS CONFIGURED FOR THE REGRESSION TREE MODEL.

Regression Tree Model	Minimum Leaf Size	Additional Hyperparameter
Fine tree	4	N/A
Medium tree	12	N/A
Coarse tree	36	N/A
Optimized tree	3	Optimizer: Bayesian Iteration:30 Acquisition function: expected improvement per second plus

Gaussian Process Regression (GPR) models find extensive application in regression and classification tasks due to the ability to make predictions integrating prior knowledge called kernels and yield uncertainty measures over predictions made [22]. For GPR to function, the kernel function is generalized to be a definite continuous symmetric positive function of the existing features [23]. GPR is a non-parametric approach of regression that identifies a distribution across potential sampling rate functions that changes with the observed sampling rate data. GPR is composed of rational quadratic (RQ), square exponential (SE), Matern 5/2, exponential, and optimized GPR. Whereas the summarized hyperparameter for the GPR setting was shown in Table 3. GPR can be used to solve issues besides regression tree problems. Naturally, like to compare the quantitative reliability and validity of the many GPR that could be paired with the data set. The probability that a set of GPR outputs would be appropriate for the training set was divided using the Bayes theorem.

Optimizable SVM	Linear	1	0.87604

TABLE III. HYPERPARAMETERS CONFIGURED FOR GAUSSIAN PROCESS REGRESSION MODEL VARIANTS.

GPR Model	Kernel Function	Signal Standard Deviation	Sigma
RQ	Rational Quadratic	Automatic	automatic
SE	Squared exponential	Automatic	automatic
Matern 5/2	Matern 5/2	Automatic	automatic
Exponential	Exponential GPR	Automatic	automatic
Optimizable GPR	Nonisotopic Squared exponential (115,7272)	3.9638	54.2206

Support Vector Machines (SVM) constitute a powerful machine-learning technology for regression and classification tasks since they can obtain a subset of support vectors that reflects a classification job produced by a limited dataset from the initial information set during the training phase [24], [25]. SVM is composed of linear, fine Gaussian, quadratic, cubic, medium Gaussian, coarse Gaussian, and optimized SVM whereas the hyperparameter set for SVM was shown in Table 4. Access in SVM for quick and reliable classification algorithm that excels even with a small amount of data to analyze. Perhaps as turned a little deeper, came across terms like linearly separable, kernel trick, and kernel functions. Support vectors for the linear classifier are used to describe all the points that fall within this minimum distance. A point that is precisely on the classifier's margin is what is meant by a support vector. A set of points x_j and their categories y_j make up the training data. The $y_j = \pm 1$ and the $x_j \dot{\in} R^d$ for some dimension d. The hyperplane in Eq.5 defines the best decision boundary.

TABLE IV. HYPERPARAMETERS CONFIGURED FOR SUPPORT VECTOR MACHINES MODEL.

Support Vector Machines Model	Kernel Function	Kernel Scale	Epsilon
Linear	Linear	Automatic	Automatic
Fine Gaussian	Gaussian	0.56	Automatic
Quadratic	Quadratic	Automatic	Automatic
Cubic	Cubic	Automatic	Automatic
Medium Gaussian	Gaussian	2.2	Automatic
Coarse Gaussian	Gaussian	8.9	Automatic

The Ensemble Learning (EL) method utilizes multiple ML methods to generate regression results based on extracted features from datasets, that will combine with several voting processes to provide a finer model [26], [27]. EL is composed of boosted, bagged, and optimized EL while the hyperparameter set for EL was shown in Table 5. Although adequate in broad terms, linear regression's performance was too low when measured against the other approaches. The ensemble approach makes use of a different method that maximizes the contribution of each prediction to the combined forecast for a particular forecasting time, giving each method a different weight.

TABLE V. HYPERPARAMETERS CONFIGURED FOR THE ENSEMBLE LEARNING MODEL.

