



## The Regression Value Algorithm

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The MPMS represents the state-of-the-art magnetometer by combining the exceptional sensitivity of SQUID-based detection with highly sophisticated software. Much of the value of the MPMS stems from the fully automated capabilities that allow continuous, unattended operation for days at a time. However, with this degree of automation comes a dependence on the hardware to operate correctly, and typically a user is absent when questionable measurement results are collected. Because of this, there must be a way to assess the quality of the data after it has been collected. For the MPMS, the regression value provides a means to differentiate between raw data that fits the expected dipole response and data, which does not.

This application note

- explains the regression value algorithm.
- provides quantitative examples so that MPMS users can make well-informed decisions when analyzing data.
- describes the most recent regression algorithm that is incorporated into the DOS code (rev. 2.28.3 and later) and the Windows™-based MPMS MultiVu application (rev. 1.11 and later). Earlier software versions utilize different regression algorithms, and although these versions produce similar general trends the specific results may differ substantially from the following results.

### Qualitative Overview of the Regression Value

The regression value indicates the match between the measured SQUID response and that of an ideal point dipole. The regression value ranges from 1 to 0, with 1 corresponding to a perfect match between the measured response and that of an ideal point dipole. As the deviation increases, the regression value decreases, with a lower limit of 0. Since the measured signal will depend on factors such as the magnitude of the magnetic moment, temperature, and magnetic field, there is no single critical regression value that automatically corresponds to “bad” data. Instead, you must determine what is an acceptable noise level and regression value for the specific measurement and reference similar data to these results.

### Calculating the Regression Value

The regression value calculation is identical for both the RSO and DC magnetic measurements. In each case a discrete series of SQUID voltages and corresponding

longitudinal positions forms the fundamental data used in the calculation of both the magnetic moment and the regression value.

This data is initially manipulated to remove a DC bias voltage and a linear voltage drift<sup>1</sup>. The software then adjusts several fitting parameters and determines the values that minimize the difference between the ideal and measured response. After computing the best fit, calculate the regression value using this formula:

$$\text{Regression Value} = 1 - \frac{1}{V_{amp}^2(N-1)} \sum_{i=1}^N \left( V_{meas}(i) - V_{fit}(i) \right)^2$$

In this expression,  $V_{meas}(i)$  is the measured voltage at the  $i$ 'th vertical position,  $V_{fit}(i)$  is the fit voltage at the  $i$ 'th position,  $V_{amp}$  is the positive amplitude of the fit, and  $N$  is the number of points comprising the scan. The calculation of  $V_{amp}$  is detailed elsewhere<sup>1</sup>, and in the context of the regression calculation it sets the relative scale.

When the difference ( $V_{meas}(i) - V_{fit}(i)$ ) is small relative to  $V_{amp}$ , the measurement noise contribution is small, and a relatively large regression value is returned. Similarly, if the discrepancy between the fit and the measured data is consistently on the order of  $V_{amp}$ , a value close to zero is returned. In the case that the scatter is much greater than  $V_{amp}$ , the above equation returns a negative value, and a default regression value of 0 is returned.

## Examples of Regression Value Calculations

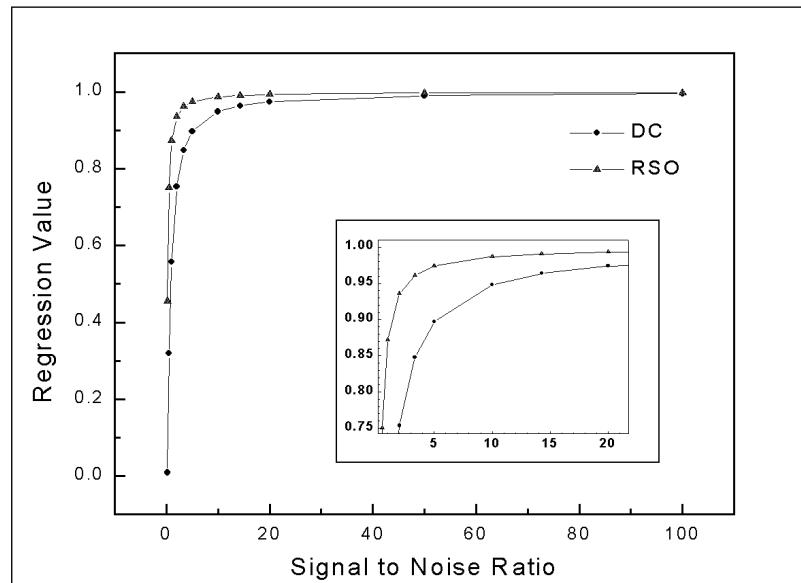
The following examples illustrate the correlation between the regression value and the noise in the SQUID output. In each case, an ideal, noise-free response is superimposed with varying amounts of random noise. The relative magnitude of the noise is characterized by the signal-to-noise ratio, which is the ratio of the amplitude of the ideal response to the amplitude of the noise envelope. The resulting signal is analyzed, and the corresponding regression value is calculated.

Figure 1 shows the relation between the regression value and the signal-to-noise ratio. Figures 2 through 9 show selected DC and RSO waveforms used to generate Figure 1. For a given regression value, these waveforms illustrate that the RSO waveform will contain a larger noise component than a DC waveform. So, be careful when comparing the DC and RSO regression values.

Remember, this is an idealized noise scenario. Depending on the measurement details, the measured response may have noise features that are beyond the scope of this application note. If the quality of the data is in question, you should observe the SQUID response curves and determine the minimum acceptable amount of noise for the specific measurement. This in turn creates a baseline regression value that can be used to differentiate between acceptable and questionable measurement results.

