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***Abstract*—In this paper we propose three low-complexity algorithms to estimate the time-varying loss of an outdoor 1550-nm free-space optics (FSO) link with 55-m transmission length. Long-term experimental measurements taken for different weather conditions demonstrate that the link loss can be predicted accurately while still using low-complexity algorithms.**

***Index Terms*—Free-Space Optics (FSO), optical communications**

I. Introduction

Free-space optics (FSO) can be used as a high-capacity alternative to traditional fiber deployments [1]. Some remote areas do not have fiber connection yet due to implementation costs, and in that case a laser interface through atmosphere can provide last mile access [2]. Despite high speed communications have been recently demonstrated [3], the implementation of FSO is still discouraged due to its uncertainty about power attenuation and the impact of meteorological phenomenon, which still requires further practical validation. [4]. The dynamic behaviour of the perturbations can modify the channel, consequently creating a time-varying link loss. This impacts the transmission performance, especially if the signal to noise margin is too short. Therefore, in order to fully exploit FSO communications, the link loss should be characterized and, if possible, predicted to be able to adapt the transmission rate to the link conditions [5].

In this work, we study the time correlation of the link loss by performing simple power measurements in a 55-m outdoor link. Our results show that there is a correlation among collected samples, suggesting channel memory on top of which different estimators are built to predict channel behavior. Two different sets of measurements are shown, one with clear weather sunny conditions and another one with periodic rainy conditions. In both cases we show that a simple estimation algorithm can predict the link loss very accurately.

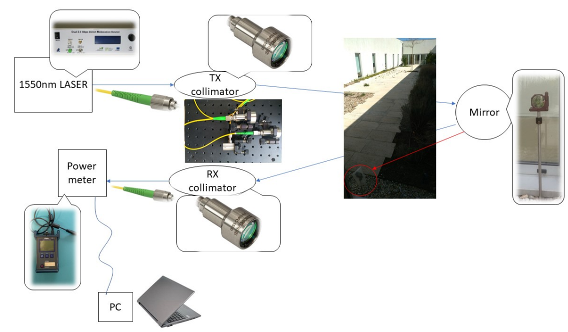

Fig. 1: Free-space optics experimental setup

II. Experimental setup

The setup used for the experiment is depicted in Fig. 1. The power source consists of a laser emitting at 1546 nm with +11 dBm maximum output power. The signal is transmitted through a fiber collimator with 24 mm diameter and 0.017° divergence angle, which has a numerical aperture of 0.24 and a focal length of 37.13 mm. The free space link also includes a concave mirror whose distance from the collimators is about 27.5 m, providing a total length of 55 m. The signal is received by another fiber collimator, with the same specifications as the transmitting one, and the received power is analyzed using an optical power meter. Finally, the power meter is directly connected to a laptop where a MATLAB script records the measured power. The positioning system is manual and fully exposed to any kind of meteorological variations. The mirror and the collimators have no protection against rain droplets which can produce scattering effects when they deposit at their surface [6].

III. Measurement analysis and data manipulation

Dealing with FSO is utterly different with respect to wired optical transmissions where stability of power is typically

