Free Space Optics Power Predictor Algorithms *

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***Abstract*—For this paper was used an optical power source to send 1550-nm wave of continuous power over 55-m free-space optical link, to develop low-complexity power estimation algorithms. Atmospheric information data was also monitored and recorded to correlate them with power samples. Data diversity was granted by taking measurements during 2 and 3 hour trials with different weather conditions.**

***Index Terms*—FSO with rain, FSO power estimators**

I. Introduction

Free space optics (FSO) ~~is still not fully explored. It~~ can provide an alternative communication mean to fiber [1]. Some remote areas ~~have still no fiber connections~~ due to implementation costs and in that case a laser interface through atmosphere can provide last mile access [2]. ~~In last decade~~ high speed communications have been proved to be possible [3]~~. However~~, the implementation of FSO is still discouraged due to its uncertainty about power attenuation and the impact of meteorological phenomenon~~, since it still requires much practical validation.~~ [4]. The dynamic behaviour of ~~all~~ the perturbations ~~can~~ affect the channel, creating ~~a~~ consequent ~~power oscillation.~~ This ~~can~~ impact the ~~connections~~, especially if the signal to noise margin is too little [5].

~~With the purpose of increasing FSO data analysis, from simple power measurements we experienced many interesting behaviors. The most important is~~ some kind of correlation among collected samples, suggesting channel memory on top of which different estimators ~~can be~~ built to predict channel behavior, ~~topic that this paper will cover. In the meantime nice weather resistance was experienced since one of the measurements was taken in soft rainy conditions.~~

II. Experimental set up

The overall set up used for the experiment is depicted in Fig.[1]. The power source consists in a ~~2.5 Gbps dual direct modulated~~ laser emitting at ~~1545.32nm or 1546.92nm~~ and +11dBm as maximum output power. The signal is sent through ~~APC~~ fibers towards a collimator~~; this is a 24mm~~ diameters ~~with~~ 0.017 divergence angle ~~collimator, which has~~ a numerical aperture of 0.24 and a focal length of 37.13mm. The free space link ~~is obtained by using~~ a concave mirror whose distance from collimators is about 27.5m~~; in this way we are able to simulate~~ a 55m link. The signal is received by another collimator, ~~of the same kind~~ of the trasmitting one, and the received power is analyzed through a optical power meter calibrated at 1550nm with a maximum input power of +26dBm. Finally, the power meter is directly connected to a laptop where a MATLAB ~~script keeps track of power variations.~~ In addition to that, the script is able to connect to the web to keep track of variations in weather indices. The positioning system is ~~analog and~~ fully exposed to any kind of meteorological variations. The mirror, as well as the collimators~~,~~ has no protection ~~from~~ rain droplets ~~and this~~ can produce ~~huge~~ scattering effects when ~~it gets hit by them~~ [6].

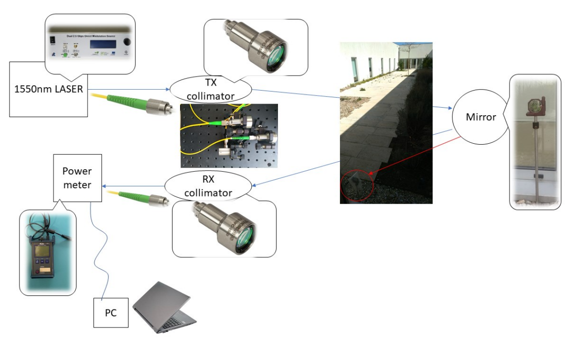

Fig. 1. Free-space optics experimental set-up

III. Measurement analysis and data manipulation

Dealing with FSO is utterly different with respect to wired optical transmissions where stability of power ~~can be seen with the most simple power meter[REFERENCE NEEDED? i dont think it is needed]~~. Fig.[4] ~~and Fig.[~~6] instead present a scenario in which power fluctuations are big,various and frequent.

First of all it's worth noticing the system loss~~: this~~ is ~~equal to~~ about 3dB considering cable,connectors and free space link losses in perfect weather conditions. In rainy conditions, loss is just of further 2/3 dB as can be seen in Fig.[4] justifying the good weather resistance mentioned at the beginning. Autocorrelation analysis is performed over the collected signals and showed in Fig.[2] and ~~Fig.~~[3]. ~~and~~ by analyzing the contour of the peak for both we ~~are able to~~ see that adjacent samples are dependent and a general channel behavior can be tracked ~~under the noise.~~ To do that, three different estimators are applied in order to exploit the channel memory and ~~to~~ predict ~~its~~ behavior : fixed number of taps moving average estimator, real time optimized adapting taps moving average estimator and differential estimator. They are all based on the mean function~~, so they are all basically a mean estimator~~ but~~,~~ treating memory differently is possible to obtain different results and improvements. In order to evaluate the quality of the estimation the mean square error is evaluated ~~in eq 1. Being y(n+1) and x(n) the estimation and the real power measured, respectively.~~

