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RESEARCH ARTICLE

Removal of sensor tilt noise in fluxgate gradiometer survey data by applying one-dimensional wavelet filtering

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Abstract

Archaeological prospection with magnetometer instruments is performed in a wide range of field configurations, ranging from single probe setups to mobile arrays that allow combining multiple sensors. The latter type, whereby instruments are mounted onto a cart system, are particularly prone to motion-induced noise. Sensor tilt, for example, causes in-line noise that can obscure magnetic variations present. To remediate these effects, image processing techniques are the most frequently applied. However, while efficient in producing more levelled data plots, these procedures are often associated with a smoothing penalty whereby low-intensity or small-scale anomalies are masked. We propose a one-dimensional signal processing approach, based on discrete wavelet analysis. By selecting wavelets that correspond to the motion-induced noise patterns, such effects can be targeted more precisely, reducing the risk of feature masking or artefact creation. Evaluation of the proposed procedure on three fluxgate gradiometer datasets collected with a hand-propelled push-cart system, proved it a valid and more dedicated method to reduce the impact of motion induced noise in magnetometry data collected with cart mounted array setups.

KEYWORDS

cart systems, denoising, magnetometry, sensor tilt, signal processing, wavelets

1 | INTRODUCTION

In archaeological prospection, fluxgate gradiometer systems occur in many different survey setups (Gaffney & Gater, 2010). Regardless of the configuration, gradiometer probes should be set in a stable vertical position to allow reliable data collection. This 'ideal' condition is sometimes difficult to uphold under field circumstances, and any sensor tilt induces noise into resultant survey data. Such motion-induced 'tilt' noise often displays specific wave patterns related to survey mode and speed, and coincides partly with operator step frequency (for manual surveys) or mechanic reverberations of mobile setups. The use of cart systems, which allow integrating multiple gradiometer sensors, tend to adversely affect motion-induced noise as subtle motions of operator or operating vehicle are propagated, and sometimes enhanced, through the cart handle or towing rod. While adding suspension to cart-systems can help reduce the impact of micro-relief and operating tilt, the need for mediating resultant noise through post-processing persists.

Commonly, image filtering is applied to reduce the influence of tilt noise. Hereby, two-dimensional (2D) low-pass filters (based on e.g. Gaussian, median or moving average filtering) are used to remove the tilt-noise. However efficient in producing a more levelled data visualization, these techniques come with a smoothing penalty and produce blurred images (Bovik, 2000; McVeigh, Henkelman, & Bronskill, 1985; Paoletti, Fedi, Florio, & Rapolla, 2007; Tsivouraki & Tsokas, 2007). For tilt noise particularly, the risk of artefact creation and removal of relevant information burdens adaptive filtering, as motion-induced noise often has the same high frequency content as anomalies in data registration (Tsivouraki & Tsokas, 2007). Nevertheless, in order to fully exploit data potential, tilt noise has to be addressed in post-processing as it can both mask relevant magnetic variations and create artefacts that make data plots difficult to interpret. We therefore propose an alternative filtering procedure that allows targeting tilt-noise variations more accurately through an adaptive processing scheme.

As motion induced noise is essentially independent of measurement positioning, but introduced as a function of sensor setup and

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the method of propagation, the resultant effect can be addressed in the time domain. Tilt noise generally causes repetitive patterns that occur perpendicularly to the direction of motion. However, as the frequency characteristics of such interference can vary slightly throughout the entire dataset, a flexible noise identification is pivotal in avoiding the introduction of artefacts. We therefore propose a filtering procedure based on the one-dimensional (1D) wavelet transform whereby the survey dataset is addressed as a time-series. The inherent flexibility of wavelet analysis allows targeting the appropriate variations by selection of a suited mother wavelet, and considering different scales of variation simultaneously. For processing magnetometry data, wavelet analysis is often used to drive filtering methods aimed at removing undulation errors between survey lines in ground surveys (Tsivouraki & Tsokas, 2007) and directional trends in airborne survey data (Fedi & Florio, 2003), albeit primarily in 2D image processing procedures. For addressing unwanted measurement interference by 1D signal processing, De Smedt, Delefortrie, and Wyffels (2016) used a 1D discrete wavelet filtering applied on electromagnetic induction data to remediate micro drift fluctuations. Here, we propose an adaptive filtering procedure, equally based on the 1D wavelet transform, that allows to isolate unwanted motion-induced noise in magnetometer datasets. After defining the cause and specific influence of sensor tilt, we investigate how adaptive wavelet filtering can help overcome the burden of tilt noise in magnetic survey data, and subsequently evaluate the efficiency of the procedure on three test cases.