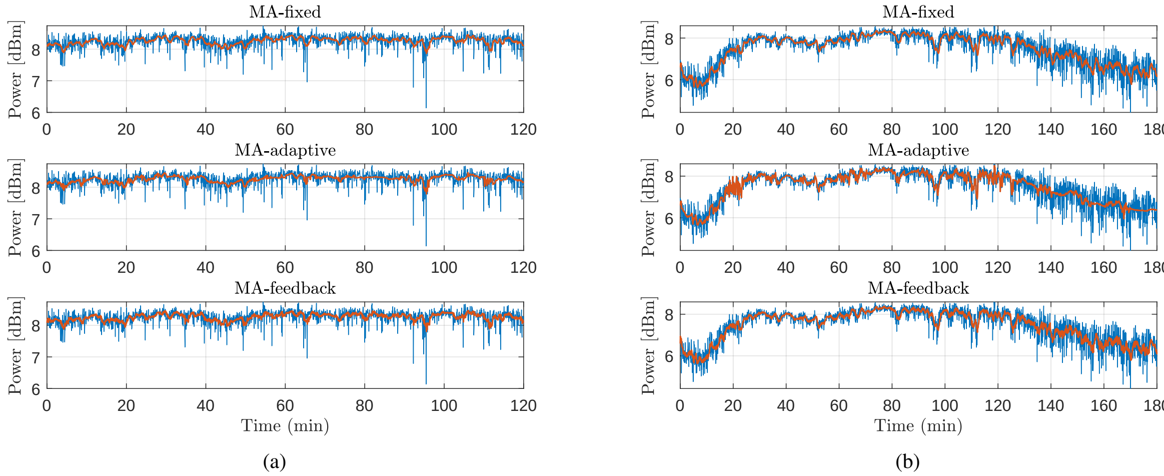

Fig. 2: Received optical power (in blue) and respective estimation (in red) using the proposed optical power tracking algorithms. a) data obtained during stable sunny weather conditions; b) data obtained during unstable rainy weather conditions.

guaranteed. Figs. 2a and 2b present a scenario in which we can observe numerous power fluctuations of large amplitude, taken for two rather distinct weather conditions. First, in Fig. 2a we show the received optical power for nearly perfect weather conditions (no rain, low humidity). Then, in Fig. 2b we show the received optical power in a day with a few rain showers, whose effect is well visible in the first 20 min and last hour of acquisition. First of all it is worth noticing the baseline system loss with perfect weather conditions, which is about 3 dB considering cable, connectors and free space link losses. Instead, in rainy conditions, the overall loss is increased by approximately 2–3 dB as can be seen in Fig. 2b. Most importantly, the optical power evolution shown in Fig. 2b clearly suggests the existence of time correlation in the FSO channel, i.e. the fluctuations of power are not merely random, but instead seem to follow a well-behaved trend. In order to get more insight into this apparent time correlation, in Fig. 3 we perform an autocorrelation analysis over the collected signals. By analyzing the contour of the peak for both cases we can see that adjacent samples are inter-dependent, which open the possibility to track a general channel behavior. In addition, it is possible to observe that the time correlation is substantially longer for the data set corresponding to periodic raining weather conditions. This is due to the slowly varying weather changes, such as rain rate and humidity, which contribute to longer-term memory effects. This rather heterogeneous characteristics of the FSO channel demand for a differentiated treatment in order to optimize the extraction of an accurate system model. To that end, three different estimators are applied in order to exploit the channel memory and predict the channel behavior:

i) moving average with fixed memory depth (MA-fixed);
ii) moving average with adaptive memory depth (MA-adaptive);
iii) moving average with feedback and proportional derivative terms (MA-feedback).

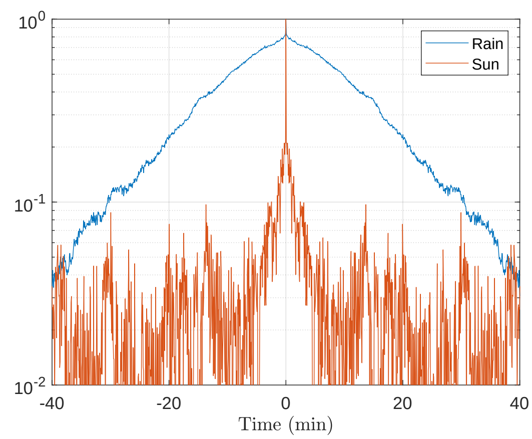

Fig. 3: Normalized auto-correlation of the received optical power under different FSO channel conditions.

It is worth noting that, although all these methods are based on a moving average function, in each variant we attempt to treat memory differently, with the aim to obtain different results and a better fit to the FSO channel. In order to evaluate the quality of the estimation, the mean square error (MSE) for entire acquisition time is calculated as,

$$\text{MSE} = \frac{1}{N_{samples}} \sum \left[y(n) - x(n) \right]^2 , \qquad (1)$$

where $y(n)$ refers to the estimation and $x(n)$ is the actual measured power.

