EXAMPLE OF SWITCHING HYBRID FSO/RF SYSTEMS

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ABSTRACT

This article addresses the issue of optical communication with Free Space Optics (FSO) and its use. The article deals with the design and construction of a monitoring system designed for the collection and processing of data characterizing the nature of conditions along the transmission path of a hybrid FSO system with a radio communication link. Due to the vulnerability of the FSO transmission channel to weather conditions, it is necessary to predict the strength of the received signal and switch to a backup line based on machine learning using decision trees.

Keywords: *FSO, decision trees, hybrid system, machine learning*

1. INTRODUCTION

Demand for high bandwidth in metropolitan networks with short access times is increasing. In addition, the requirements of flexibility and cost-effectiveness of service provision cause imbalances. This issue is often referred to as the "last kilometer obstacle".

Optical fiber is the first most visible way of addressing the lack of bandwidth. Fiber is undoubtedly the most reliable means of optical communication, but digging, fiber storage costs and time to market are the most serious disadvantages of optical fiber. The second option is communication via radio frequency (RF) [1]. This technology is advanced and often deployed today. Radio-based networks require huge investments to obtain spectrum licenses, but they cannot be compared to fiber-optic transmission capacity. The third alternative is Free Space Optics (FSO) communication. FSO is the optimal solution in terms of technology, bandwidth scalability, deployment speed and cost-effectiveness [2].

Free Space Optics (FSO) communication involves the transmission, absorption and scattering of light through the Earth's atmosphere. The atmosphere interacts with light due to the composition of the atmosphere, which normally consists of molecules of various gases and small suspended particles called aerosols [3].

Hybrid Wireless Free Space Communication (FSO) and Radio Frequency Communication (RF) (Fig. 1) is a way to ensure reliable communication for critical real-time outdoor traffic as weather like fog affects FSO much more than RF connections [4]. The main condition for using the FSO is that the receiver must be in line of sight with the transmitter [5]. This interaction delivers a wide range of optical phenomena:

- Selective mitigation of radiation that is propagated in the atmosphere.
- Absorption at specific optical wavelengths due to molecules.
- Generation by distraction (blue sky, red sunset, etc.)
- Radiation emission of the optical beam.
- Scintillation action due to air refractive index change [6].

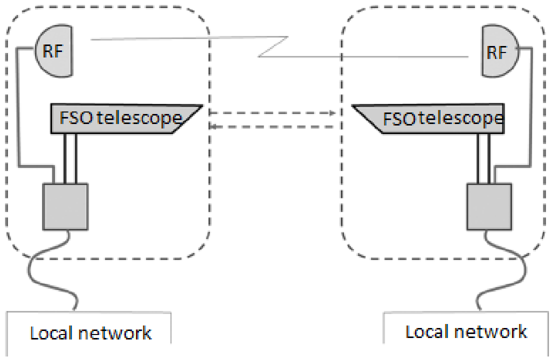

Fig. 1. Figure caption

2. HYBRID FSO/RF SYSTEMS

An important task for the operation of a hybrid FSO/RF system is to monitor weather conditions along the atmospheric channel using sensors such as a temperature, humidity, wind speed sensor and more [7]. The measurement results are used as inputs for machine learning methods, for processing and prediction of received optical power, which is the implementation of Received Signal Strength Indicator (RSSI) parameter in hybrid FSO/RF line switching (Fig. 2).

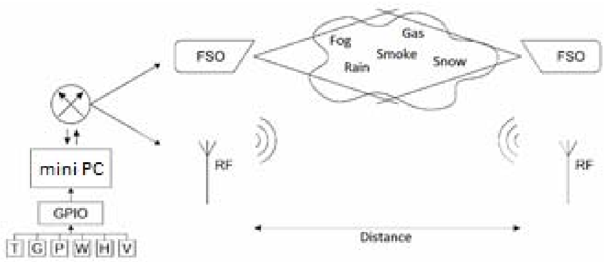

Fig. 2. Scheme of the Hybrid FSO/RF System

Computational performance and open operating system are suitable features of a minicomputer to be implemented in an experimental system to analyze the availability and reliability of FSO systems [8]. A substantial part of the selected minicomputer is the GPIO bus, which is used to connect analog and digital sensors.