TABLE 1 Summary statistics of the three test datasets

Values in nT	Kemmel	Oostkerke	Alkeveld
Mean	7.67	4.14	−0.23
Median	−0.3	−0.3	−0.3
Maximum	10000	2563.9	6018.9
Minimum	−9868.8	−1265.3	−6965.8
Interquartile range	45.8	27.7	7.4
Standard deviation	278.17	49.54	61.34

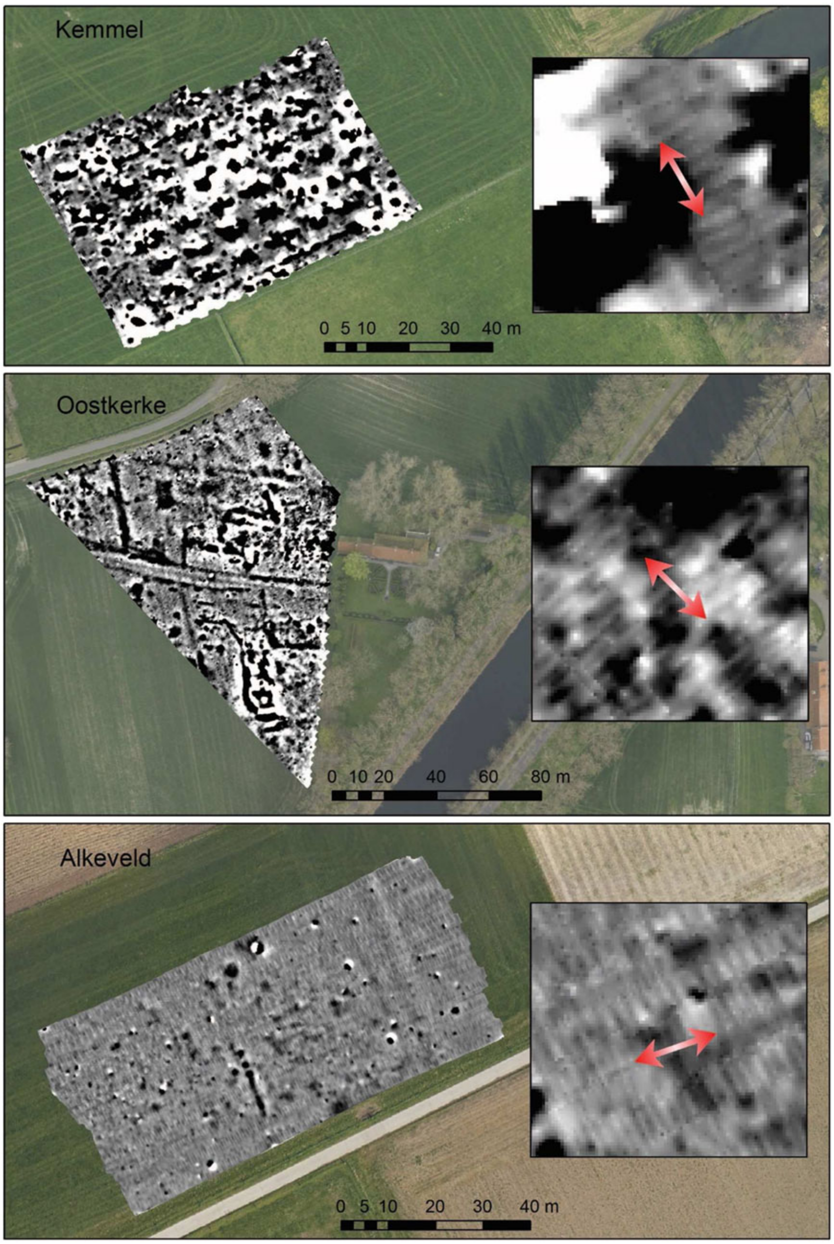

FIGURE 1 Display of the three magnetometer datasets with a grey scale set from -25 nT (white) to +25 nT (black). The direction of profiling is indicated by a double arrow on a zoomed detail of the dataset where the noisy wave pattern is visible [Colour figure can be viewed at wileyonlinelibrary.com]

2 | SURVEY STRATEGY AND TEST SITES

To evaluate the proposed procedure, magnetometry data from three test locations were considered. All data was collected using a five-probe sensor array, incorporating five FGM650/3 fluxgate gradiometers (SENSYS, Rabenfelde, Germany) with a measurement range of ±10,000 nT (SENSYS, 2016). These sensors were mounted 0.5 m apart in a push cart whereby measurements were obtained manually at a sampling rate of 20 Hz. The data output file shows 85 measurements per metre for each probe. All surveyed sites were located in Belgium and display different magnetic contrasts (summary statistics are shown in Table 1). The first site is located at the World War I front line in Kemmel, situated 10 km from Ypres. The foundations of a barrack camp were prospected. The phenomenon of metal shrapnel pollution originating from World War I causes strong anomalies in the whole area (Saey *et al*., 2016). The second site is located at Oostkerke in the Bruges area (Trachet *et al*., 2015). This survey is conducted at the location of a former medieval town. Settlement foundations (bricks) and a road were buried beneath the surface. The third location is a roman settlement in East-Flanders, named Alkeveld. Unlike the previous test sites, magnetic field variations have a more restricted range (Table 1). All three datasets are visualized in Figure 1 with addition of a window containing a detail of the noisy wave pattern and the direction of profiling.

3 | NOISE IDENTIFICATION

After interpolating push cart survey data, a repetitive wave pattern was detected with fluctuations around 5–10 nT perpendicular to the survey direction in every acquired dataset and in all separate probe measurements (Figure 1). To isolate the cause of this noise pattern, two tests were conducted aimed at assessing the influence of measurement drift and sensor tilt.

