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A General Approach for Simulating Signals of Scattering Light Detectors

1 Introduction

The simulation of fire signals is an important tool in automatic fire detection. It is useful for developing new detection algorithms or for testing existent algorithms. Simulations make it possible to develop algorithms for fire detection without expensive measurements in fire detection laboratories. This article introduces a first approach of a general method of simulation. The basis of such a simulation is a statistical model of the measured signal which describes the fire. In this article the point of view lies on the signal processing and decision making part of the automatic fire detection [1], where we concentrate on scattering light detectors. Those signals (figure 1) often include impulsive parts, which have been seen as noise in earlier approaches [2, 3]. There, the impulsive noise has been

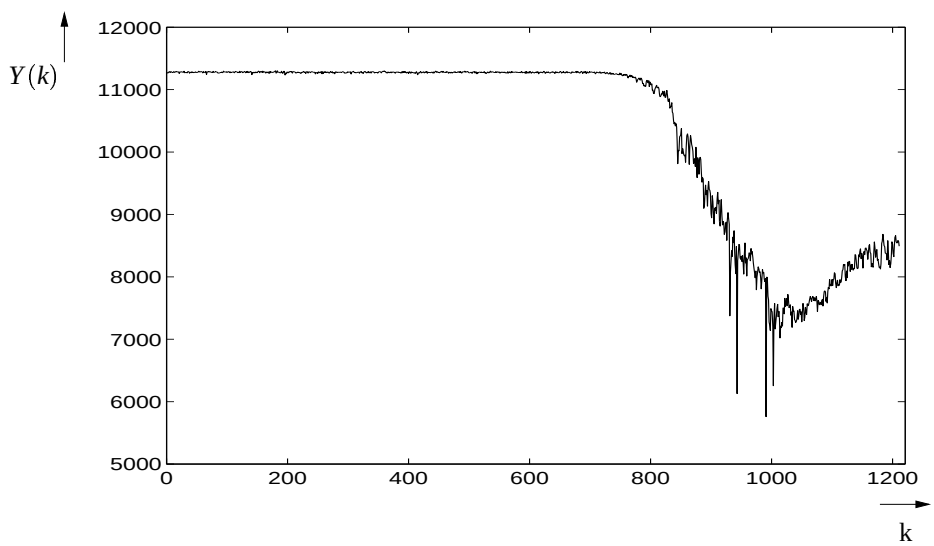

Figure 1: Signal of scattering light detector (sampling rate 1hz)

suppressed in a first step of data processing and has been added in a further step as additve noise signal. Here, in our general approach the impulses are seen as a part of the signal and will be simultaneously considered by simulating the signal to circumvent the inefficient and maybe unprecise two-step approach.

2 Motivation

One advantage of simulating fire signals is the possibility of testing detection algorithms with a few number of measured fire signals. Fire signals which were measured by testfires can be used to simulate new fire signals. So after changing the parameters of an algorithm or developing a new algorithm, these simulated signals can be used to test the algorithm. This test can be done on a PC without implementing the algorithm on any hardware. To achieve comparable testresults a large number of tests with different data are necessary. With simulating fire signals it is possible to generate a large number of data *without* measuring a lot of test fires. This means saving time and costs. Difficulties with simulating the signals of a scattering light detector are described in the next section.

3 Model of the Signal

The basis of the simulation is an additive model of the signal, that can be described as follows:

$$Y(k) = X_d(k) + X(k)$$

with

$Y(k)$: measured signal

$X_d(k)$: deterministic part of the fire signal

$X(k)$: statistic part of the fire signal including noise

The figures 2 and 3 show the deterministic and the statistical part of the signal shown in figure 1. The deterministic part is supressed in the first step of processing the signal simply by highpassfiltering, only the statistical part will be simulated. The figure 3