A. Moving average with fixed memory depth

In this case, the optimum number of taps is firstly evaluated by minimizing the MSE over the first 10 minutes of acquisition time. This approximation assumes that the channel behavior is somehow static over time, thus allowing to simplify the estimation approach. However, this will also introduce some estimation error, as the static channel premise does not hold under unstable weather conditions. Following this approach, the MA-fixed predictor calculates the estimation as

$$y(n+1) = \frac{1}{N_{\text{taps}}} \sum_{k=0}^{N_{\text{taps}}-1} x(n-k), \quad (2)$$

where N_{taps} is the optimized number of memory samples. This type of estimator is of low complexity. However, as the channel response can change over time, the number of taps will not adjust to that change. For a non-optimized number of taps, if the value is too high the system fails to track quick 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 short, the predictor will tend to follow the fast variations even though the conditions are quite stable.

B. Moving average with adaptive memory depth

In order to adjust to the varying FSO channel conditions a dynamic number of taps should be the preferred approach. However, the dynamic adaptation of the number of taps in the moving average incurs a higher complexity than the MA-fixed approach previously described in section III-A. The best number of taps is calculated for each iteration to minimize the instantaneous square error between the estimated and measured power, where $y(n)$ is the previous estimated power obtained from (2). This approach assures that the best number of taps is used on a per-sample basis. Using this optimized number of taps, the moving average is then updated as follows,

$$y(n+1) = \frac{1}{N_{\text{taps}}(n)} \sum_{k=0}^{N_{\text{taps}}(n)-1} x(n-k). \quad (3)$$

The improvement with respect to the fixed number of taps is that anytime we predict a new value, the number of taps is optimized in order to provide the minimum MSE.

C. Moving average with feedback and proportional derivative terms

The differential method is conceived to provide an estimation based on a moving average, akin to the previous algorithms, however the previous estimation error as well as the increment between the current and previous power information are now taken into account. These 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 weighting the effects of both the feedback and the differential action,

$$y(n+1) = \frac{1}{N_{\text{taps}}} \sum_{k=0}^{N_{\text{taps}}-1} x(n-k) \frac{1}{1+\delta(n)+\epsilon(n)}, \quad (4)$$

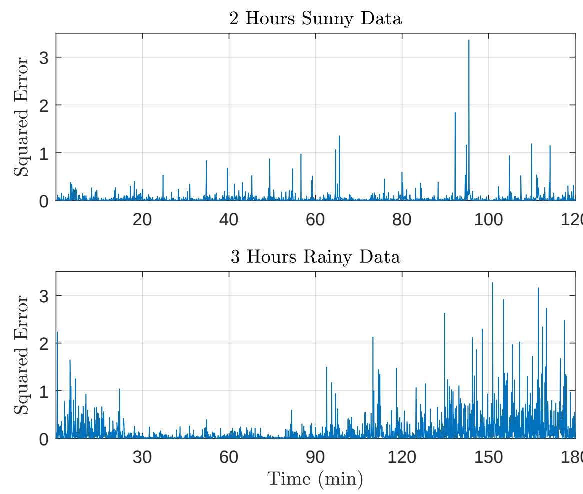

Fig. 4: Instantaneous square error over time using the MA-fixed algorithm.

where $\epsilon(n)$ takes into account the previous estimation error,

$$\epsilon(n) = (y(n) - x(n-1)) \cdot C_1, \quad (5)$$

and $\delta(n)$ is a proportional derivative term,

$$\delta(n) = (x(n) - x(n-1)) \cdot C_2. \quad (6)$$

In this work, we have optimized $C_1 = 0.001$ and $C_2 = 0.0077$ for the acquired data during a sunny day and $C_1 = 0.0001$ and $C_2 = 0.026$ for the rainy one.

IV. RESULTS

As previously mentioned, the studies are performed over two different data sets, one for sunny conditions and the other for rainy conditions. Tables II and I show the mean and maximum squared error for each estimation algorithm, as well as the optimum number of taps obtained with the MA-adaptive algorithm. Besides the MSE, the maximum squared error also plays an important role, since it captures the impact of error spikes, which might be harmful for ultra-reliable communications, as it is the case of 5G.