In a first test, stationary measurements were conducted with a fluxgate gradiometer probe at a fixed location (Figure 2). The observed variations display a range smaller than 1 nT in field circumstances which corresponds with the sensor's stability in its technical sheet (SENSYS, 2016). However, these small amplitude variations do not explain the repetitive noise pattern. If we consider longer stationary recordings (five minutes or more), drift over time becomes clearly visible. As such drift introduces low frequency trends in final data plots, this phenomenon can also be excluded as possible noise factor for the repetitive noise.

A second test was conducted with a sensor moving along one trajectory to test the effect of tilting on the signal acquisition. In the first measurement, a gradiometer was moved vertically in one direction. In the second measurement, a subtle tilting motion was introduced to the sensor (Figure 3). These data show how sensor tilt results in noise with a similar range and sinusoidal pattern as observed in the field data (Figure 1).

A simplified representation of the cart carrier frame is shown in Figure 4 with indication of the two relevant tilt axes (the vertical yaw axis does not influence the vertical sensor position and is therefore not taken into account). Axis 1 is orientated parallel to the direction of motion. Any roll around this axis is caused by the terrain's roughness and the absence of suspension on the cart wheels. Micro-relief causes

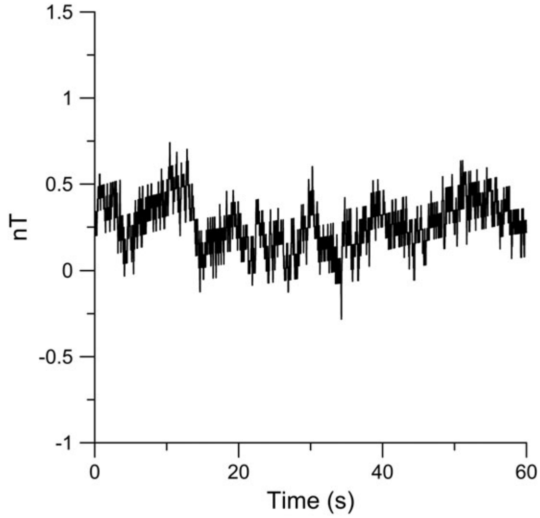

FIGURE 2 A 60 seconds FGM650 gradiometer stationary data example

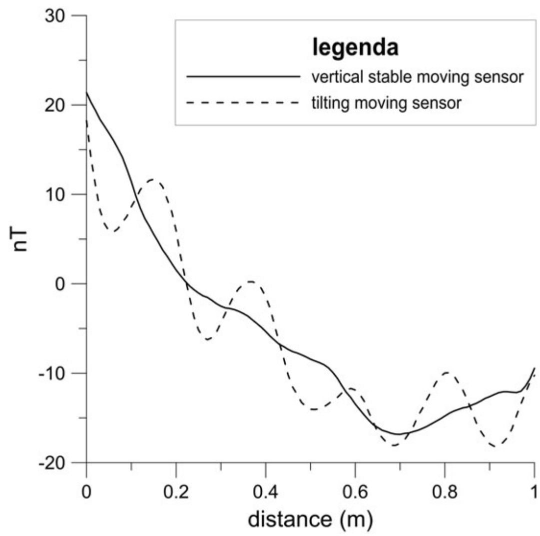

FIGURE 3 Gradiometer signals of a vertical stable moving sensor (full black line) and a subtle tilting moving sensor (dashed line) along the same trajectory

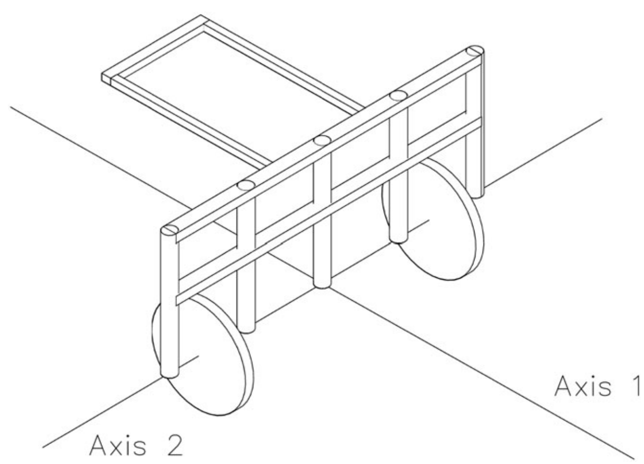

FIGURE 4 Schematic representation of the magnetometer push cart with an indication of the tilt axes. Axis 1 aligns with the direction of movement while Axis 2 is perpendicular to Axis 1 at the height of the sensor array through the wheel basis

the carrier frame to rotate and vibrate. The use of more than two wheels and/or suspension on the cart would give the system a better stability. The pitch around Axis 2 is caused by the operator movement (step frequency, walking speed, the ability to keep the sensor array stable, operator faults, etc.), therefore this results in tilt noise as demonstrated in Figure 3 and present in the datasets in Figure 1.