$$e(n) = (y(n+1) - x(n))^2 \tag{1}$$

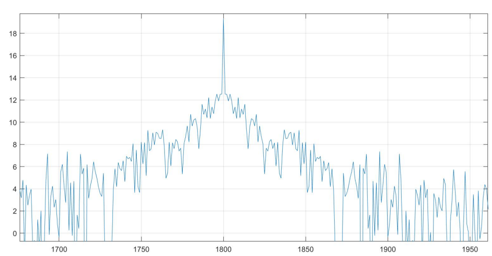

Fig. 2. Autocorrelation 2 hours

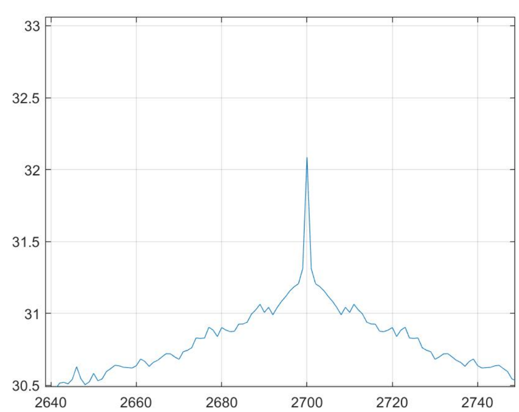

Fig. 3. Autocorrelation 3 hours

A. Fixed number of taps

In this case, a set of data is extracted during a 10 minutes measurement and the fact that the power over the channel, in terms of average behaviour, is quite homogeneous has to be taken into account. For the evaluation data, the predictor calculates the estimation as shown in equation 2, with taps varying from 1 to 100. The error of estimation is minimized only with respect to the number of samples of memory. After the evaluation period the estimator runs with fixed number of taps. This type of estimator is of low complexity ~~and has the main advantage of low CPU usage.~~ As power pattern can change during one experience, the number of taps doesn't adjust to that change. For an unbiased number of taps, if the value is too high the system fails to track high variations, as usually happens when atmospheric conditions change. On the other hand, if the system has too much power noise and the memory is too little, the predictor will tend to follow the fast variations even though the conditions are quite stable. In order to adjust to the condition variations a dynamic number of taps approach is presented in III-B.

$$y(n+1) = \frac{1}{Taps} * \sum_{t=0}^{Taps-1} x(n-t) \tag{2}$$

B. Real time adaptive number of taps

In this methodology there is higher CPU load when compared with III-A. The best number of taps is calculated each iteration to minimize the error function on III-B. This assures that the best number of taps is used. In equation III-B the averaging system is specified with taps recalculated when new sample is acquired.

The improvement with respect to the fixed number of taps is that anytime we predict a new value , the history of the signal up to the 100 past value is taken into account i.e. the number of taps is tried from 1 to 100 and for each value the MSE is performed. The number of taps minimizing the MSE will be used to estimate the next value and so on.

$$\begin{cases} Taps(n) = \min\{e(n)\} \\ y(n+1) = \frac{1}{Taps(n)} * \sum_{t=0}^{Taps(n)-1} x(n-t) \end{cases}$$

C. Differential

The differential method is conceived to provide an estimation based on the mean as the previous algorithms, however ~~here two information are taken in account,~~ the previous estimation error as well as the increment between the current and previous power information. This two features allow the estimator to detect spikes and neglect them partially. The estimation error allows the program to neglect the differential effect as the error increases fading the differential effect in those cases. Constants C_1 and C_2 allow for weighing the effects of both the feedback and the differential action.

$$y(n+1) = \frac{1}{Taps} * \sum_{t=0}^{Taps-1} x(n-t) * \frac{1}{1 + D_{ifferential} - P_{error}} \tag{3}$$

$$P_{error} = (y(n) - x(n-1)) * C_1 \tag{4}$$

$$D_{ifferential} = (x(n) - x(n-1)) * C_2 \tag{5}$$

IV. Results

As already ~~told~~, analysis ~~were~~ performed to two different data sets, one for sunny conditions and the other for rainy conditions. To access weather conditions impact, some information ~~was~~ extracted from http://climetua.fis.ua.pt, physics department of Aveiro University site, that has a meteorological monitoring station less then 500-m away from FSO test area. The mean squared and maximum error were registered for each estimation algorithm as well as the optimum number of taps obtained for each data in table I and II. The maximum squared error is of some importance, because if one estimator needs to respect a certain threshold of approximation during all transmission the error spikes can be harmful.