Ensemble Learning Model	Min. Leaf Size	Number of Learner	Additional Hyperparameter
Boosted trees	8	30	N/A
Bagged trees	8	30	N/A
Optimized ensemble	8	30	Number of predictors to sample: 1

3. RESULTS AND DISCUSSIONS

A. *Correlation of parameters*

To examine aliasing and optimize the sampling rate's performance on sloping roads, several parameters play a crucial role. Current, power, weight, road slope angle, velocity, and acceleration are all interconnected. The current supplied to the motor influence torque and power output, impacting the vehicle's acceleration and ability to overcome slopes. Power, determined by current and motor efficiency, affects the vehicle's resistance and ability to maintain the desired velocity. Weight influences overall performance and stability. The angle of the road slope directly affects force and the need for power. Velocity impacts resistances like aerodynamic drag and rolling resistance, requiring more power at higher speeds. Acceleration, influenced by slope, weight, and power, is vital to overcome resistive forces. Choosing an appropriate sampling rate is essential to avoid aliasing, and accurately capturing parameter variations. A comprehensive understanding of these correlations improves identify critical points for accurate sampling and optimizes system performance on sloping roads.

Using the 36,050 datasets and Minitab 20 software the calculation of correlation signifies the increase in velocity between transmitter and receiver dipoles towed in the vehicle increases the sampling rate and has weakly decreased during slopes shown in Fig. 4. This statement offers a thorough clarification of aliasing, which denotes the occurrence of extraneous components in the reconstructed signal that were not originally present in the source signal. In the event of an inadequate sampling rate, the reconstructed signal may exhibit a loss of specific frequencies from the original signal, leading to frequency convergence and consequent aliasing. Furthermore, the high-frequency components of the transmitter signal are susceptible to noise interference or may lack pertinent information. Additionally, it is important to highlight that variations in the current tend to align with fluctuations in power and are particularly influenced during transitional phases or slopes.

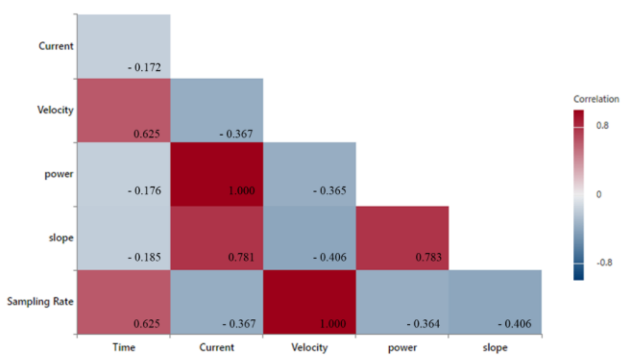

Figure 4. Correlogram of an electric vehicle with towed capacitive imaging trailer array parameter

B. *Dynamics of Regression Models of Sampling Rate*

The quantitative regression model for constant frequency sampling was determined using different supervised ML Regression models. Table 2 illustrates the regression models used to the result of their validation data in terms of RMSE, R^2, MSE, MAE, training time, and the coefficient of determination to the testing data [29]. Thus, the GPR outperforms the RTree, SVM, and ER with their RSME, SME, MAE, and R^2 values. The GPR consists of different model names, rational quadratic (RQ), square exponential (SE), Matern 5/2, exponential, and optimized Gaussian process regression with MSE of 1.938e-10, $1.735e^{-10}$, $1.663e^{-10}$, $3.785e^{-6}$, and $3.254e^{-10}$ respectively. The employed pre-processing and feature extraction operation have a significant impact on the totality of the regressor's performance that consequently made the GPR model Matern 5/2 kernel function as the best parameter for both the interpolative and extrapolative data. The NyRoNet and the Rational Quadratic (RQ) Gaussian process regression were notable, as illustrated in Fig. 6 which presents the comparison of target-predicted Nyquist Rate output of the Regression models [28], [29], [30]. However, NyRoNet completed an earlier convergence curve than the others, implying superior performance. Based on the line trend in Fig.5, it can be seen that it has the lowest MSE value.