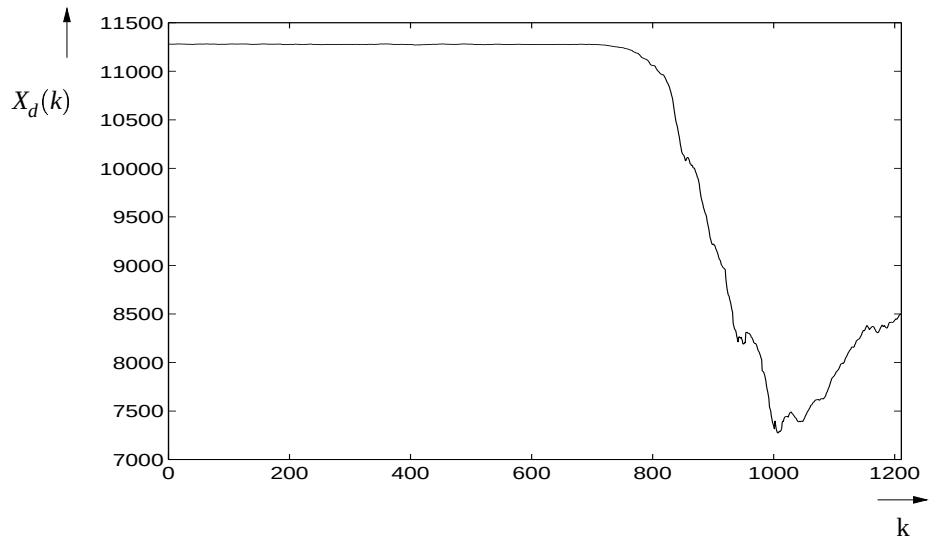

Figure 2: deterministic part of the fire signal

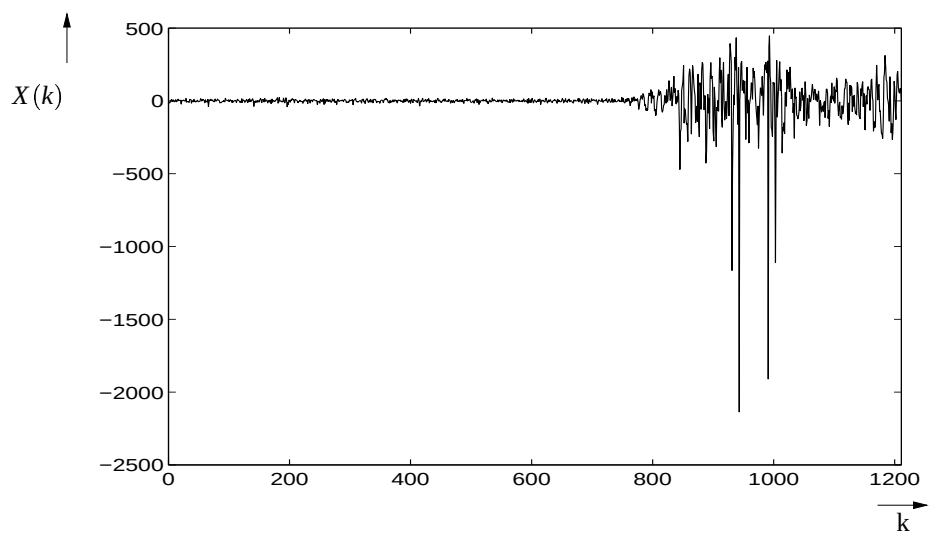

Figure 3: statistical part of the fire signal

shows that the fire signal is not stationary, the statistic properties change with time. But the signal can be separated into stationary segments of different length. This is done after filtering the deterministic part of the signal. Therefore the signal power of the signal is evaluated. It is obvious that the signal energy of the signal in figure 3 for $0 < k < 700$ is

less than the energy for $k > 700$. he stationary segments of the fire signal are described by an autoregressive AR) process $X(k)$ of the order p, which looks as follows

$$X(k) = \sum_{i=1}^{p} a_i X(k-i) + N(k),$$

where $X(k-i)$ are former samples of the signal $X(k)$ and $N(k)$ is a so-called stable distributed random process. So $X(k)$ at the discret time k is the sum of former values of the signal $X(k-i)$ which are weighted with the coeffients a_i and the noise signal $N(k)$ at the same point of time. For simulating the signal the coefficients a_i have to be estimated by the given measured signal $X(k)$. Figure 4 shows such an AR model, where z^{-1} is a time