4 | WAVELET-BASED FILTERING PROCEDURE

4.1 | 1D wavelet analysis

Wavelet analysis is based on translations (~time/location) and dilations (~frequency/scale) of a predefined mother wavelet function $\psi(x)$ to divide a signal in components of different resolution respective to the applied scales of the mother wavelet (Daubechies, 1992). Original signals (s_o) are divided into approximations (a_j) and details (d_i) until a certain level (j), whereby details contain the high-passed, and approximations the low-passed information for each decomposition level. It follows that the original signal can then be reconstructed by the summation of the obtained details and approximations as:

$$s_o = \left(\sum_{i=1}^{j} d_i\right) + a_j \tag{1}$$

<NI>Selecting an appropriate mother wavelet is pivotal in any wavelet analysis, and highly dependent on the characteristics of the targeted signal. For analysing magnetometer data, Shen, Sarris, and Papadopoulos (2008) and Tsivouraki and Tsokas (2007) proposed that Daubechies 2 (db2), Daubechies 4 (db4) and Coiflet 1 (coif1) wavelets (Härdle, Kerkyacharian, Picard, & Tsybakov, 1998) are the most suited. After evaluating the efficiency of different wavelets to isolate tilt noise present in the datasets considered in this paper, the db2 and coif1 wavelets were deemed the most apt to drive the filtering procedure.

4.2 | Isolating tilt noise

To compensate for the effect of tilt noise in data collected with mobile sensor arrays, a first step consists of considering measurements for

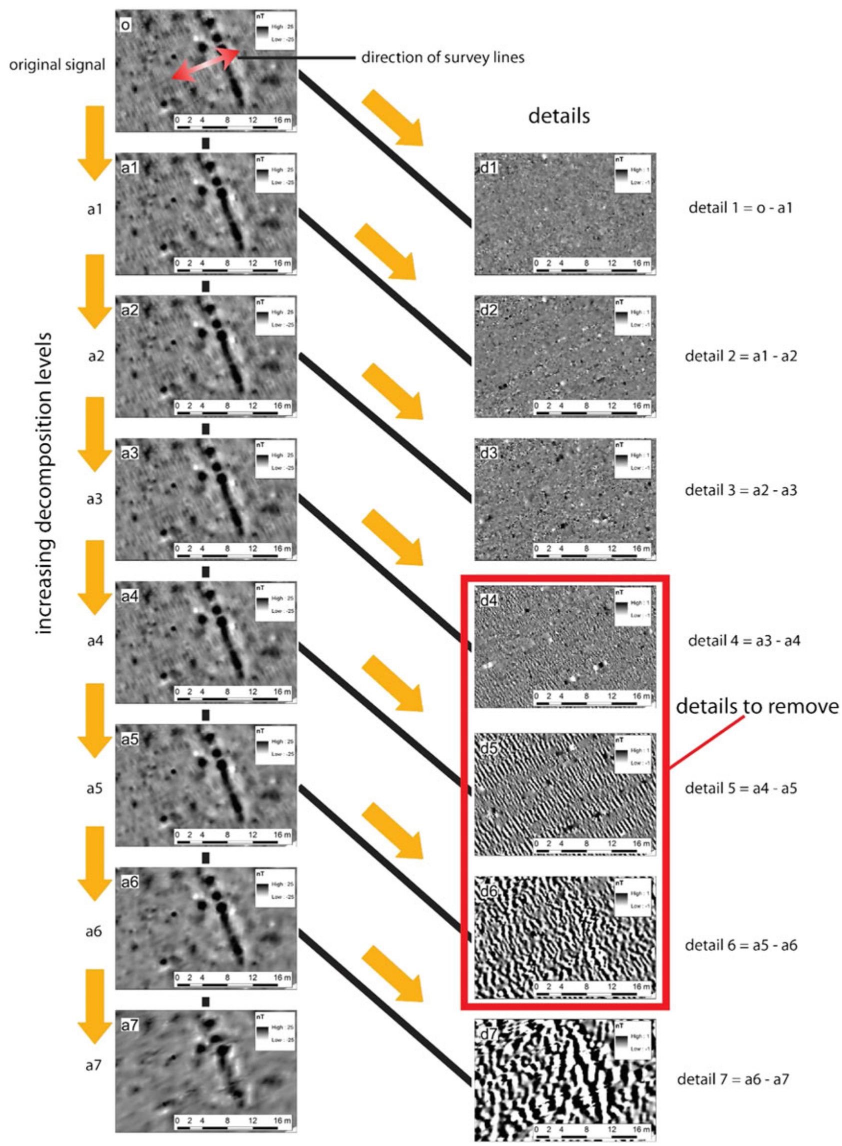

FIGURE 5 Interpolated details and approximations from a part of the Alkeveld dataset. For this wavelet decomposition, the Coiflet 1 wavelet is applied, starting at level 1 to 7. The details with the perpendicular striping pattern are selected [Colour figure can be viewed at wileyonlinelibrary.com]

each sensor probe separately. Next, the signal components of each data series are evaluated through the 1D discrete wavelet transform. The resultant details and approximations are interpolated to a resolution of 0.15 m. These grids are examined in a decomposition tree structure to determine at which scale the tilt pattern appears. After identifying decomposition details coinciding with the targeted noise pattern, these can be removed from the original signal. In Figure 5, a decomposition tree, obtained by using a coif1 mother wavelet, is presented with part of the gridded Alkeveld dataset. Here, the tilt pattern is isolated in details d_4 to d_6. Consequently, removing these detail levels would reduce the influence of tilt noise of final data plots. Filtering out details of level 7 or higher, however, would introduce artefacts, i.e. data deformations in the direction of survey motion.