The first head from the used steam FSO line located in the area of the Technical University of Košice (TUKE) is located on the roof of the building marked PK13. The second FSO warhead is located on the roof of the main building TUKE (Letná 9) shown in fig. Distance between FSO heads is around 230 meters.

The author presents his main ideas, mathematical formulations and their derivation. This part should be accompanied by exact references.

3. METHOD OF SWITCHING FSO/RF SYSTEM

Machine learning techniques are widely used today for many different tasks. Different data types require different methods. The task of machine learning in a hybrid FSO/RF system is to predict the strength of the received optical signal, which is affected by weather conditions [9]. A form of machine learning to the gradient boosting on the decision tree, which works by gradually training more complex models, is designed to maximize the accuracy of predictions. Gradient enhancement is particularly useful for predictive models that analyse organized data and categorical data. Decision trees are used for RSSI classification prediction.

A decision tree is a classifier expressed as a recursive part of an instance space. A decision tree consists of nodes that form a rooted tree, which means that it is a directional tree with a node called "root" that has no incoming edges. All other nodes have exactly one incoming edge. A node with outgoing edges is called an internal or test node. All other nodes are called leaves [10]. In the decision tree, each inner node divides the instance space into two or more subspaces according to a certain discrete function of the input attribute values [11]. In the simplest and most common case, each test considers one attribute, so the instance space is divided by the value of the attributes. For numeric attributes, the status refers to a range.

Enhancing decision tree is one of the most efficient ways to make models. The combination of gradient enhancement with decision trees enables results in applied applications with structured data. There are two types of errors that can lead to inappropriate inductive bias: overfitting and underfitting [12]. Overfitting occurs when the prediction model selected by the algorithm is too simplified to represent the underlying relationship in the dataset between descriptors and the target function. Underfitting, on the other hand, occurs when the prediction model chosen by the algorithm is so complex that the model is too closely associated with the data file and becomes sensitive to noise in the data. It is an effort to use techniques to get your own model in an iterative way. During the first iteration, the algorithm learns the first tree to reduce errors. If the model has a significant error, it is not a good idea to create large decision trees, including preliminary data. The second iteration (Fig. 3), in which the algorithm learns one tree to reduce the first tree error. The algorithm repeats this procedure until the appropriate model.

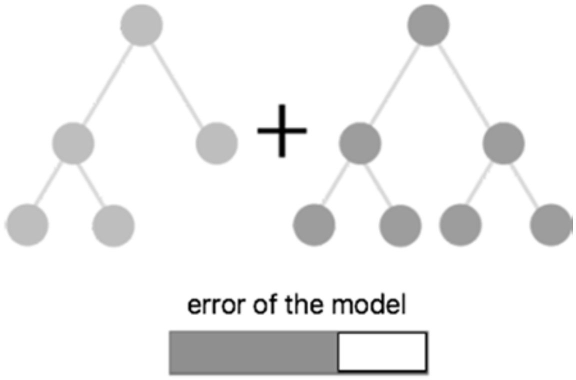

Fig. 3. Scheme of the Hybrid FSO/RF System

Gradient Boosting (GB) is a method of implementation in the absence of an objective function. The normal pre-classification approach utilizes logarithmic loss, while regression optimizes with mean squared error (MSE). Each GB step combines the following steps:

- Gradients of the loss function are calculated for each input object.
- Prediction of loss gradients using decision tree [13].

In the classification problem, use different metrics as a criterion for tree splitting. One option is an index that expresses the measure of total variance between classes *K*. When creating a decision tree, the input and training set is divided into smaller subsets, which gradually characterize the values of the output variables. The recursive division process is performed until the termination condition is met. In the process of atmospheric channel analysis for the FSO/RF system, a relatively extensive system of cases of input variables *X* with the corresponding mute output stages was designed. variables *y*. The output variable *y* is RSSI in this case. The general training set of cases has the following structure.

$$P = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1k} & y_1 \\ x_{21} & x_{22} & \dots & x_{2k} & y_2 \\ \dots & \dots & \dots & \dots & \dots \\ x_{n1} & x_{n2} & \dots & x_{nk} & y_n \end{bmatrix} \tag{1}$$

The input and training set is split to create a decision tree smaller subsets that gradually characterize the values of the output variables. The training matrix of the input variables for the FSO/RF system has the following structure.