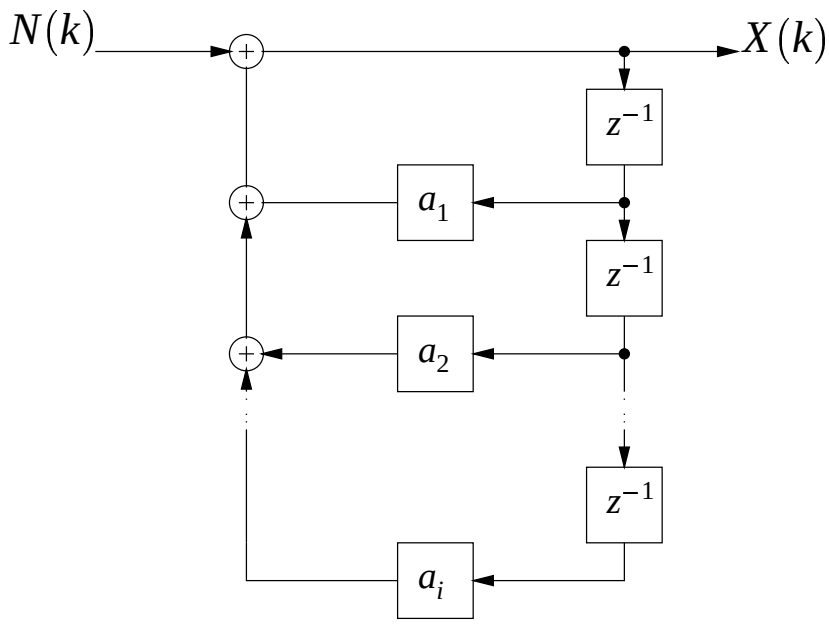

Figure 4: autoregressive (AR) model

delay of one sample.

4 Symetric α-Stable ($S\alpha S$ Noise)

In this general approach symetric α-stable ($S\alpha S$) noise with zero mean is used as input signal for the AR model to simulate the fire signal. A ra ndom variable is called α-stable,

if its characteristic function (the Fourier transformation of the probabilty density function) can be described as follows [6]

$$\varphi(z) = e^{\gamma|z|^{\alpha}}$$

with

$0 < \alpha \leq 2$: characteristic exponent

$\gamma > 0$: dispersion

Figure 5 shows an example for a $S\alpha S$ stable random signal $N_{S\alpha S}(k)$ with $\alpha = 1.5$. A special case of the symetric α-stable distribution is the gaussian distribution which is described by $\alpha = 2$. Figure 6 shows the probability density function $p_{N_{S\alpha S}}(n)$ of $S\alpha S$

