Pulsed laser weld quality monitoring by the statistical analysis of reflected light.

R. Olsson, I. Eriksson, J. Powell and A.F.H. Kaplan
Luleå University of Technology, SE-971 87 Luleå, Sweden
www.ltu.se/tfm/produktion
rickard.olsson@lasernova.se

Abstract

This paper describes a technique for monitoring the quality of laser welds by statistical analysis of the reflected light signal from the weld surface. An algorithm is used which analyses the variance of the peak values of the reflected signal as a measure of surface weld dynamics during pulsed Nd:YAG laser welding in the heat conduction mode. Kalman filtering is used to separate a useful signal from the background noise. A good correlation between weld disruption and signal fluctuation has been identified. This technique could be used in tandem with the present practice of simply using the peak values of the reflected (or emitted) light as an indicator of weld quality.

Keywords: Monitoring, Laser welding, Kalman filtering, Quality, Nd:YAG laser, Signal Processing

1. Introduction

Several workers have attempted to use the light emitted and reflected from the laser welding process to predict the quality of the weld produced e.g [2.. 6]. However, feedback systems in this field are always hampered by the high signal to noise ratios involved. Informative electromagnetic signals from the weld zone often overlap, both spatially and in their frequency range, with high levels of noise which carries no useful information.

The simplest and most common method of weld monitoring is to apply a tolerance band to a chosen electromagnetic signal (eg the plasma temperature or the reflected laser light from the weld zone), based on historic data of a repeated welding process. Defects are then associated with the signals which exceed this tolerance band. This approach is commonly applied to the monitoring of CO_2 laser welding e.g. Precitec [4], Prometec [5] and Tönsdorff [6]. Generally, a dynamic threshold for fault detection, which adjusts its value to gradual changes in signal level (see figure 1) is employed. Kaierle [7] describes another approach; the monitored values from different parameters are grouped together as vectors and these 'feature vectors' are then allocated threshold values or decision boundaries.

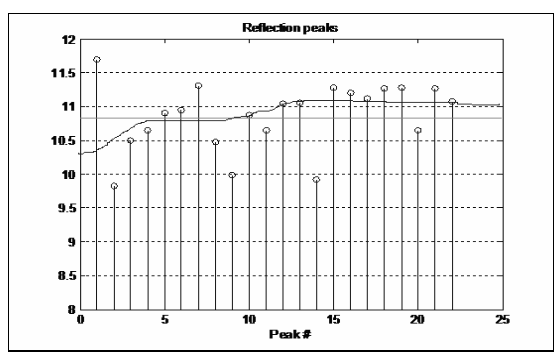

Figure 1. *The usual method of weld monitoring would involve a threshold value for the observed signal. Dynamic thresholds, which self-adjust with time (eg. dark line) are often more effective than static thresholds (eg. grey line).*

However, in certain cases the simple application of a tolerance band may not supply sufficient feedback about disruptions to the process. In this paper a different approach to processing the data collected from a laser welding process is investigated. The variance of the peak values of the reflected light gives an extra dimension to the feedback from the signal received from the weld pool, and could be used in tandem with existing techniques to improve welding process control.

For this research a new strategy was employed to overcome the problems associated with the high signal to noise ratio and at the same time introduce a computationally moderate approach enabling real time implementation. Rather than simply analysing the electromagnetic signals coming from the weld pool, the rate of variance of those signals was analysed as follows;

1. Reflection data was collected from the weld zone using a pin diode at a sampling rate of 8kHz. This gave the raw data of the type shown in figure 2. The data shown here spike represents the reflected signal from one laser pulse acting on the weld zone. A Kalman filter [7..9] was used to attenuate the noise from the signal - see figure 3.

There are two reasons for the choice of Kalman filtering in preference to low pass filtering;

- Kalman filters are the optimal linear estimator of a signal of a varying process whose measurements are disturbed by noise.
- The signal from the reflected light exhibits such sharp peaks and edges it contains a considerable proportion of high frequency information. LP-filtering tends to smooth the peaks and thus disturb the measured signal shape. In this experiment keeping the shape was important.

