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## Estimating petrographic composition of aggregates by means of reflectance spectra using support vector machines

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The increasing physical and technical demands placed on construction materials, especially as they are being used more and more up to the limits of their mechanical strength, and as ecological standards are thightened, has led to the demand for ever more careful assessment of the rock particles making up the aggregates. Engineering properties of aggregates (mechanical, thermal and durability properties) are to a great extent determined by the petrological composition of the rock aggregates. However, today's test methods are extremely time-consuming and require highly trained or educated staff. This raises the question, wether a statistical classification of rock aggregates is possible using reflectance spectra of visible and infrared light.

However, the classification of rocks is complicated by the fact that the optical behaviour of minerals forming the rock often appears muted. In addition, minor constituents may dominate the spectrum. Furthermore, the relevant spectra form high dimensional data that are extremely difficult to analyze statistically, especially when curves are very similar.

To take into account many of the rock types referred to in the European standard for petrographic description of aggregates, the present investigation is bases on reflectance spectra for 12 different rock types and variants taken from varous deposits in Europe. In particular, rock types of worldwide economic importance are chosen for this analyis. The rock types include sampels of Granite, gabbro, rhyolite andesite, dacite, basalt limestone, dolomite, chert, amphibolite, gneiss, sepentinite. Ten particles per class were selected and irradiated with visible and near infrared light. The particles were irradited from different locations in order to combat confusion arising as a result of variation in mineralogical texture, and its influence on the appearance of the spectra. This measurement procedure yielded 1 to 3 measurements per particle whereby the number of measurements depended on the particle sizes. Altogether, 313 spectra were collected. The spectra were measured in reflectance mode from 338 nm to 1100 nm.

Classification is carried out using linear support vector machines. Originally, support vector classification is based on finding a separating hyperplane such that the margin between two groups is a maximum. To cope with a multiclass problem a one-against-one strategy followed by majority voting is applied. Due to the functional structure of the spectra, support vector machines are applied to the coefficients of a B-spline basis representation of the spectra. The cost parameter is chosen adaptively. Classification error is estimated by 5-fold cross-validation. Table 1 shows classification error depending on the rock type.

Rock type	Error	Rock type	Error	Rock type	Error
Greywacke	0.0733	Basalt	0.0849	Rhyolite	0.0378
Andesite	0.0484	Chert	0.0822	Limestone	0.0656
Dolomite	0.1400	Dacite	0.0549	Granite	0.0824
Gneiss	0.1120	Gabbro	0.0322	Serpentinite	0.0667

Table 1: Classification error depending on the rock type using one-against-one SVM