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**DUST DISPLACEMENT DETECTION IN THE SCOPE OF CHEMCAM RMI IMAGE DATA** Ana Lomashvili<sup>1</sup>, Kristin Rammelkamp<sup>1</sup>, Olivier Gasnault<sup>2</sup>, Elise Clavé<sup>1</sup>, Christoph H. Egerland<sup>1</sup>, Susanne Schröder<sup>1</sup>; <sup>1</sup>German Aerospace Center (DLR), Institute of Optical Sensor Systems, Berlin, Germany, <sup>2</sup>IRAP-CNRS, Toulouse, France; ana.lomashvili@dlr.de

**Introduction:** NASA’s Mars Science Laboratory (MSL) rover Curiosity is equipped with the ChemCam instrument suite to analyze chemical composition of rocks and soils in Gale crater [1, 2]. The instrument consists of two components: the first planetary science Laser-Induced Breakdown Spectrometer (LIBS) and a Remote Micro-Imager (RMI) [3]. The LIBS instrument, composed of a powerful laser, creates a light-emitting plasma whose radiation is collected by spectrometers. The LIBS plasma is accompanied by a shock wave, which has an additional effect on the target sometimes causing dust displacement[4]. The RMI instrument images through the same telescope as the LIBS providing context to the samples. The RMI dataset consists of images taken before and after the LIBS measurements [3]. Until now, the instrument pictured approximately more than 4000 targets and collected LIBS spectra from multiple points of each target (5-25 points per target). Often, the images taken after LIBS measurements display a shape of dust removal by the LIBS plasma’s shock wave, as it is shown in Fig 1. Investigating dust displacement phenomena can be helpful in characterizing dust in terms of thickness, composition, etc. This in turn leads to a broader topic of laser-target coupling and further development of LIBS data normalization. This study focuses on detecting whether dust displacement took place during LIBS measurements based solely on RMI images. In this work, a limited number of samples are manually labeled, preprocessed, and trained on a machine learning pipeline employing Transfer Learning and Random Forest classifier.

**Data Preparation:** The images for this study are retrieved from *PDS Geosciences node* [5]. 250 RMI images are chosen by visually selecting targets with dust displacement and the same amount with no dust displacement. In this way, the training set is balanced and machine learning models are not biased by any of the classes.

Furthermore, data exploration showed the model being confused with the variance of texture. This leads to the decision to remove the information containing texture from the training set. This can be achieved by training only difference images. Subtracting before and after LIBS images should leave only the difference in the field of view such as dust displacement, letting the model focus on that information. As the mast moves along a LIBS raster, an offset occurs between the before and after LIBS images. Therefore, subtracting consecutive images em-

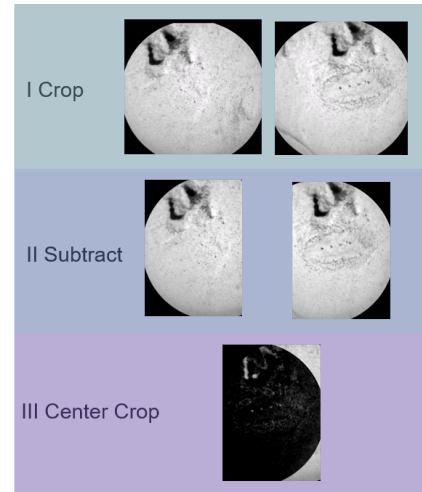


Figure 1: *Schematic representation of preprocessing steps for RMI images. Target name Barouffieres.*

phasizes offset rather than dust removal. Fig 1 shows the preprocessing steps that are employed to overcome the difference due to the offset. In the first step, RMI images are cropped according to the offset values preparing them to be subtracted. As the RMI has a circular field of view, after subtraction the resulting images still contain textural information in the corners. This information is removed by center cropping the difference image. Finally, by taking all these preprocessing steps, the dataset is ready to be split into training, test, and validation sets. After splitting the data, the training set is augmented by several different filters such as random flip, random rotate, brightness adjustment, etc.

**Model:** Convolutional Neural Networks (CNN) have proven their usefulness in image classification multiple times [6]. A known caveat of CNN is the need for a large training set. Considering our training set to be less than 200 samples per class, a CNN has a high chance of overfitting. In this case, Transfer Learning (TF) sounds promising rather than training a network from scratch. TF is a method of using an already pretrained network. The network which is trained on millions of images has learned filters that best describe the input samples. These filters can be applied for classifying a small dataset, in other words, one can repurpose a large-scale pretrained network for a specific small dataset. This is achieved by removing the last layer of the network and attaching the appropriate one according to our needs. TF has already been successfully applied to ChemCam RMI data to de-

tect the texture of the targets [7].