This approach produced a feedback system which is far more reliable and informative than simple signal processing. [See Appendix 1]

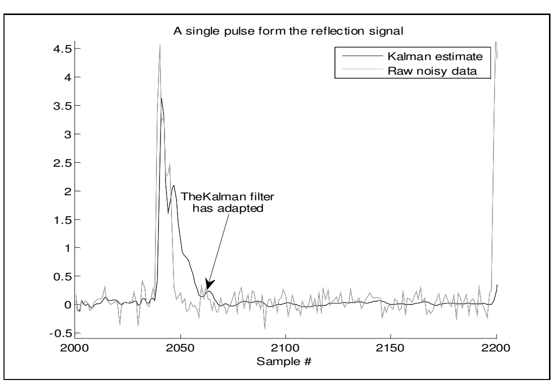

Figure 2. *An example of the raw reflection data collected from a weld zone.*

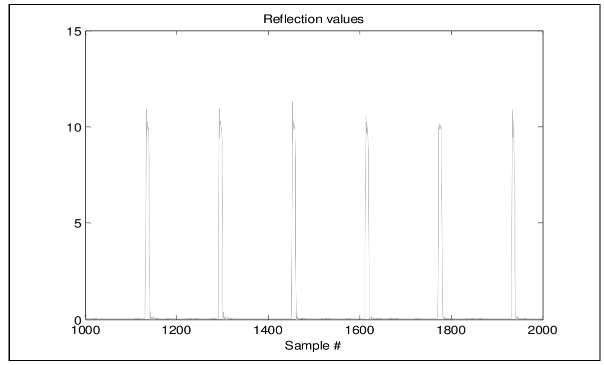

Figure 3. *An example of Kalman filtered (noise reduced) reflection data collected from a weld zone.*

2. The raw data was transformed by the CUSUM algorithm (see appendix 2), **into simple peak value data** – as shown in figure 4.

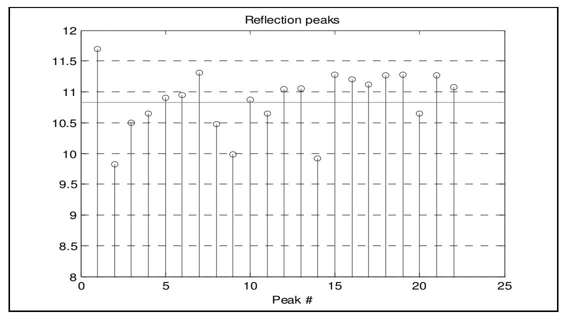

Figure 4*. The raw data was simplified into peak values only.*

3. The variance between the data peaks was calculated as each new peak (figure 4) was plotted. This gave clear information about perturbations in the welding process – see figure 5.

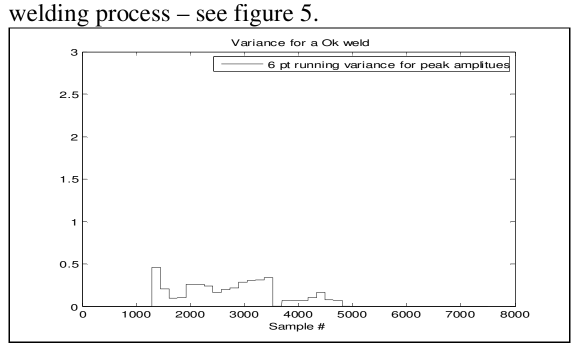

Figure 5*. The variance of the peak values presented in figure 4.*

The variance values of the type shown in figure 5 give valuable information about the stability of the process and this principle could be used in the design of the next generation of laser welding monitoring systems. A preliminary investigation into this technology is presented in this paper.

2. Experimental procedure

Two sheets of 0.14mm thick Inconel were mounted side by side as shown in fig 6, and welded with an edge joint. The welding parameters were, pulse frequency 50Hz, pulse length 1ms, feederate 500 mm/min, Average laser power ~ 70W

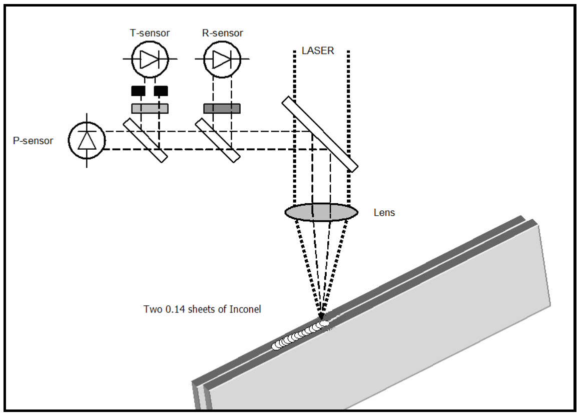

Figure 6 *A schematic of the edge welding geometry.*

The weld pool was illuminated by a Cavitar Cavilux illumination system using a wavelength of 809nm. The illumination gave a peak power of several hundred Watts in 1us pulses synchronized with the high speed camera. The process was filmed at either 2000 fps or 4000 fps with the Motion Pro Camera.
Measurement data was converted into MatLab format for off line analysis and algorithm development. A real time implementation was made in LabView for simultaneous presentation of video and measurement data.