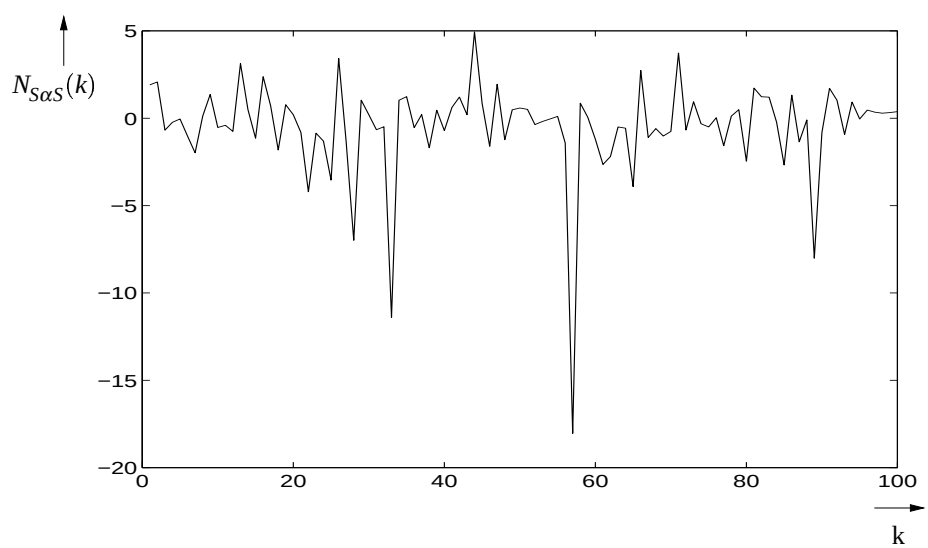

Figure 5: α-stable distribution with $\alpha = 1.5$

signals with different characteristic exponents α. The diagram shows that with decreasing α the tails of the function becomes heavier. For $\alpha = 2$, the gaussian case, the tails are the smallest. Because of the heavy tails there is one problem with processing signals with α-stable distribution. The moments with a order of α or higher *do not exist* except for the special case of the gaussian distribution. For this reason estimation procedures which use second or higher order moments can not be used in the case of α-stable distribution with $\alpha < 2$ as the popular least squares (LS) method for example. In this case other methods have to be used. In the literature there are different solutions for this problem [6, 4]. Some of these solutions are modified LS methods or use lower order $(p < 2)$ moments.

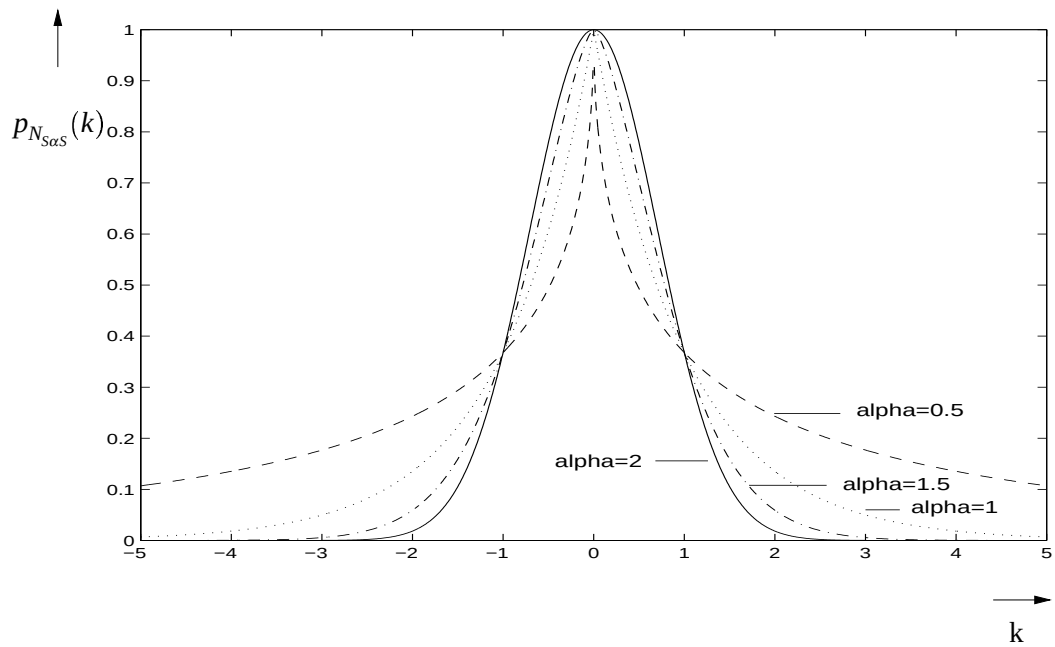

Figure 6: α-stable distribution with $\alpha = 1.5$

5 Simulation with gaussian Noise

The object of this approach [2] is the estimation of the parameters of the AR process which describes the signal. As described before the signal $X(k)$ has to be separated in stationary segments. The segmentation is done with the Maximum-Likelihood method where the energie of the prediction errors of different signal segments are compared. The prediction error is calculated in the following way

$$\hat{n}(k) = \sum_{i=1}^{p} \hat{a}_i x(k-i) + x(k),$$

where $\hat{n}(k)$ and $\hat{a}_i$ are estimated values. The AR parameters $\hat{a}_i$ are estimated by minimizing this prediction error. During this segmentation algorithm the impulsive part of the signal is supressed. If the energy of the prediction error exceed a threshold the signal is extrapolated at this point of time. The extrapolated value of the signal is calculated by an AR process using former values of the signal as input in the following way

$$\hat{x}(k) = \sum_{i=1}^{p} \hat{a}_i(k) x(k-i),$$

where the AR parameter change with every step of iteration. After finding the steady segments their AR parameters are estimated by using the least squares methods for each

of the segments. With this AR parameters and the limits of the segments the stationary segments of the fire signal can be simulated. After the simulation a random signal is generated which contains the impulses. This signal is added to the simulated signal. Figure 7 shows a schematic diagram for this classical approach.