$$\begin{bmatrix} P_1 & T_1 & G_1 & V_n & H_n & \dots & W_1 \\ P_2 & T_2 & G_2 & V_n & H_n & \dots & W_2 \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ P_n & T_n & G_n & V_n & H_n & \dots & W_n \end{bmatrix} \tag{2}$$

where *P* is barometric pressure (hPa), *H* represents ambient humidity (%), *T* is air temperature (°C), wind speed *W* (m/s), *G* represents concentration Airborne particulate matter (mg/m3) and visibility (m). The matrix of the output variable *y* (target), which represents the received optical power of RSSI, is interpreted as follows:

$$y = [y_{RSSI.1} \quad y_{RSSI.2} \quad > \quad y_{RSSI.n}\ ]^T \tag{3}$$

Different termination conditions and methods for selecting the next node lead to different learning approaches. The best-known of these approaches are leaf and depth schemes. Using the leaf node approach, the algorithm divides the area to achieve the best improvement in the lossy function, and the process continues until a fixed number of leaves is obtained [14]. The depth approach algorithm builds tree-by-level until a fixed-depth tree is created. Choosing such decision trees has several advantages over conventional trees:

- Simple installation.
- Effectively implement on CPU.
- The ability to produce very fast model applicators.
- Provide benefits for many tasks due to regularization.

Shared memory can be used for aggregation, which is characterized by its speed. Since one limitation is the size of shared memory, it is convenient to group several functions into one to achieve maximum computational performance. The learning algorithm of the classical decision tree is computationally demanding. In order to find further distribution, we have to evaluate the number of observation times for different distribution conditions. This leads to a large number of possible differences for large data sets through continuous inputs and, in many cases, overfitting. Fortunately, it is possible to significantly reduce the number of divisions that we need to consider. We can make a rough approximation of the input functions. The easiest way to quantify is to use the quantiles of the input element distribution.

The algorithm solves feature problems and supports category-based functions. Handling categorical elements is one of the challenges of machine learning. The most commonly used technique for solving categorical predictors is single hot-coding. The original function is removed, and a new binary variable is added for each category. This approach also has disadvantages:

- Deep decision trees need to be built to restore dependencies in the event of high cardinality. This can be solved by a hash trick, but such an approach significantly affects the resulting quality.
- Such an approach does not work for values of unknown categories such as values that do not exist in the learning data set.

Training set is used to create a description that can be used to predict previously unseen examples. Attributes (sometimes called fields, variables, or functions) are typically one of two types: nominal (values are members of an unordered set) or numeric (values are real numbers). Attribute a, it is useful to mark its domain values $v_{i,j} \in$ *dom(a*$_i$*)* as:

$$dom(a_i) = \{v_{i,1}, v_{i,2}, \dots, v_{i,|dom(a_i)|}\} \tag{4}$$

Instantial space (a set of all possible examples) is defined as the Cartesian product of all input attribute domains:

$$X = dom(a_1) \times dom(a_2) \times \dots \times dom(a_n) \tag{5}$$

Universal instance space U is defined as the Cartesian product of all inbound attribute domains X and target attribute domains *dom(y)*:

$$U = X \times dom(y) \tag{6}$$

A training set is an instance consisting of a set of m-tics. Formally, the training file is marked as $S(B) = (\langle x_1, y_1\rangle, \dots, \langle x_m, y_m\rangle)$ where $x_q \in X$ and $y_q \in dom(y)$ [15]. It is usually assumed that the training sets are generated randomly and independently according to some fixed and unknown common probability distributions of attribute domain D above U. Generally, it is a generalization of a deterministic case when the supervisor classifies the set using the function $y = f(x)$ [7].