To evaluate the effect of removing the relevant detail levels, visual inspection along with the assessment of the relative signal energy loss (ε_r) (Münch, Trtik, Marone, & Stampanoni, 2009), i.e. the relative mean squared error between original and filtered signal, can serve as a quick indicator for how strongly the wavelet filtering influences the overall data variation. Hereby, a combination of satisfactory removal of visible tilt noise and a low ε_r is pursued. Consequently, the mother wavelet that enables removing sensor tilt noise with the lowest energy loss ε_r is most apt for any wavelet based filter procedure targeting such interference. Transect-wise evaluation of filtering a low range (Figure 6, left) and high range (Figure 6, right) field dataset using coif1/db2/db4 mother wavelets, shows us that:

- use of Daubechies mother wavelets (db2 and db4) introduces artefacts around strong anomalies (> 100 nT). The db2 wavelet is the least sensitive to this phenomenon, and can therefore be considered the most suited to filter magnetometer data. When we analyse the small data range example too many dissimilarities with the original signal (amplitude under-estimation and peak stretching) were introduced in the filtered data. This effect increases with large anomalies. In addition, the Daubechies wavelets also affect the spatial location of the detected objects (stretching and peak translation). Combined, these signal deformations are reflected in large relative energy losses (ε_r db2 = 30.9% and 10.5%; ε_r db4 = 16.8% and 34.9%).
- use of the coif1-wavelet does not cause large artefacts around strong anomalies. In both data series, the coif1 filtered data fits best to the original signal and produces the lowest relative energy losses (ε_r = 3.4 and 4.4%). While some peaks are introduced due to

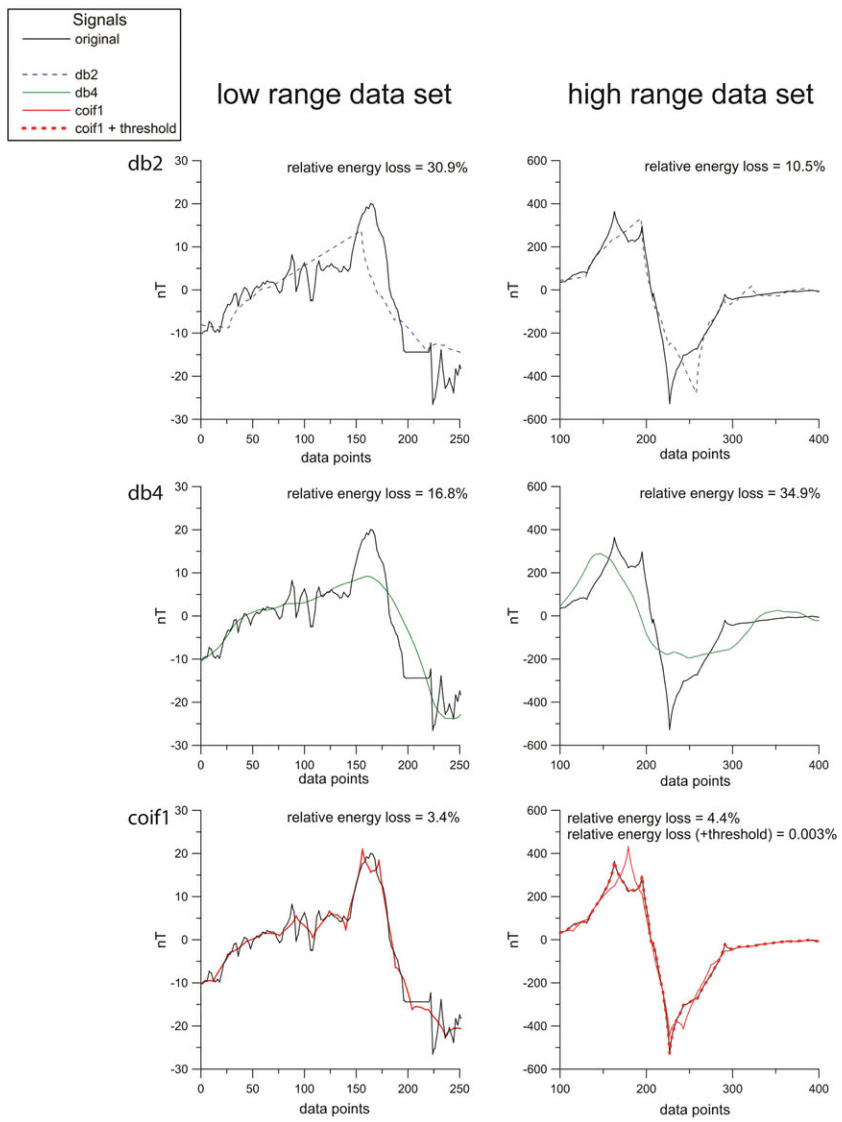

FIGURE 6 The representation of two samples of denoised signals and their relative energy loss ε_r, visualized for three types of analysing mother wavelets: Daubechies 2 (db2), Daubechies 4 (db4) and Coiflet 1 (coif1). The two example evaluation datasets represent a low range and a high range data set to assess the results in two conditions [Colour figure can be viewed at wileyonlinelibrary.com]

the shape of the coif1-wavelet, this limited artefact creation is outweighed by the efficient tilt pattern filtering.