TABLE I
3 Hour Rainy Data

	Fixed	Dynamic	Differential
MSE	0.1321	0.1228	0.1352
Taps	13		13
Max Squared Error	3.273	4.178	3.529

TABLE II
2 Hour Sunny Data

	Fixed	Dynamic	Differential
MSE	0.04274	0.0405	0.0434
Taps	13		13
Max Squared Error	3.36	3.375	3.503

A. Rainy day

From the curves in Fig.[4] it is visible that the three techniques are a good approximation of the data. With fixed number of taps is noticeable that the real time adaptive estimator produces an overall more dynamic estimation, being an indicator of the fact that the ~~real~~ power has periods of faster variation. For the two other strategies it is visible a similar behaviour as they are based on the same number of taps. The differential presents however higher skepticism to spike data and when the data set is a rainy one and has higher number of spikes, the mean squared error raises. From error distribution at Fig.[5] it is noticeable that at the final part of the experience there was an increase on the error as it is related to a continuous drop in the power that the estimators fail to predict because they are related to previous power conditions. The most affected predictor in this part of the data was the dynamic that has a behavior of high memory rejecting fast variations.

B. Sunny day

In this graph there is an overall stabilized power, characteristic of optimal optics conditions. The variations mainly isolated suggest that they can be related with random phenomenon. The dynamic approach displays a low variation estimate, this suggests that the number of taps must be high when compared with the fixed one. Fixed number of sample memory and

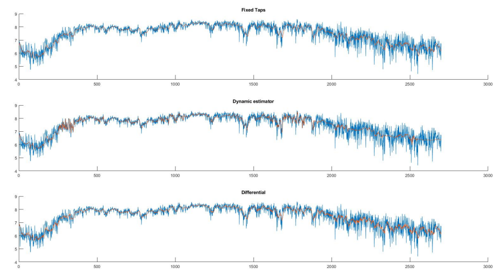

Fig. 4. Estimated power 3 hour rainy day

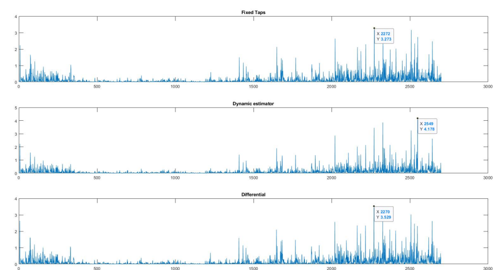

Fig. 5. Error distribution of 3 hour estimators

differential algorithms show similar behaviour in Fig.[6]. From the error distribution at Fig.[7] it's clear that all methods present similar results. There is a low error density in the stable weather day, and the error appears correlated with the random power spikes present.

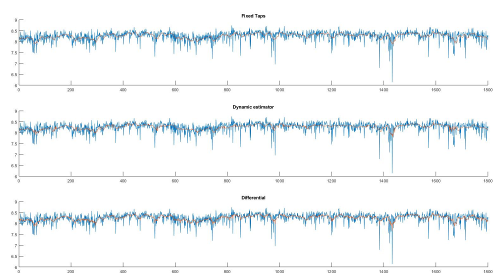

Fig. 6. Estimated power 2 hour sunny day

To further improve our results and search correlation between climate phenomena and power variations, in Fig.[8] normalized ambient conditions are displayed alongside the power data. There is however a limitation in terms of refresh rate of the climatic status.

V. Conclusions

This work has shown how with very simple tools it's possible to predict channel behaviors in terms of power. Power has direct implications in the quality,performance and reliability of transmissions and tons of work can be done; in fact better estimators can be studied, and in dealing with adaptive modulations the channel prediction can be an extremely

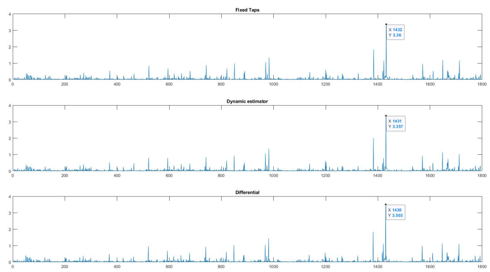

Fig. 7. Error distribution of 2 hour estimators

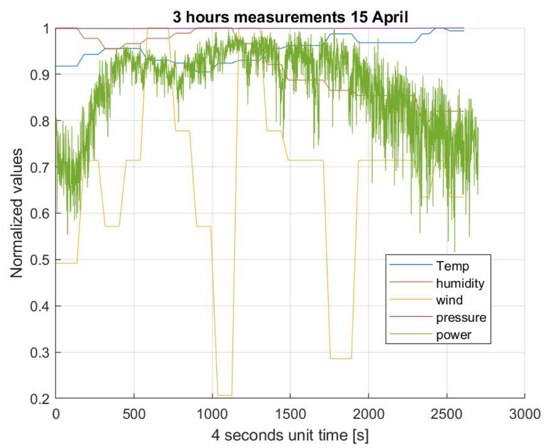

Fig. 8. Weather and power data

advantageous tool to use. With the estimators presented, the results show that they provide better results when output power is more stable, being that a symptom of good weather conditions. A good approach to improve the estimators here presented would be the integration of the optimum number of taps in the differential method. Using meteorological information, long data could be taken and a channel model could be created with sensibility to the weather perturbations. The improvement of the practical setup in terms of alignment and rain protection of the collimators and mirror could produce improved power results. However, it was shown that even with rain phenomenon it is plausible to consider communications possible.

ACKNOWLEDGMENT

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