To create a prediction w using a node in a tree that contains a set of instances, the weight of the instance in the current tree is predicted:

$$MSE(a, X) = \frac{1}{l}\sum_{i=1}^{l}(a(x)_i - (y_i))^2 \tag{7}$$

Overwritten in terms of residues:

$$MSE(a, X) = \frac{1}{l}\sum_{i=1}^{l}(r_i^2 - 2r_i w + w^2) \tag{8}$$

After simplifying the substitution for $\sum_{i=1}^{l} r \ as \ R$:

$$MSE(a, X) = \frac{1}{l}\sum_{i=1}^{l} r_i^2 - Rw + \frac{1}{l}nw^2 \tag{9}$$

By substituting for the loss function for the simultaneous iteration and simplifying, we get the effect of predicting w^* in the given leaf:

$$MSE(a, X) = \frac{1}{2}\sum_{i=1}^{l} r_i^2 - \frac{1}{l}\frac{R^2}{n} \tag{10}$$

As a basic algorithm it can be usually choose the simplest algorithm, for example short decision tree:

$$b_1(x) = argmin_b \frac{1}{l}\sum_{i=1}^{l}(b(x_i) - y_i)^2 \tag{11}$$

The second algorithm must be designed to minimize system error:

$$b_2(x) = argmin_b \frac{1}{l}\sum_{i=1}^{l}(b(x_i) - (y_i - b_1(x))^2 \tag{12}$$

Then it is possible to derive the formula $b_N(x)$:

$$b_N(x) = argmin_b \frac{1}{l}\sum_{i=1}^{l}\left[b(x_i) - \left(y_i - \sum_{n=1}^{N-1} b_n(x_i)\right)\right]^2 \tag{13}$$

One of the most popular opensource libraries for machine learning in the Python programming language is Scikit-learn. The scikit-learn [17] library contains a *Decision-Tree-Classifier* class that can train a binary decision tree with entropic impurities. The prediction of RSSI parameter that can be used to switch the FSO line and backup RF line [18].

Determination coefficient or score determines the probability of how well the learning model will predict future samples of the output variable y [19]. The best achievable score value is 1. The max depth parameter is selected based on optimum *mse* and *score* values. For the selected algorithm, the max depth parameter was gradually tested from value 5 with step 1 to value 300. Fig. 4 shows the development of the *mse* and score depending on the max depth. The cyclic training model showed that the optimal value of the parameter max depth (blue line) for *mse* = 0.94.

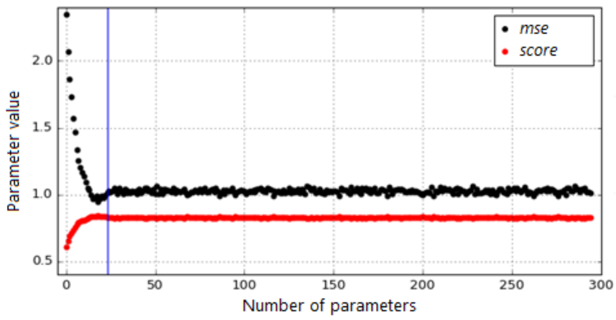

Fig. 4. Max depth parameter

The comparison of predicted and real RSSI values is shown in Fig. 5.

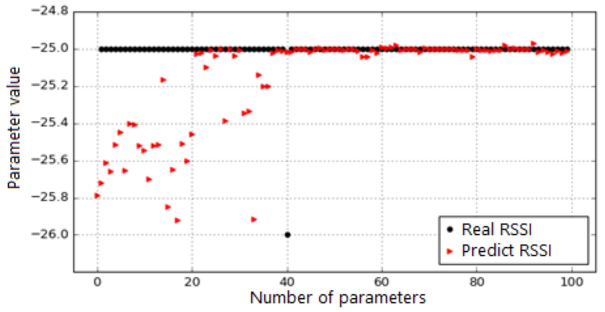

Fig. 5. Measured and predicted data from the input matrix

4. CONCLUSIONS

Due to the high impact of weather on FSO transmission a backup RF line is required, which is less prone to weather condition, but much slower than FSO link. For this reason, a hybrid FSO/RF line is required, which can be switched to the hard or soft switching principle. To create such a system, it is necessary to analyse the conditions and thus obtain the characteristics of the variables that affect the transmission channel. Appropriate weather prediction, using machine learning methods, makes it possible to quickly switch over communications over the RF line and back to a faster FSO line. In this way, it is possible to increase the efficiency of communication via the hybrid FSO/RF system.

For efficiency, the tree can also be pruned using the max depth parameter. However, it is not always easy to find out which value is best to do a grid search or cross validation. Of course, it is extremely important to avoid over-specialization in the training set, which could lead to a model learning, so it is often necessary to carve a tree at a certain level. In this way, it is easier to find a good compromise between training and accuracy. If the model is not too large, it is possible to manually test different values and select the optimum value.

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