<NI>Based on these observations, the coif1 mother wavelet was implemented in the processing procedure. However efficient in reconstruction the magnetometer signal, wavelet filtering adversely affects data quality where large peaks (e.g. >100 nT) are present (Figure 6, right column). As the targeted tilt effect is dominant in the narrower data range, isolating data within a predefined range (***rt***) can help overcome the introduction of artefacts. Within these boundaries wavelet filtered data is used integrally. For data beyond these limits, the original signal is retained. Hereby, peak introduction and response over−/under-estimation are successfully avoided (e.g. Figure 6, right column, bottom graph). To prevent this method from introducing large data jumps at transition points, a threshold defining the allowed maximum difference (d_{max}) is set between the original and filtered signal. When this difference is greater than d_{max}, the original data is again retained. For the presented datasets ***rt*** was set at ±50 nT, while a d_{max} of 20 nT was allowed between the original and filtered signal. These applied adjustments result in a much lower ε_r which indicates that tilt noise removal has only a relatively small effect on the total signal energy content. The threshold effect is particularly apparent in the high range dataset (Figure 6, bottom, right), where only 0.003% of energy loss occurs after wavelet filtering when only the ***rt*** range is targeted. The remaining data points fall beyond the set threshold range and are therefore not addressed by the filtering algorithm.

4.3 | Result evaluation

The original and filtered datasets of the three prospected areas are gridded at a resolution of 0.15 m and partially visualized in Figures 7–−9 based on the processing choices made in the previous sections. A grey scale with boundaries of ±25 nT is chosen to compare the results in a similar manner.

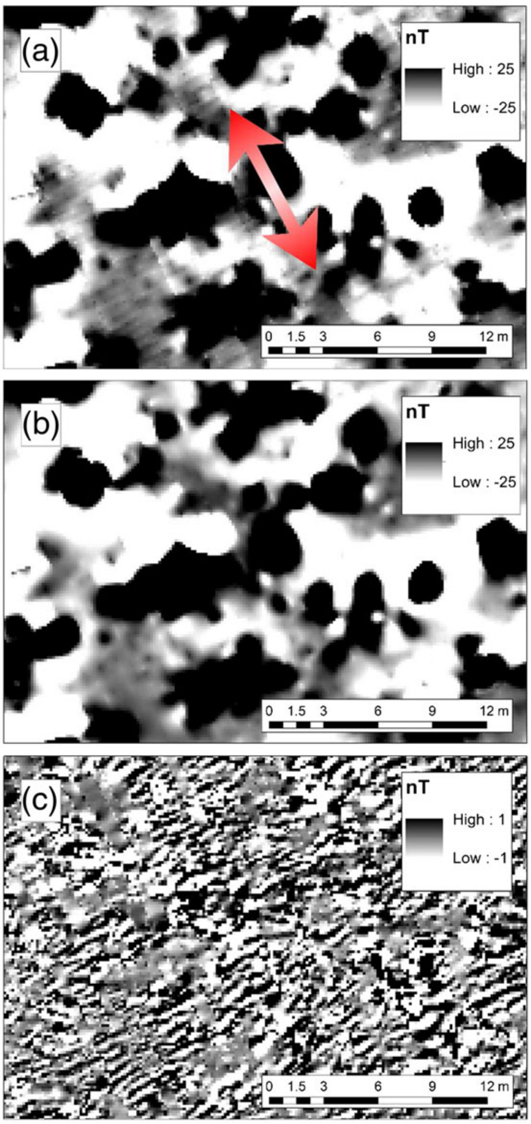

FIGURE 7 A comparison between the original (a) and filtered (b) interpolated signal and the residuals (c) between a and b of the Kemmel dataset. The double arrow indicates the survey line direction [Colour figure can be viewed at wileyonlinelibrary.com]