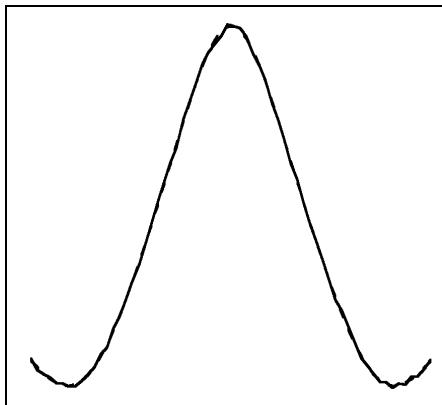
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<sup>1</sup> See Quantum Design application note 1014-203, “An Outline of the Data Regression Routines.”

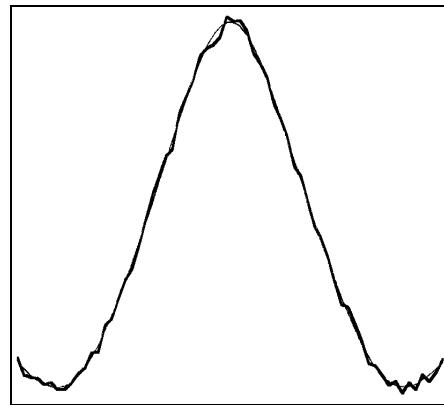


**Figure 1.** Regression Value Versus Signal-to-Noise Ratio

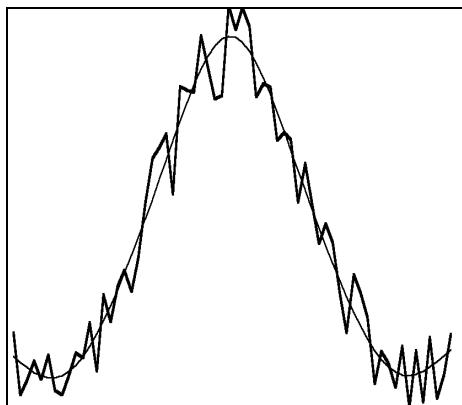
## Raw DC Response Curves, the Curves of Best Fit, and their Corresponding Regression Values



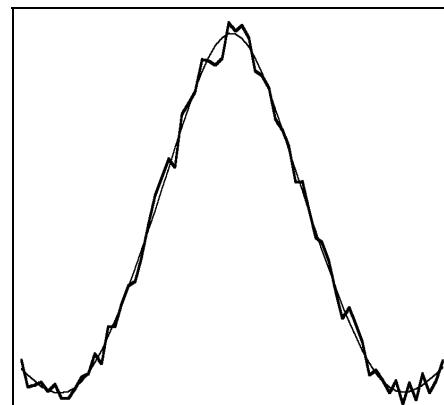
**Figure 2.** S/N = 50, Regression Value = .990



**Figure 3.** S/N = 20, Regression Value = .974

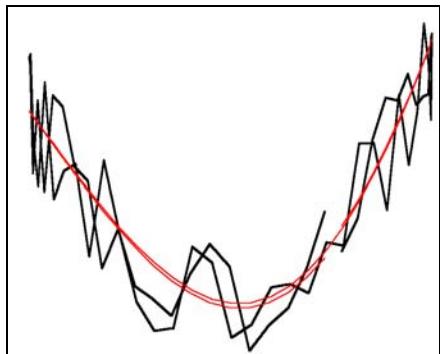


**Figure 4.** S/N = 3, Regression Value = .848

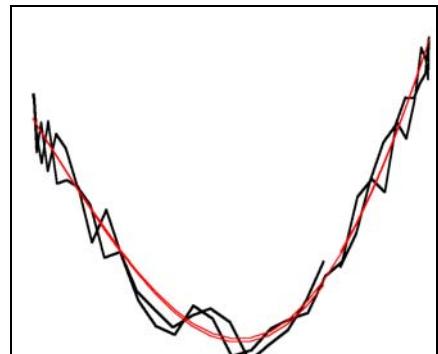


**Figure 5.** S/N = 10, Regression Value = .948

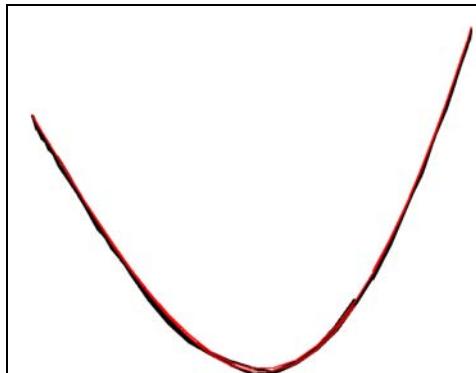
## Raw RSO Response Curves, the Curves of Best Fit, and their Corresponding Regression Values



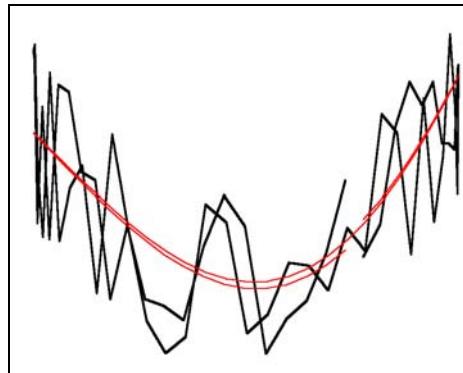
**Figure 6.** S/N = 2, Regression Value = .936



**Figure 7.** S/N = 5, Regression Value = .974



**Figure 8.** S/N = 50, Regression Value = .997



**Figure 9.** S/N = 1, Regression Value = .872