In this study, common pretrained networks have been used such as VGG16, InceptionV3, and ResNet. Working directly with the pretrained models and applying fine-tuning to their last layers for our data resulted in accuracies around 80% but not higher. Consequently, it was decided to introduce an additional model to deal with the limited size of the input dataset. The pretrained models were preserved in the pipeline as a mechanism for extracting features from images. Those features were then fed to the Random Forest classifier. Random forest is an ensemble tree model, known for handling small datasets well [8]. Various combinations of pretrained models were tested with a random forest classifier. The best performance was achieved by extracting features with the first 10 layers of VGG16 and then fine-tuning Random Forest classifier to the inputs. The fine-tuned forest contained 1000 estimators. Such a pipeline reached 92% average accuracy in cross-validation. Cross-validation takes into account multiple splits of the input dataset and returns an average accuracy. Below-provided Table 1 summarizes the best models and their performance.

Pretrained Model	Attached Model	Accuracy
VGG16 10layers	RF	92%
VGG16 fine-tuned	RF	88%
VGG16	RF	86%

Table 1: *Best performing pipelines and their accuracy.*

This model can be applied to the whole ChemCam dataset. The results, whether or not there was dust displacement, can then be visualized at specific locations along the rover traverse or by sols since the start of the mission, allowing experts to interpret results efficiently rather than going through all the targets. Fig 2 showcases 1925 targets from the initial sols up to sol 3778 and whether dust displacement occurred while taking LIBS measurements. A darker shade indicates that no dust displacement is occurring in the corresponding sol. The plot shows that dust displacement is observed less frequently in the early sols when the rover was on the crater floor and foothills of Mt. Sharp than later, higher on Mt. Sharp.

**Challenges:** There are a few challenges that still confuse the model. After carefully exploring erroneously predicted samples the following delicate cases were obtained. Offset values: as the rover’s head moves, an angle difference is introduced and cropping images by x and y offset coordinates can no longer reduce information containing texture. Soil(drill): the soil displacement caused by shooting a laser looks similar to the dust displacement in the difference images. Hence the model is confused and erroneously predicts dust displacement. Dust displacement observed on the edge of an RMI image: as the last step of the preprocessing is to center crop the differ-

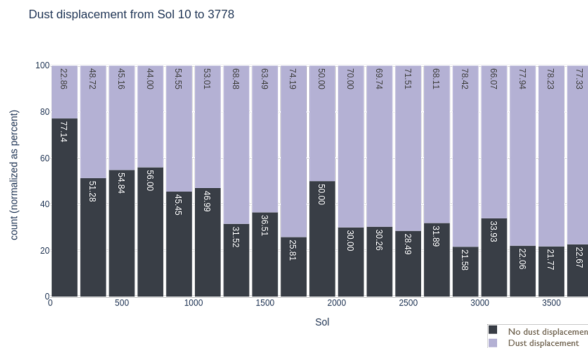


Figure 2: *Bar plot showcasing percentile ratio of dust displacement sol wise. Each bin contains 200 sols. In total 1925 targets are processed.*

ence image, the information about dust displacement is lost in case of being located on the edge.

**Outlook:** The study is planned to continue in the direction of investigating the shape of the dust displacement and what can be learned about laser-target coupling and physical properties of the target from it. The results can be used to derive parameters of dust layer thickness along the rover traverse, dust induration on targets, and their effect on laser coupling. Additionally, dust displacement detection can be combined with texture classification in order to find a possible correlation between these two parameters.

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**References:** [1] Wiens et al. “The ChemCam Instrument Suite on the Mars Science Laboratory (MSL) Rover: Body Unit and Combined System Tests”. In: *SSR 170* (2012). [2] Maurice et al. “The ChemCam Instrument Suite on the Mars Science Laboratory (MSL) Rover: Science Objectives and Mast Unit Description”. In: *SSR 170* (2012). [3] Mouélic et al. “The ChemCam Remote Micro-Imager at Gale crater: Review of the first year of operations on Mars”. In: *Icarus* 249 (2015). [4] Cremers et al. *Handbook of Laser-Induced Breakdown Spectroscopy*. 2006. [5] R Wiens. *MSL ChemCam Remote Micro- Imaging Camera raw data*. MSL-M-CHEMCAM-RMI-2-EDR-V1.0, NASA Planetary Data System. 2013. [6] Ajit et al. “A Review of Convolutional Neural Networks”. In: *International Conference on Emerging Trends in Information Technology and Engineering* (2020). [7] Lomashvili et al. “Rock classification via transfer learning in the scope of ChemCam RMI image data”. In: *LPSC* (2023). [8] Fawagreh et al. “Random forests: from early developments to recent advancements”. In: *Systems Science Control Engineering* (2014).