The system setup consisted of:

- Precitec, LWM. Sensors for Plasma (P), Temperature(T) and Reflection (R)
- High speed camera, Redlake Motion Pro X3
- Illumination laser , Cavitar Cavilux Smart, 810 nm

3. Results and Discussion

Figure 7 is taken from the high speed imaging of the welding process. The photo shows the start of a stable, high quality weld. Figure 8 presents the reflection data collected during the production of this weld, together with a graph showing the variance of the peak values of the reflection data estimated from the previous six peak values. It is clear from figure 4 that there is only a minor amount of variance in the reflection signal peaks in the case of this high quality weld produced by a stable welding process.

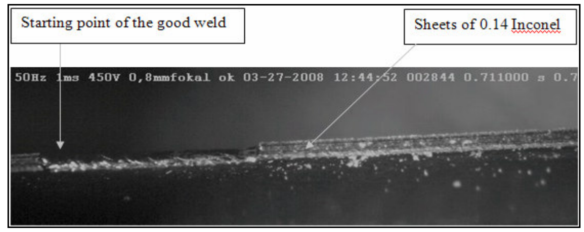

Fig 7 *The start of a good weld*

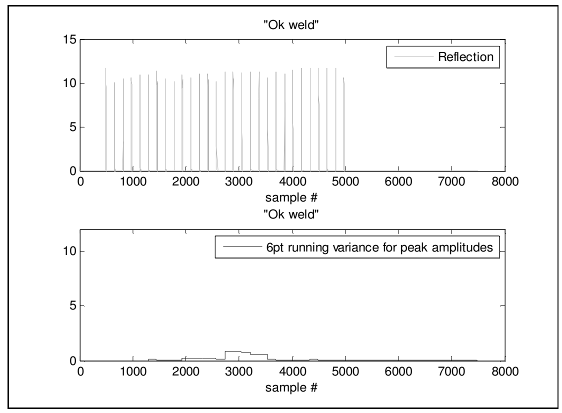

Fig 8. *Data and Matlab calculations for the good weld; 8a. Reflection data, 8b. Variance of reflection data peak amplitudes.*

Figures 9 and 10 present the same data set as figures 7 and 8 but, in this case, the welding process was unstable and the resulting weld was of poor quality. In this case it is clear that the peak variance plot (figure 10b) is larger – indicating that the reflection signal, and the welding process which produced it, are unstable. The initial peak of the variance graph needs some explanation, as it is simply the result of the unusually high reflection signal from the first laser pulse. This pulse (see fig 10a) is larger than the others because the first pulse is the only one to encounter metal which is cold and therefore highly reflective. Subsequent laser pulses interact with liquid or recently solidified melt. The variance signal is calculated on a moving six point average and so no variance signal is provided until six pulses have been monitored. This first variance value is high because it includes the unusually energetic first pulse reflection In general however, the fluctuations in the reflected signal are a function of the fluctuations in the shape of the reflecting surface of the weld. The melt surface geometry changes shown in the snapshots of figure 9 tend to give a reduced reflection signal but, occasionally, the turbulent melt surface provides a more effective reflector than a stable weld (as happened here in the pulse three from the end of the measurement). In some cases the surface of a poor quality weld might result in repeated high reflection values. In this situation a monitoring device based on a simple threshold might be misled into providing feedback that the process was continuing successfully.

It is for this reason that a system designed around the variance of the signals might give additional, useful feedback.