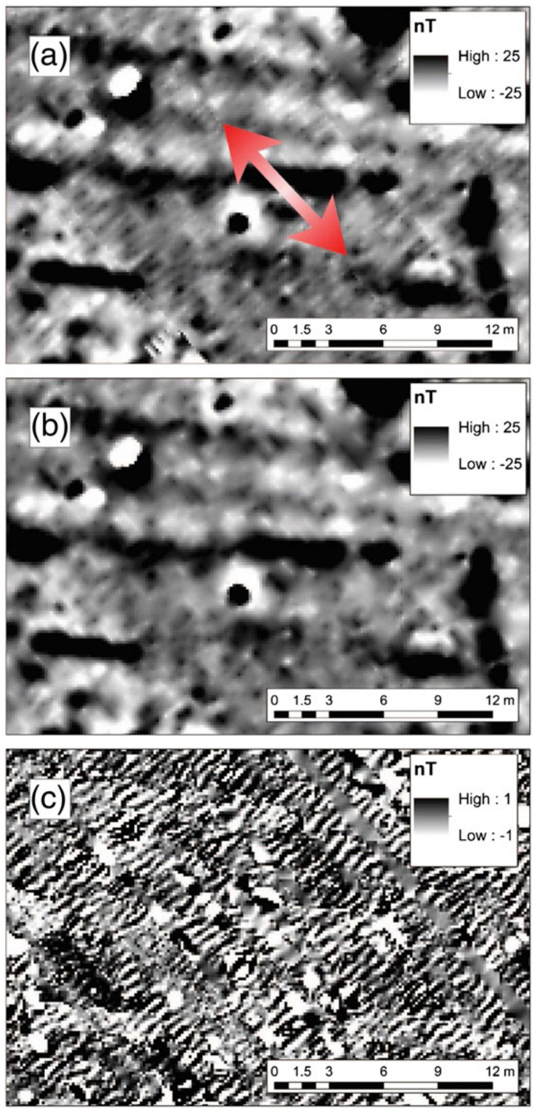

FIGURE 8 A comparison between the original (a) and filtered (b) interpolated signal and the residuals (c) between a and b of the Oostkerke dataset. The double arrow indicates the survey line direction [Colour figure can be viewed at wileyonlinelibrary.com]

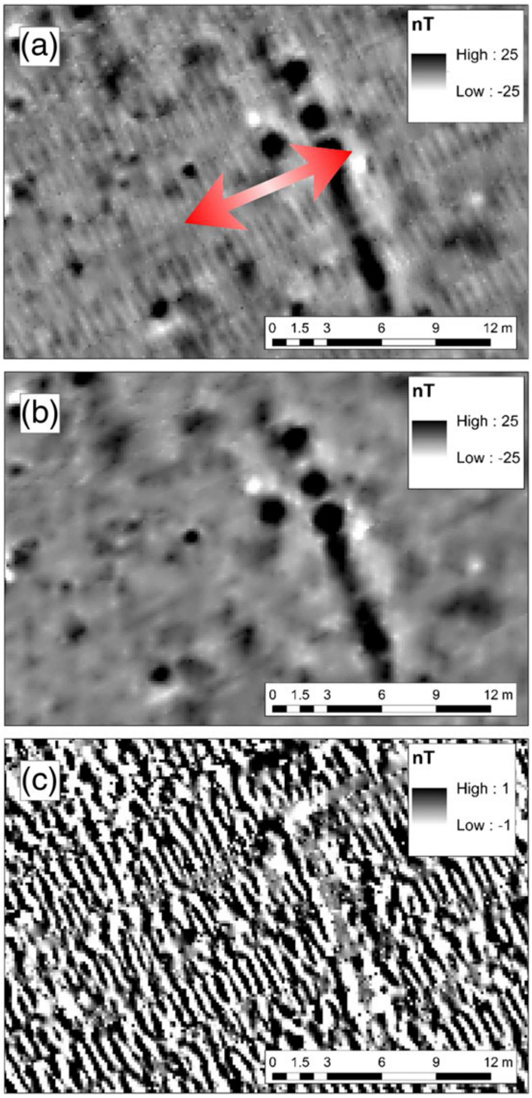

FIGURE 9 A comparison between the original (a) and filtered (b) interpolated signal and the residuals (c) between a and b of the Alkeveld dataset. The double arrow indicates the survey line direction [Colour figure can be viewed at wileyonlinelibrary.com]

On all investigated datasets, the applied procedure allowed to reduce the effect of tilt noise to an extent where it could no longer be discerned clearly in the final data plots. When the filtering residuals are examined (Figures 7c, 8c and 9c) the targeted repetitive tilt pattern is isolated with little added variation included. While high amplitude anomalies do influence the filtering result, and, particularly for the Oostkerke dataset (Figure 8) affect the tilt pattern residuals (Figure 8 c), this effect remains limited and without observable consequences in the filtered data plot (Figures 7b, 8b and 9b). As can be expected, the effect of wavelet filtering is most apparent in the narrow range dataset (Alkeveld, Figure 9), resulting in a practically tilt noise free result.

To evaluate the processing quality of wavelet filtering with traditional applied techniques, a visual comparison with a 2D Gaussian (3 × 3 kernel, five passes) and a moving average filtered dataset (3 × 3 kernel, five passes) was made. This is shown in Figure 10, applied on the Alkeveld dataset. Figure 10 demonstrates that the filter parameters chosen by the authors, mask the tilt errors sufficiently. If we look just at the tilt induced noise, our suggested procedure produces the best result in terms of image sharpness. Despite that, other effects such as pixel outliers and traces from which the direction of motion can be distracted, remain present. To deal with this problems, 2D low-pass filters are more suitable. Also the phenomenon of peak stretching (as mentioned earlier) is visible, resulting in anomaly deformation in the direction of motion. This phenomenon is absent in the moving average or Gaussian low pass filtered data. In practice, a combination of the wavelet based filtering, outlier detection algorithms and 2D smoothing techniques will be applied on the same dataset to process different kinds of noise.