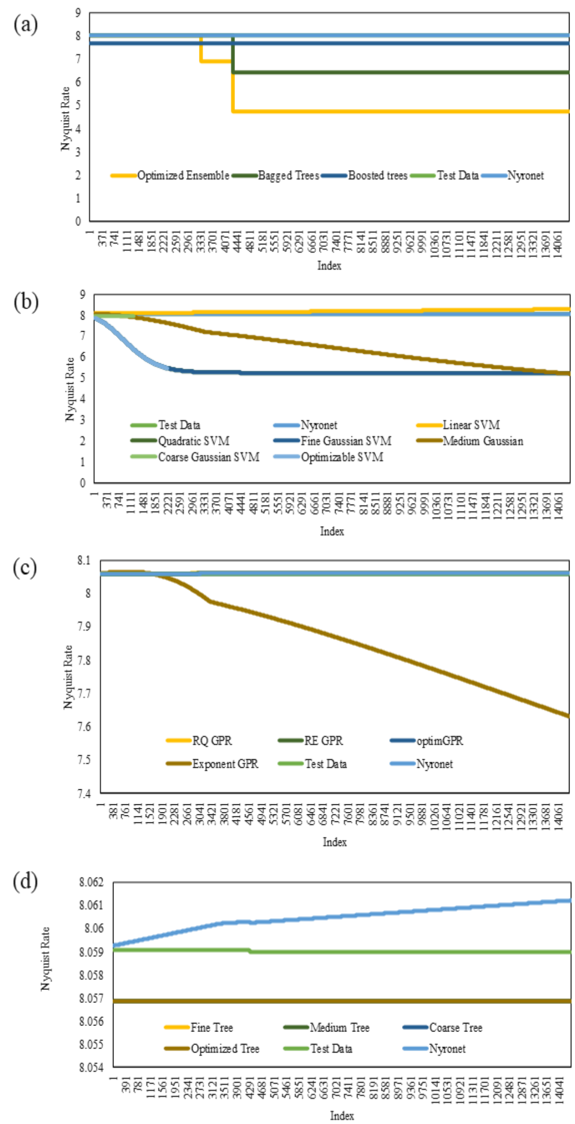

Figure 5. Comparison of target-predicted Nyquist Rate output of the Regression models of the test data and the developed NyRoNet Model: (a) Regression Tree, (b) Support Vector Machine, (c) Gaussian Process Regression, and (d) Ensemble Learning

The accuracy that may be acquired relies on data gathering factors including sample rate, trace intervals, and profile intervals. The sample rate should be high, and the trace and profile intervals should be brief to accurately visualize the subterranean structure. The LR, DTs, ensemble trees, SVMs, and GPR techniques, as well as their sub-methods, are all included in the MATLAB regression learner plugin. Table 6 displays a comparative graph of the regression models employed together with the testing data. The model that demonstrated the highest performance can be observed is the Matern 5/2 GPR with an R^2 value of 1.000 and 0.654, an MSE of $1.56e^{-7}$ and

$1.66e^{-10}$, and MAE of $3.14e^{-4}$ and $1.46e^{-3}$ with the validation data and testing data, respectively shown in Table 6. Other Regression models such as Rational Quadratic GPR and Squared Exponential GPR, also performed well with the test data. The regression model of Cubic SVM underperformed due to an erroneous performance exhibiting low R^2, high MSE, and MAE. With this, Matern 5/2 regression model was considered as NyRoNet.