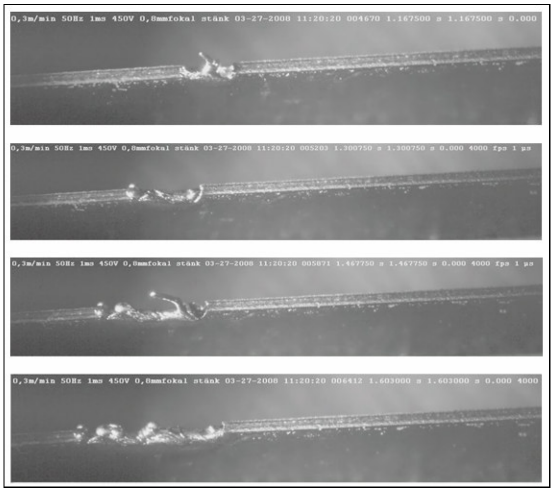

__Fig 9__. An unstable weld after: 9a 0.167s Sample #1000; 9b 0.300s Sample #2000 9c 0.467s Sample #3000; 9d 0.603s Sample #4800

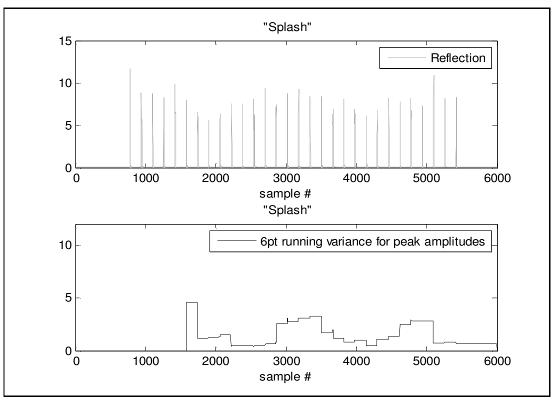

__Fig 10__.Data and Matlab calculations for an unstable weld; 10a. Reflection data, 10b. Variance of reflection data peak amplitudes.

In order to test the effectiveness of this monitoring system, a weld was produced which was initially stable but, after a planned interval, became unstable. This was achieved by clamping the two work pieces together at one end of the intended weld line and separating them at the other. This caused the two work pieces to diverge after an initial 5mm section of close contact (see figure 11). With a feed rate of 500 mm/min and a sampling frequency of 8 kHz this means that the gap occurs after ~3000 samples.
Figure 12 presents the data and variance analysis from this weld and it is clear that around sample 3000 the welding process becomes extremely unstable as the gap between the work pieces grows to unacceptable levels.

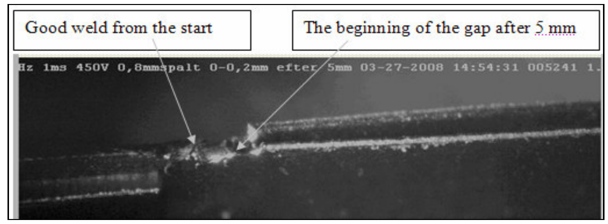

__Fig 11__ The start of the 'diverging work piece' weld.

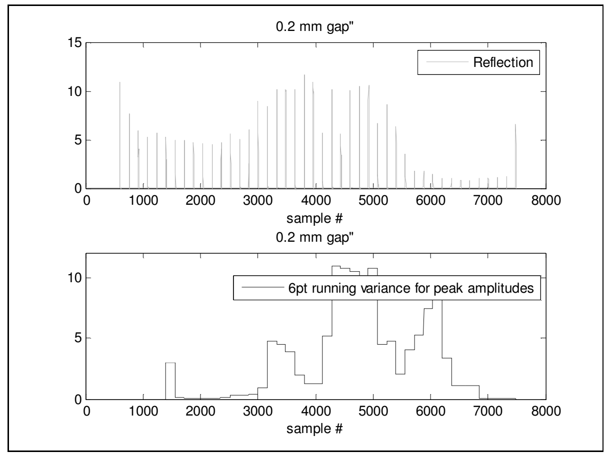

__Fig 12.__ Data and Matlab calculations for the' diverging work piece' weld; 12a. Reflection data, 12b. Variance of reflection data peak amplitudes.

From figure 12a it is interesting to note that the signal peak values for the poor quality welds are higher than they are for the stable weld. This does not necessarily mean that more laser energy is absorbed in the high quality weld (because less is reflected), it merely suggests that the melt geometry of the poor quality weld is a more effective reflector of the laser light. This makes some sense from a phenomenological point of view because, in the early stages of workpiece separation, the weld would achieve a broader and flatter top surface profile as it bridges the gap between the workpieces. This flatter profile would reflect a larger proportion of the beam back in the direction it came from – ie. back to the detector. Eventually (after sample 5500), the strength of the reflected signal diminishes down to a very low value because the weld bridging the gap between the two workpieces collapses and most of the laser beam then travels downwards through the gap. Under these circumstances there is no join between the two workpieces and reflection levels off the individual workpiece edges are low.
Figure 12b tells the story of the variance between the peak values of figure 12a. For the first 5 pulses the system gives no feedback as it is still accumulating data for the variance calculation. At pulse 6 we get our first reported value – which is high as a result of the high reflection value of the first pulse, mentioned earlier. After this initial 'glitch' the variance of the signal is very low during the production of the high quality weld. As workpiece separation begins (at about