TABLE I: 2 Hour Sunny Data

Estimator	MA-fixed	MA-adaptive	MA-feedback
MSE	0.04274	0.0405	0.0425
Taps	13	27 (avg.)	13
Max Squared Error	3.36	3.357	3.554

TABLE II: 3 Hour Rainy Data

Estimator	MA-fixed	MA-adaptive	MA-feedback
MSE	0.1321	0.1228	0.1297
Taps	13	17 (avg.)	13
Max Squared Error	3.273	4.178	3.508

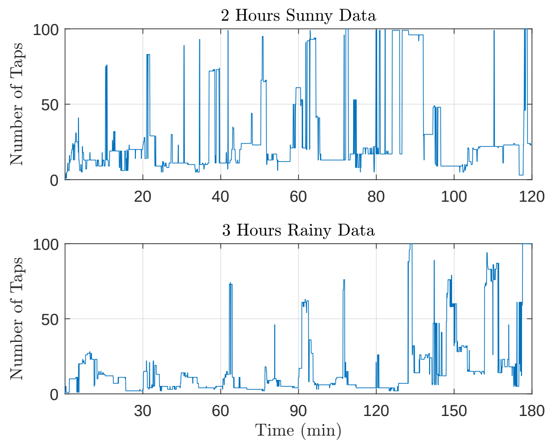

Fig. 5: Real time variation of number of taps using the MA-adaptive algorithm.

A. Sunny day

The time evolution of the instantaneous squared-error using the MA-fixed algorithm during a sunny day is shown in the top row of Fig. 4, which shows an overall stabilized power, characteristic of optimal optics conditions. The variations are mostly isolated, suggesting that they can be related with random phenomena. The adaptive memory approach displays a low variation estimate, in fact the number of taps is higher when compared with the MA-fixed algorithm, as depicted in Fig. 5. MA-fixed and MA-feedback algorithms show similar behaviour in Table II. There is a low error density in the stable weather day, and the error appears correlated with the random power spikes presented in Fig. 4.

B. Rainy day

From the curves in Fig. 2b it is visible that the three techniques are a good approximation of the data. Comparing the MA-fixed and MA-adaptive algorithms it is noticeable that the latter enables a more dynamic estimation, being an indicator of the fact that the link loss has periods of faster and slower variations. In this case, in Fig. 5 (bottom) it can be seen that a lower number of taps is used to better track variations due to rain. For the two other strategies we observe a similar behavior as they are based on the same number of taps. However, the MA-feedback algorithm presents 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 in Fig. 4 (bottom) it is noticeable that at the final part of the experience there was an increase on the error related to alignment problems. The most affected predictor in this part of the data was the MA-adaptive, which has a behavior of high memory confirmed in the last part of Fig.5(bottom) rejecting fast variations.

V. Conclusions

In this work, we have demonstrated that it is possible to accurately model and predict the link-loss of an FSO channel in real-time using very simple estimation algorithms. Optical link loss has direct implications in the quality, performance and reliability of an FSO transmission system and therefore an accurate prediction of the current channel status can be an extremely advantageous tool, which can be used in order to adapt key transmission parameters, such as transmitted power, modulation format and data rate [7]. Our experimental results, obtained under rather different weather conditions, have shown that the time correlations on the received optical power can be effectively monitored and tracked using a simple moving average algorithm with an optimized number of taps. A possible approach to improve our simple power estimation techniques could be the integration of the optimum number of taps in the feedback method with proportional derivative terms. In addition, using meteorological information, longer-term data can be taken and used to refine an FSO channel model taking into account the knowledge of the weather perturbations. The improvement of the practical setup in terms of alignment and rain protection of the collimators and mirror can also produce improved power results. Nevertheless, the experimental analysis provided in this paper has shown that FSO-based communications can be made resilient to adverse channel conditions, including rain and pointing errors.

VI. Acknowledgment

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