TABLE VI. EVALUATION SUMMARY OF REGRESSION MODEL FOR PREDICTING NYQUIST RATE

Model		Validation					Testing		
		RMSE (%)	R (%)	MSE (%)	MAE (%)	Train time (s)	R (%)	MSE (%)	MAE (%)
Regression Tree	Fine Tree	$1.4e^{-2}$	1	$1.8e^{-4}$	$6.0e^{-3}$	3.20	$1.1e^{-15}$	$3.3e^{-10}$	$2.2e^{-3}$
	Medium Tree	$1.4e^{-2}$	1	$1.8e^{-4}$	$6.0e^{-3}$	2.16	$1.1e^{-15}$	$3.3e^{-10}$	$2.2e^{-3}$
	Coarse Tree	$2.2e^{-2}$	1	$4.9e^{-4}$	$8.2e^{-3}$	$7.96e^{-1}$	$1.1e^{-15}$	$3.3e^{-10}$	$2.2e^{-3}$
	Optimized Tree	$1.4e^{-2}$	1	$1.8e^{-4}$	$6.0e^{-3}$	29.9	$1.1e^{-15}$	$3.3e^{-10}$	$2.2e^{-3}$
Gaussian Process Regression	RQ GPR	$4.0e^{-4}$	1	$1.6e^{-7}$	$3.2e^{-4}$	410	$6.5e^{-1}$	$1.9e^{-10}$	$1.6e^{-3}$
	SE GPR	$3.9e^{-4}$	1	$1.5e^{-7}$	$3.1e^{-4}$	203	$6.5e^{-1}$	$1.7e^{-10}$	$1.5e^{-3}$
	Matern 5/2	$4.0e^{-4}$	1	$1.6e^{-7}$	$3.1e^{-4}$	356	$6.5e^{-1}$	$1.7e^{-10}$	$1.5e^{-3}$
	Exponential GPR	$6.3e^{-4}$	1	$4.0e^{-7}$	$1.4e^{-4}$	528	$6.2e^{-1}$	$3.8e^{-6}$	$1.9e^{-1}$
	Optimized GPR	$1.6e^{-14}$	1	$2.5e^{-28}$	$1\ e^{-14}$	$9.13e^{3}$	$1.1e^{-15}$	$3.3e^{-10}$	$2.2e^{-3}$
Support Vector Machines	Linear SVM	$1.0e^{-1}$	1	$1.1e^{-2}$	$9.0e^{-2}$	29.1	$6.0e^{-1}$	$3.8e^{-1}$	$1.3e^{-1}$
	Quadratic SVM	25.8	-145	$6.5e^{2}$	6.08	$1.60e^{3}$	$5.9e^{-1}$	$5.0e^{-1}$	294
	Fine Gaussian SVM	$1.4e^{-1}$	1	$1.8e^{-2}$	$1.5e^{-1}$	18.8	$3.3e^{-1}$	$5.0e^{-1}$	2.60
	Medium Gaussian SVM	$1.1e^{-1}$	1	$1.3e^{-2}$	$9.9e^{-2}$	28.1	$6.7e^{-1}$	$2.2e^{-4}$	1.54
	Coarse Gaussian	$1.1e^{-1}$	1	$1.1e^{-2}$	$9.1e^{-2}$	24.4	$5.5e^{-1}$	$1.7e^{-1}$	$2.8e^{-1}$
Ensemble Learning	Boosted Trees	$2.8e^{-1}$	0.98	$7.8e^{-2}$	$2.6e^{-1}$	22.5	1	$3.4e^{-1}$	$3.5e^{-1}$
	Bagged Trees	$1.2e^{-2}$	1	$1.4e^{-4}$	$2.9e^{-3}$	26.4	1	$1.3e^{-4}$	1.13
	Optimizable Ensemble	$5.0e^{-2}$	1	$2.5e^{-3}$	$1.4e^{-2}$	435	$9.7e^{-1}$	$5.4e^{-4}$	2.39

C. Accuracy Evaluation of NyRoNet

This study developed NyRoNet to correct the sampling rate collection of the towed vehicle of an underground imaging system. The ideal resistivity map can be achieved by a constant sampling rate due to the uniform velocity of the electric vehicle. In an actual application, the constant velocity of a vehicle is challenging to achieve due to obstruction, road conditions, speed bumps, road slope angle, and the banking of the road. Also, this study denotes that Simulink is a well-known continuous simulation that investigates systems amenable to differential equation analysis and may be used in the subterranean imaging system. The sudden change in velocity during the scanning process results in parallax distortion which produced image may result in an inaccurate location of subsurface utilities due to distortion, elongation, size, length, the diameter of the pipe, or an abridged result of the image as shown in Fig. 7a. and 7b. Whereas Fig. 7a displays a noticeable effect during the speed-up of velocity resulting in parallax distortion. In Fig. 7b an anomaly is displayed at the 60m mark in normal constant velocity however, when a varying velocity applies in the case the anomaly is displayed at the 50 m mark, this shows inaccuracy in the resistivity imaging system when varying velocities happen. With that scenario that velocity in actual application can't be accurately constant, an algorithm was developed that adopts the Nyquist rate of underground imaging into varying velocity, called NyRoNet. In cases where the sampling rate is inadequate, the reconstructed signal may exhibit a loss of certain frequencies from the original signal, ultimately leading to the convergence of frequencies and consequent aliasing. Furthermore, it is worth noting that the high-frequency components of the transmitter signal can be susceptible to noise or may lack pertinent information.