sample 3000), the variance rises rapidly and remains at high values until the weld collapses.
A comparison of figure 12a and 12b shows that the information given by the two methods is complementary – in some cases (eg where the welding process collapses at approximately sample 5500) the raw pulse data gives a faster feedback on the situation, in other cases (eg where the work pieces begin to diverge just after sample 3000) the signal from the variance gives a clearer indication that something is going wrong.
It is suggested that peak variance analysis be included in the design of future weld monitoring equipment to achieve a more robust but sensitive feedback system.

4. Conclusions

Kalman filtering is a superior to employing a cut off frequency when extracting informative data from noisy signals.
Signal variance data can be used in conjunction with raw signal data to improve the sensitivity and robustness of laser welding monitoring devices.

Acknowledgments

The authors are grateful to VINNOVA – The Swedish Innovation Agency (project DATLAS, no. 27744-2, Laser Nova AB Östersund, Sweden for their funding and cooperation in the research.

References

[1] Gustafsson 2000. F. Gustafsson. Adaptive filtering and change detection, Wiley, New York (2000).

[2] Kuhl, M.; Neugebauer, R. 'Quality and Process Control of Nd: YAG - Laser Welding Using fuzzy Pattern Recognition Techniques for Multisensor Systems'. Emerging Technologies and Factory Automation, 2006. ETFA apos;06. IEEE Conference on **Volume , Issue** , 20-22 Sept. 2006 Page(s):1329 – 1332. Digital Object Identifier 10.1109/ETFA.2006.355387

[3] R. G. H. K. Tonshoff, A. Ostendorf and W. Specker, "Online monitoring and closed-loop control of laser welding processes," vol. 1405. In Proc. of 12th international symposium for electromachining (ISEM), May 1998, pp. 603–612.

[4] "www.precitec.com." [Online]. Available: www.precitec.de

[5] "www.prometec.com." [Online]. Available: www.prometec.com

[6] R. G. H. K. Tonshoff, A. Ostendorf and W. Specker, "Online monitoring and closed-loop control of laser welding processes," vol. 1405. In Proc. of 12th international symposium for electromachining (ISEM), May 1998, pp. 603–612.

[7] J. K. E. P. R. G. J. R. H. Kaierle, S. Beersiek, "Online control of penetration depth in laser beam welding," vol. 3. Aachen,Germany: Industrial Electronics Society, 1998. IECON '98. Proceedings of the 24th Annual Conference of the IEEE, Sep 1998, pp. 1694–1698.

[8] http://www.cs.unc.edu/~welch/kalman/

[9] Mohinder S.Greval Angus P Andrews
Kalman Filtering Theory and Practice using MatLab J,Wiley 2001,
ISBN 0-471-39254-5

[10] Kalman, R. E. (1960). A New Approach to Linear Filtering and Prediction Problems. Transaction of the ASME—Journal of Basic Engineering, 82(Series D), 35-45.

Rickard Olsson is R&D manager and a partner of Laser Nova AB,Sweden and also industrial PhD student at Luleå University of Technology.
He received his M.Sc degree in Applied Physics and Electrical Engineering, from Linköping University, Sweden in 1985. He has been working with laser technology since 1986 and has also been a part time lecturer at the Mid Sweden University in Digital Signal Processing and DSP programming. He is currently working with on line supervision of weld quality and beam profiling for pulsed lasers at Laser Nova together with Luleå University of Technology.

Appendix 1. Kalman filtering

The Kalman filter is named after R.E. Kalman who, in 1960, presented a paper [10] describing a recursive solution to the problem of discrete data linear filtering of a time varying process with measurements disturbed by noise.
The Kalman filter is an algorithm rather than a actual filter. Mathematically it is the optimal solution for the linear-quadratic problem i.e. estimating a systems "state" whether it may be observable or not using measurement data and minimizing the quadratic error of estimation error covariance.
The filter has found a widespread use from telecommunication to image processing, control theory