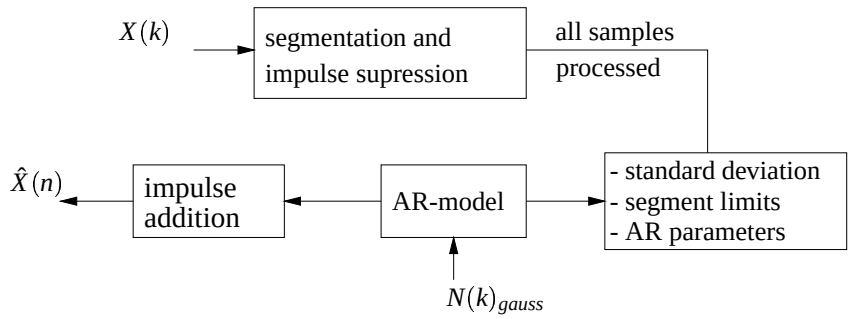

Figure 7: Structure of classical simulation approach

6 Simulation with α-stable Noise

In our approach of simulating a fire signal, the impulses are not interpreted as noise but as a part of the signal. Contrary to the algorithm described in the in section before the impulses are not supressed but considered at the estimation of the AR parameter. There are different methods described in the literature to estimate AR parameter for models with impulsive noise as input signal [6, 4]. In this work a method is used which minimzes the p-th order moment. The minimizing problem of this l_p-norm looks as follows:

$$argmin_{\hat{\mathbf{a}}} \sum_{k=1}^{K} |x(k) - \sum_{n=1}^{N} \hat{a}_n x(k-n)|^p$$

where

$\hat{a} = [a_1, a_2, \ldots, a_N]^T$: estimated AR coeffients

$x(k) = 0$ for $k \leq 0$

$1 < p < \alpha$

K: single length of $x(k)$

N: order of AR model

This l_p norm is a generalization of the least squares deviation where p is equal to 2. In this work the iteratively reweighted least squares (IRLS) algorithm is used to solve the minimization problem [4, 8]. The algorithm starts with the LS solution and in every step it solves a weighted LS solution whereby the weights are the iteratively calculated residuals of the signal. The algorithm looks as follows [4, 5]

1. $\mathbf{a}(0) = (\chi^T\chi)^{-1}\chi^T\mathbf{s}$
2. $r_k(i) = [\mathbf{s} - \chi\mathbf{a}(i)]_k$
3. $W_{kk}(i) = p|r_k(i)|^{p-2}$
4. $\mathbf{a}(\mathbf{i}+\mathbf{1}) = (\chi^T\mathbf{W}(i)\chi)^{-1}\chi^T\mathbf{W}(i)\mathbf{s}$
5. IF $\frac{||\mathbf{r}(i+1)||_{(p)} - ||\mathbf{r}(i)||_{(p)}}{||\mathbf{r}(i)||_{(p)}} < \varepsilon$ then stop
   else go to step 2)

where

$\mathbf{a}(i)$: the parameters of the AR model at the i-th iteration

$\mathbf{s}$: one value shifted version of the data vector $x = [x(k-1), x(k-2), \ldots]$

$\mathbf{r}$: residual vector

$\mathbf{W}$: diagonal matrix of the residuals (weight matrix) $W_{i,j} = 0$ if $i \neq j$

$||_{(p)} =$: the p-th norm $|\mathbf{r}(i)|_{(p)} = \sqrt[p]{\sum_k |r_k(i)|^p}$

χ: matrix of the data

$$\chi = \begin{pmatrix} x(1) & 0 & \ldots & 0 \\ x(2) & x(1) & \ldots & 0 \\ \vdots & \vdots & & \vdots \\ x(P) & x(P-1) & \ldots & x(1) \\ \vdots & \vdots & & \vdots \\ x(L) & x(L-1) & \ldots & x(L-P+1) \end{pmatrix}$$