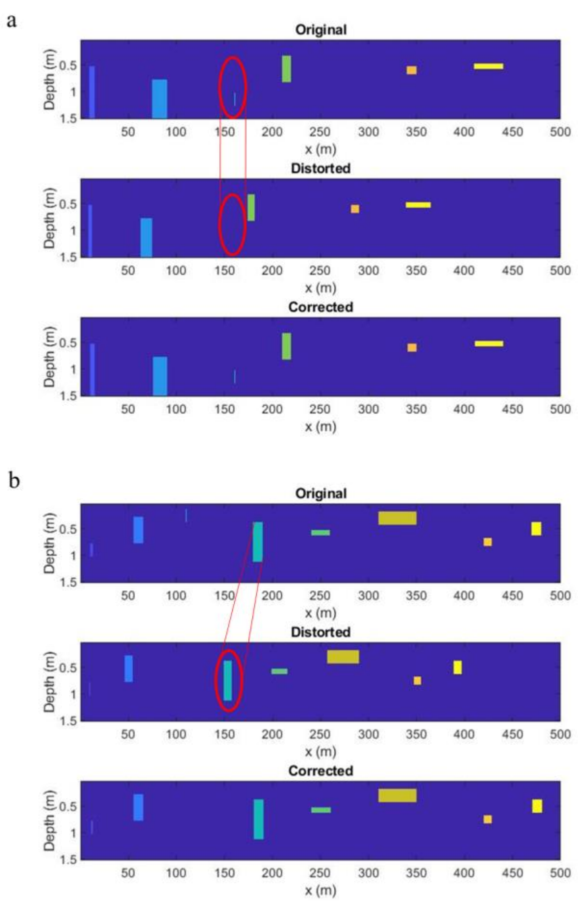

Figure 6. Matplot of resistivity map which illustrates a resistivity map scanning with constant velocity (above), resistivity map scanning with the sudden change in velocity (middle), and resistivity map scanning with the sudden change in velocity with the supervision of NyRoNet model (a) noticeable effect during speed up of velocity results to parallax distortion, (b) Noticeable elongation of the image due to slowing down and position misalignment due to speed up of the vehicle.

In this case, the NyRoNet shows the correct location of underground utilities even in the presence of sudden change in velocity comparatively with images of resistivity map of electric vehicle scanning with constant velocity and the map without NyRoNet model for sampling rate selection which results in distortion of images shown in Fig. 7. The NyRoNet was able to select the appropriate sampling rate based on the changes and behavior of velocity of the electric car. It is capable of displaying the correct position, size, length, and diameter of the pipe on the resistivity imaging system and comparing it to the original resistivity map while compromising constant velocity values to the intended value line. This suggests that the NyRoNet demonstrated significant investigation and utilization of sample rate correction as a function of electric vehicle velocity, current, power, slope angle, and voltage, which explicit the best fitness curve. In comparison to other recent works in the field of subsurface imaging and antenna systems, the presented investigation greatly adds to the improvement of correction factors for the underground imaging system's sampling rate collection approach.

4. Conclusion

This study introduced a novel strategy to correcting the Nyquist rate collection technique for the underground imaging system tower vehicle for subsurface imaging of utilities underneath by optimizing various computational intelligence such as regression models. Each element of the electric vehicle was modeled using Simulink in MATLAB R2022a as the electric vehicle system's tower for underground imaging. The dataset for the modeling was extracted using this method. Input parameters such as the target speed, weight, and slope angle were employed to create the Nyquist rate for each algorithm, which was then entered into the e-vehicle speed controller. With this, four regression optimizations, namely regression tree (RTree), gaussian process regression (GPR), support vector machine (SVM), and ensemble regression (ER), with a total of 19 models were developed. Based on the evaluation metrics' results, Matern 5/2 GPR was considered as NyRoNet with an R^2 value of 1 and 0.654, an MSE of $1.56e^{-7}$ and $1.66e^{-10}$, and MAE of $3.14e^{-4}$ and $1.46e^{-3}$ in the validation and testing data, respectively. MATLAB/Matplot was used to generate a resistivity map that illustrates the validation of NyRoNet or the correction of parallax distortion due to the influence of speed in response to the sloping road surface. It is suggested that future research could focus on the optimization of the sample rate and identification of the road factors influence on the result of the Nyquist rate model.

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