TECHNISCHE UNIVERSITÄT BERGAKADEMIE FREIBERG
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AN IMAGE SEGMENTATION APPROACH FOR THE DETECTION OF SMALL-SCALE MAGNETIC ANOMALIES

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1. MOTIVATION

Field of Interest: UXO Detection

- Problem: hazard potential due to buried unexploded ordnance
- Aim: reliable detection of target objects by an improved interpretation of geomagnetic survey data

Fig. 1: Cluster munition (AzVision, 2020)

Experimental Design:

1. Simulation of the anomaly field for realistic survey conditions
2. Implementation of an adequate artificial neural network
3. Building a model to recognize the magnetic signature of potential target objects

2. GENERATION OF REPRESENTATIVE SURVEY DATA

Data basis:

$$B(P) = \frac{\mu_0 m}{4\pi r^3}[3(\hat{m}\cdot\hat{r})\hat{r} - \hat{m}]$$

- Calculating the magnetic dipole potential *B(P)* of a homogeneously magnetized sphere by Blakely (1996), where *P* denotes the observation point
- Considering the geographical latitude
- Simulation routine by Gödickmeier (2020)

Experimental Field	
Location	Freiberg ≈ 49400 nT
Investigation Area	200 x 200 m
Measuring & Profile Distance	Δx = 0.5 m Δy = 0.5 m
Gaussian Noise	none / 0,1 / 0,3 nT
Object Properties	
Number per Field	1 to 20
Depth	0 to 15 m
Sphere Radius	0,01 to 0,1 m
Dipole Axis Orientation	Random

Tab. 1: General simulation parameter

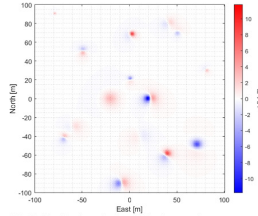


Fig. 2: Simulated unnoised multi-dipole-scenario

3. PREPROCESSING OF THE INPUT DATA

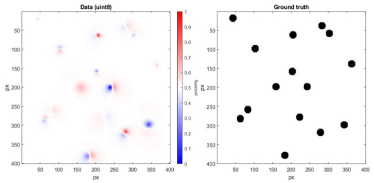


Fig. 3: Processing results: Normalized unit8 RGB image (left); Labeled mask (right)

Compression:

- Raw: Fig. 2
  → [400x400] real-value double matrix
- Compressed: Fig. 3 left
  → [400x400x3] normalized uint8 RGB matrix

Labeling:

- Mask sample containing labels for each anomaly to be detected; Fig. 3 right
- Center corresponds to exact dipole position
- Radius indicates detection accuracy

4. NETWORK ARCHITECTURE

U-Net: Convolutional neural network to perform semantic image segmentation

- Input: 30000 samples in total (70 % Training set; 30 % Evaluation set)
- **a) Contracting path** → Feature extraction
- **b) Bottleneck** → Passes tensor dimension
- **c) Expansive path** → Localization of features
- Output: Segmentation map (Pixel-wise prediction for the input image)

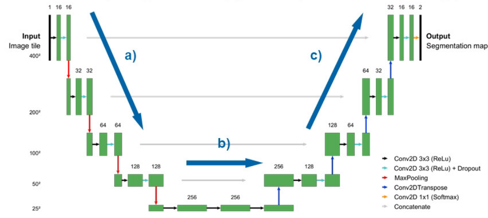


Fig. 4: U-Net architecture for semantic image segmentation (based on Ronnerberger et al. 2015)

5. TRAINING

Model History:

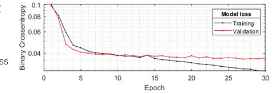


Fig. 5: Exemplary loss curve for a model based on Tab. 2

Learning Rate (Opt. „Adam")	0.001
Epochs	30
Batch Size	32 Samples
Steps per Epoch	525
RGB Channels (Colormap)	[1 0 1]

Tab. 2: General training information and hyperparameter

Binary Crossentropy Loss:

$$L = -\frac{1}{n}\sum_{i=1}^{n} \underbrace{y^{(i)}}_{true} \log\big(\underbrace{f(x^{(i)};W)}_{predicted}\big) + (1-\underbrace{y^{(i)}}_{true}) \log\big(1-\underbrace{f(x^{(i)};W)}_{predicted}\big)$$

x – Ground truth; y – Prediction; W – Weights

- Training and evaluation is performed using the Keras API for Tensorflow

6. EVALUATION

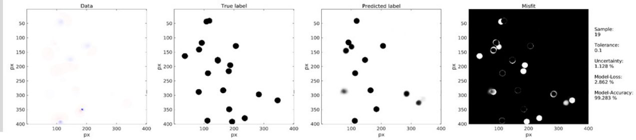


Fig. 6: Predicted sample with 19 randomly generated anomalies; Input: Data & ground truth (left), Output: Segmentation map & calculated misfit (right)

Criteria:

- **Progression of cross validation loss** during training process (Fig.5 upper panel)
  → Fast training dynamic; overfitting: Drifting apart of training and validation curve
- **RMS error** from the deviation between ground truth and prediction (Fig. 7)
  → Generally low loss; great performance; more right-skewed distribution preferred
- **Misfit plot** of ground truth and prediction for visual evaluation of individual samples
  → Extremely weak signals due to depth/size-ratio not detectable
  → Sufficiently strong signals detected with high certainty and high position accuracy