P: order of the AR model

L: length of the signal

The structure of the algorithm is shown in figure 8. This algorithm has been implemented

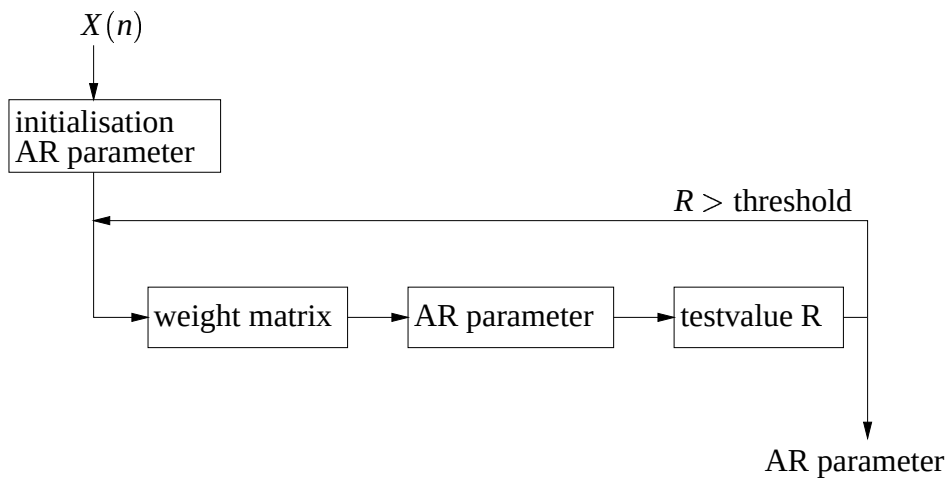

Figure 8: Structur of the IRLS algorithm

to estimate the AR parameter for *simulating the signal of a scattering light detector*. The structure of simulating a signal with the IRLS algorithm is similar to the one shown in figure 7 except that the impulse supression is not necessary and the input of the AR filter is $S\alpha S$ noise.

6.1 Simulation of Fire Signals

After estimating the AR parameter the stationary segments of the measured fire signal can be simulated by using an AR model with the estimated parameters. This leads to another signal which exhibits the same *statistical* properties as the measured signal. Of course it does not look the same. The input of this filter is α-stable noise with the same standard deviation as the fire signal. α can be estimated from the signal. There are different approaches for the estimation of α. In this work the $log|S\alpha S|$ [6, 7] estimator is used. With the $log|S\alpha S|$ estimator a new random variable Y is evaluated where $Y(k)$ is

$$Y(k) = log|X(k)|,$$

$X(k)$ is a $S\alpha S$ random variable. For the estimation of α exists the following equation:

$$Var(Y(k)) = \frac{\pi^2}{6}(\frac{1}{\alpha^2} + \frac{1}{2})$$

which only depends on α. The variance of $Y(k)$ exists and can be estimated from the samples of the known signal $Y(k)$ and the mean value. This estimation gives very good

results for a large number of samples (e.g. 10000 samples) for signals with few samples (e.g. 100 samples) the simulated value of α deviates from the real value. Figure 9