5 | CONCLUSIONS

Sensor tilt is identified as the primary cause for repetitive wave patterns in magnetometer data collected with cart-mounted sensor arrays. This tilt is related to different external factors including the terrain's micro-relief, motion characteristics, and operating specifications. The signature of the repetitive tilt pattern in the direction of profiling enables applying a 1D discrete wavelet transformation directly on the gradiometer signal to subsequently reduce the influence of motion induced noise. By identifying tilt patterns in the wavelet decomposition levels, noise related details can be selected and removed from the original signal. As the proposed filtering procedure relies heavily on the selected mother wavelet, using a poorly suited wavelet function can adversely affect the shape and positioning of magnetic anomalies. We have shown how the coif1 mother wavelet is most suited for isolating tilt noise in magnetometry datasets, reducing the risk of artefact introduction. In addition, we demonstrated how tilt noise can be targeted more precisely by defining threshold values that ascertain filtering only the narrow data range, resulting in a more adaptive and performant filtering procedure. Compared to conventional 2D low-pass filters that inherently address different types of signal interference simultaneously, the presented procedure allows to target repetitive tilt noise more precisely. This results in a dataset in which relevant anomalies remain sharply delineated. If needed, other types of unwanted data variations can subsequently be filtered through more adaptive processing procedures.

While the proposed filtering procedure allows achieving a tilt-noise free result, the mechanical origin of such interference should be equally addressed. Improving survey conditions by using suspended cart systems or through the integration of real time axis compensation will partly relieve the burden on subsequent filtering procedures. As the use of both manually and vehicle operated cart-systems in archaeological prospecting increases, the need for integrated and adaptive means of overcoming associated data issues grows. To fully exploit the potential of the resultant datasets, developing and making available remediating procedures, as the one proposed in this paper, remains essential.

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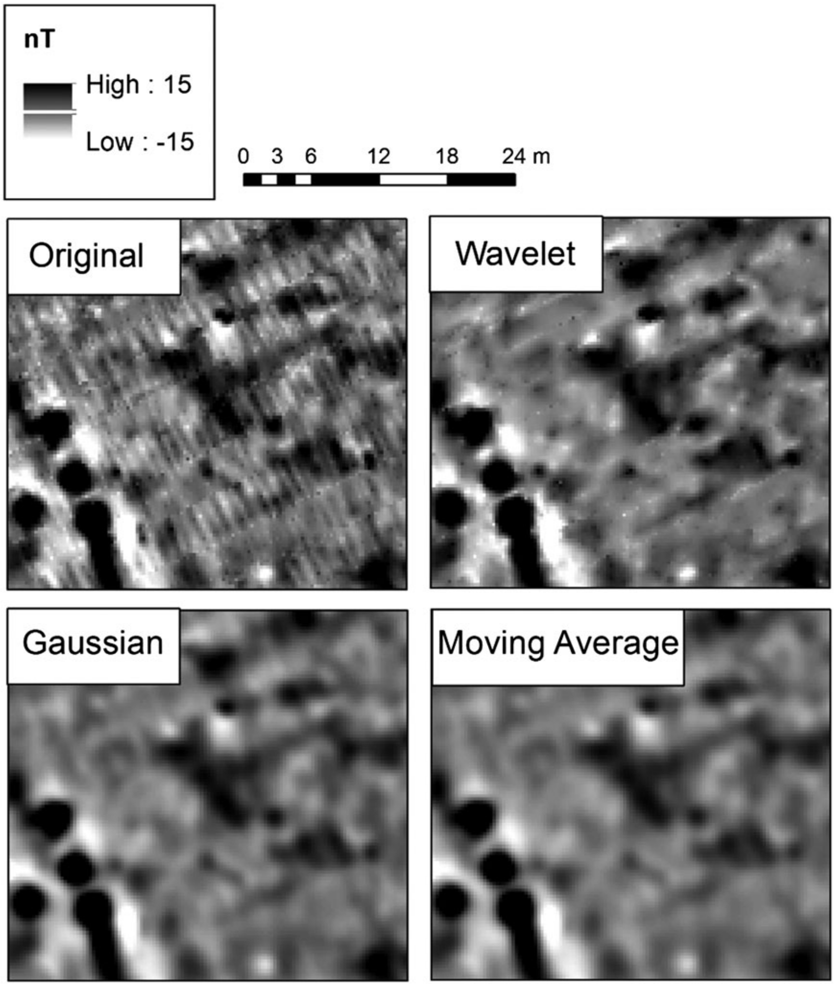

FIGURE 10 Focus window on a part of the Alkeveld dataset for the original dataset, a one-dimensional (1D) wavelet based filtered result, a two-dimensional (2D) Gaussian low-pass filtered result (five passes of a 3 × 3 kernel) and a moving average filtered dataset (five passes of a 3 × 3 kernel)

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