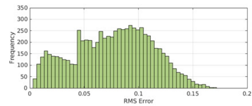
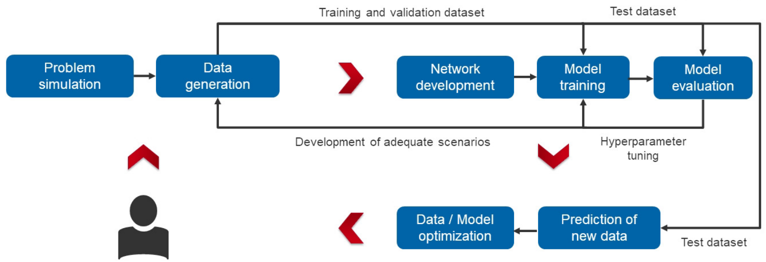


Fig. 7: Histogram of the RMS errors for 7500 evaluated samples (trained with model from Fig. 5 for 16800 samples)



7. DATA-RELATED OPTIMIZATION APPROACHES

3-Channel-Colormap:

- Accelerates training dynamics
- Faster adjustment of weights in the first epochs → steeper gradient
- More information processed at the same time

Areasine hyperbolicus:

- Scales signals for an improved recognition
- Lower losses than unscaled scenario after 30 epochs
- Intensifies overfitting (uncertainties due to noisy samples)
- Manipulates signal-to-noise ratio (inflated noise)

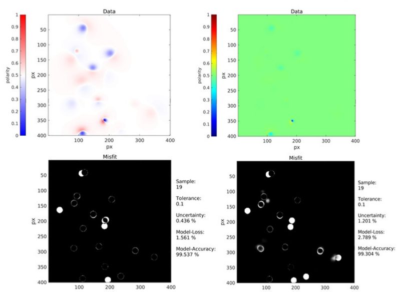


Fig. 8: Transformed data and Misfit (belonging to Fig. 6): Areasine hyperbolicus (left); Colormap all three RGB-channels

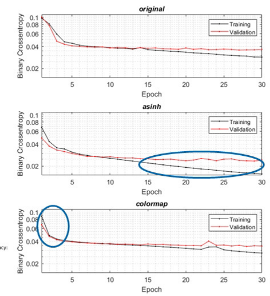


Fig. 9: Loss curves of training with transformed data in comparison to original input data

8. MODEL-RELATED OPTIMIZATION APPROACHES

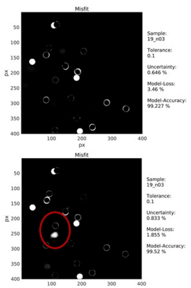


Fig. 10: Misfit: Original data (top), Areasine hyperbolicus (down); 3-Channel-Colormap

Steps per Epoch

- Reduction from 525 to 250 batches; compare with Fig. 9 lowest panel
  → Time saving with similar results
  → Asinh creates artifacts due to noise

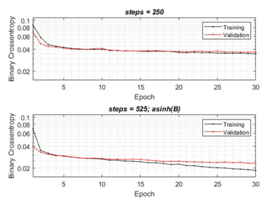


Fig. 9: Loss curves for reduced number of steps per epoch in combination with areasine hyperbolicus; 3-Channel-Colormap

9. DISCUSSION ON PREVIOUS STUDIES

Data-related optimization approaches:

- Asinh not applied further because of generating artifacts in the presence of noise
- Colormap with 3 channels applied further because of accelerating the learning process during early epochs

Model-related optimization approaches:

- Tuning of batch size and dropout deliver no significant improvement to training as well as prediction
- Reduced steps per epoch causes a great gain in time for training with qualitatively still accurate predictions

10. PRELIMINARY MODEL RESULT

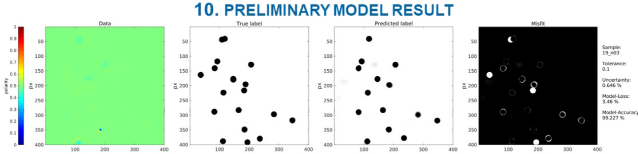


Fig. 11: Predicted sample with 19 randomly generated anomalies; Input: Data & ground truth (left), Output: Segmentation map & calculated misfit (right)

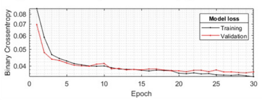


Fig. 12: Loss curve for the preliminary best performing model based on Tab. 3

- Low loss and great generalization (Fig.12) achieved by ncluding various noise levels and adequate amount of input data
- High accuracy in localizing individual anomalies by transition to 3 RGB channels and reduction of artifacts
- Few weak signals undetectable due to superposition, noise or technical limitation while measuring

Learning Rate (Opt. „Adam")	0.001
Epochs	30
Batch Size	32 Samples
Steps per Epoch	250
RGB Channels (Colormap)	[1 1 1]

Tab. 3: General training information and hyperparameter

11. OUTLOOK

Opportunities for further improvement:

- Increase the complexitiy of the data basis
  → Additive, irregular background field representing an individual regional field (e.g. Fig.)
  → Additional non-target structures (e.g. archaeological structures, cables, pipelines, etc.)
- Adjustment of ground truth parameters
  → Gray-scale labels carrying depth information
  → Label radii determining achievable position accuracy

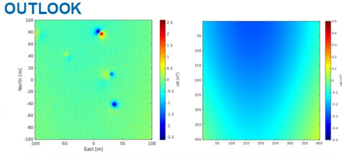


Fig. 13: Extended noise simulation: Survey data with additive gaussian noise and an overlaying background field (left), Irregular background field only (right)

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