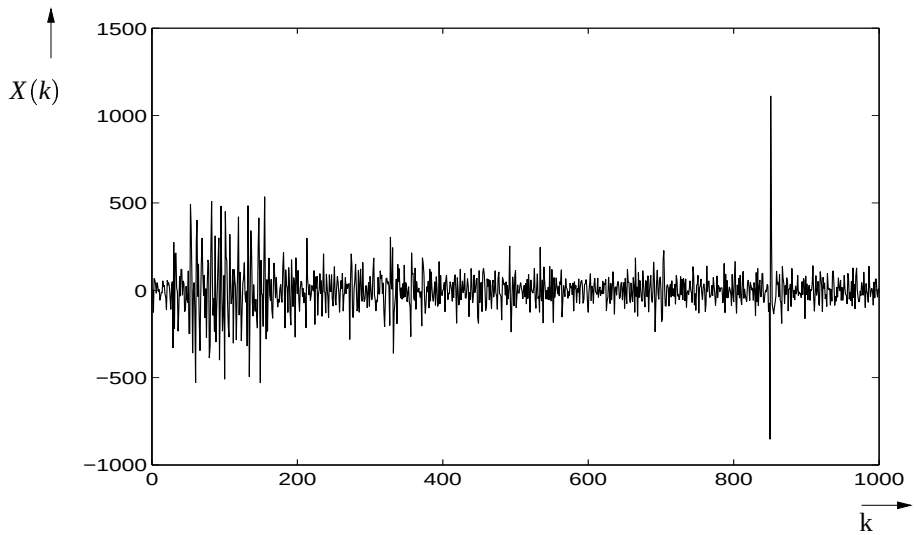

Figure 9: Measured and highpass-filtered fire signal part

shows the high frequence part of the signal of a testfire measured with a scattering light detector, figure 10 shows a simulation of this fire signal with stable noise with the characteristic exponent $\alpha = 1.8$. It can clearly be seen that both signal have he same statistical properties.

7 First Conclusion

Both the model using gaussian noise as well as the one which uses general stable noise have advantages and disadvantages. In the first algorithm not all the impulses of the signal are suppressed and after the simulation not all the found impulses are added to the signal again. The correlation of the impulses gets lost by fitting the impulses into the simulated signal in a brutal manner. One benefit of the estimation of AR model parameters by using least squares is that it is a well known procedure and the algorithm converges fast. By using the IRLS algorithm the supression of the impulses is not necessary. On the other hand using an AR model with impulsive noise to simulate the fire signal exceeds the following problem. The number and the amplitude of the impulses depends on the value α. If α decreases the number of impulses and the amplitude increases. It is not

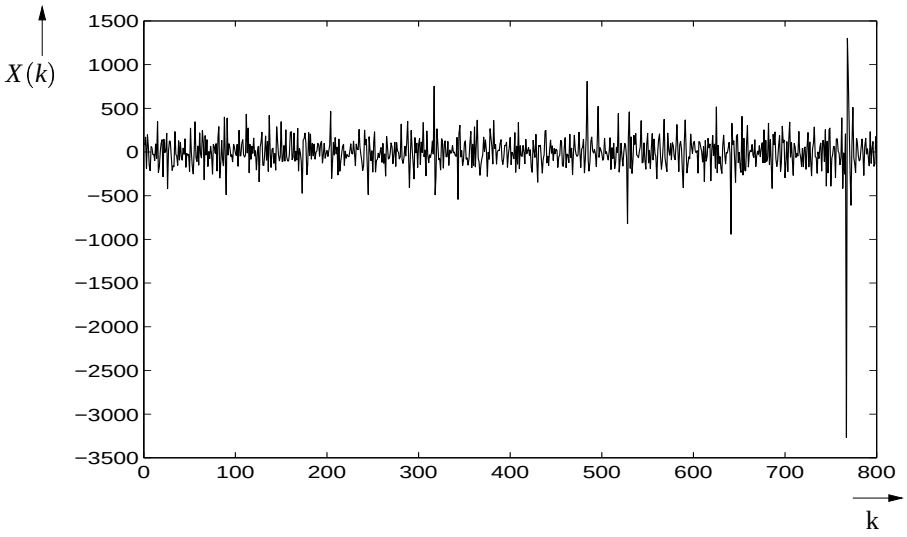

Figure 10: Simulated fire signal part

possible to generate noise with less impulses but with a high amplitude by using α-stable noise. In the signals of scattering light detectors there are few impulses with a high amplitude compared to the signal. So it may be necessary to choose another input signal then α-stable noise.The figures 9 and 10 show an example where the simulated signal corresponds very good to the measured signal, but this must not be. One advantage of the algorithm using stable noise is that the correlation of the impulses is still contained in the simulated signal.

Actually a combination of both described algorithms is already realised. The segmentation is done with the algorithms using the LS method, then the AR parameters for the model are estimated with the IRLS algorithm for every found segment. In the literature exist fast evaluation echniques for the IRLS algorithm which are based on FFT [9], so that the implemented IRLS algorithm become faster.

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