and military applications such as target tracking etc. A good introduction to the subject can be found in [8] and a more thorough derivation in [1]. MatLab applications are treated in [9].
The observed reflection signal *y(t)* in our experiment was modelled as a sum of the reflection signal *s(t)* (reflected laser light) plus white noise *n(t)* with covariance *R*. I.e. the received signal can be written as

$$y(t) = s(t) + n(t) \qquad (1)$$

The received signal was modelled in discrete time as an nth order Auto Regressive (AR)-process i.e :

$$y_k = a_1 y_{k-1} + a_2 y_{k-2} + + + a_n y_{k-n-1} \qquad (2)$$

plus a piecewise linear trend between consecutive samples represented at time instant k as b_1+b2_k. When combining these two into one we can write the received signal y_k as:

$$y_k = a_1 y_{k-1} + a_2 y_{k-2} + + a_n y_{k-n-1} + b_1 + b_2 k =$$

$$\begin{bmatrix} y_{k-1} & y_{k-2} & .. & y_{k-n-1} & 1 & 0 \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ .. \\ a_{n-1} \\ b_1 \\ b_2 k \end{bmatrix} = CX_k \qquad (3)$$

i.e. in matrix formulation: $Y_k = CX_k$ (4)
Using arcov off line in MatLab to estimate the AR coefficients identified that a model order of 2 was sufficient.
I.e the process can be modelled with two coefficients as a AR-process and a 1:st degree polynomial

$$y_k = a_1 y_{k-1} + a_2 y_{k-2} + b_1 + b_2 k \qquad (5)$$

b_1 and b_2 could now be estimated for each iteration and subtracted from the measured values y_k.
Using Kalman formulation we had:
The internal state of the process: X (6)
The state transition matrix A:

$$A = \begin{pmatrix} & & 0 & 0 & 0 \\ \mathbf{I}_{nxn} & & .. & .. & 0 \\ 0 & & .. & 1 & 1 \\ 0 & & .. & 0 & 1 \end{pmatrix} \qquad (7)$$

Kalman gain K_k (8)

Covariance of the estimation error: $y_k - \hat{y}_k$
P_k (9)

Covariance of the measurement noise:
R (10)

The Kalman equations are given in their iterative form as follows;

$$K_k = AP_k C_k^T / (C_k P_k C_k^T + R) \qquad (11)$$

$$X_{k+1} = AX_k + K_k(y_k - C_k X_k) \qquad (12)$$

(13)

$$P_k = (A - K_k C_k) P_k (A - K_k C_k)^T + K_k R K_k^T \qquad (14)$$

$$\hat{y}_k = C_k X_k \qquad (15)$$

where y_k is the observed (measured value) and $\hat{y}_k$ is the estimated value (used in later calculations) .

Appendix 2. The CUSUM algorithm

To detect the leading and trailing edges of the reflected laser light signal the CUmulative SUM, (CUSUM) - algorithm has been used.

The CUSUM algorithm is defined as follows [1]:
Assume that we want to detect a change in mean of magnitude v of the signal *s(k)*.
First we form an objective function *g(k)*:

$$g(k) = \max(g(k-1) + s(k) - v, 0);$$

$$\text{alarm if } g(k) > h \qquad (16)$$

where the alarm level h is a design parameter and v is an offset.
To detect negative changes we simply use min instead of max and negate both h and v.
If we now use $\hat{y}_k$ as s(k) then, when the negative alarm is triggered, the actual reflection value $\hat{y}_k$ is picked from the most probable time of change into *peak(k)*. As a rule of thumb [1] the value is taken at the point

$$k - h/(0.5 - \upsilon) \qquad (17)$$

I.e $$peak(k) = \hat{y}(k - h/(0.5 - \upsilon)) \qquad (18)$$

and remains constant until the next peak is detected.
For every sample instant k, the variance $\mathrm{var}(k)$ was calulated in a straight forward manner as:

$$\mathrm{var}(k) = \tfrac{1}{5} \sum_{j=k-5}^{k} (peak(j) - \overline{x})^2; k = 6..N. \qquad (19)$$

(Note that *peak(k)* is a vector of length N but piecewise constant between each peak)
N is the number of samples and $\overline{x}$ the overall mean of the peaks, i.e the average peak value. The number 6 was chosen as a compromise the get a reasonably fast response.
In a real world application it would of course be possible to use e.g. an electronic trigger signal from the laser to identify the rising edge of the signal and e.g. a leaky capacitor solution to detect the peak. An advantage of using CUSUM is that this algorithm is robust to noise and gives a statistically significant indication of an actual change in the measured signal.