**Semi-automated field boundary delineation**

1. State of the art & aim of current application

* Clear trend towards using object-based approaches in favour to pixel-based analyses [1,2]
* Brief literature review
  + older studies often focus on manually engineering & redefining of borders extracted by edge filters and on vector-based refinement of line segments [3], etc, implementation often with complex rulesets hard to implement [4,5]
  + most recent publications favour neural net approaches, but require huge amounts of training data & set some requirements on processing power
* Problems so far
  + Lot of training samples for AI-based delineation
  + Lack of transferability of other approaches (site-specific)
  + No ready-to-use tools – complex ruleset or code not freely accessible
* Aim
  + Semi-automated delineation based on a few samples provided by the user
  + Transparent, knowledge-based approach
  + High degree of transferability
    - Independent of AoI & structure of fields
    - No hardcoded thresholds need to be adjusted
  + Ready-to-use tool
* Main considerations
  + Basis: Watkins & Co – investigations towards an operational field boundary approach using Sentinel 2, not only performance for single place but to some degree also transferability already assessed
  + Idea to follow Watkins as this study seemed to be very close to an automated, ready-to-use approach with limited complexity, other easy comprehensible workflows still rely on some fixed/externally set thresholds [6] which let them appear unsuited for achieving transferable methods with minimal supervision needed
  + use of multitemporal S2-imagery -> enables to include phenological development of plants & more powerful than single image, S2 world-wide freely available
  + samples have to be collected anyway to assure accuracy of delineation, could thus also be directly used for parameter adjustment during workflow
  + hybrid approach with edge detection & region-based growing based on assessed superiority of these

1. Methodology & Workflow
2. Field delineation

* choosing the right parametrisation of algorithms for segmentation is often based on a trial-and-error approach under re-iterative visual inspection of the obtained results [7,8], time-consuming and likely to get only sub-optimal results
* the general superiority of object-based approaches is consistently mentioned across studies [7], though the accurate delineation of objects is a necessary prerequisite for the following steps of classification
* Finding that universal adaptation of the parameters for segmentation does not do justice to the variability of the field structures, for automated approach and multi-site delineation visual determination definitely not feasible anymore [9]
* ESP tool as possibility to derive at more objective selections of scale parameter [10,11], used as unsupervised mechanism to optimise segmentation
* Other unsupervised approaches with different metrics have been tested, global score metric computed by summing up the intra-segment uniformity and inter-segment dissimilarity within a segmented polygon achieved proved to achieve better results than ESP [12]
* Watkins and van Niekerk [13] choice of the overflow height by employing Jenkins, some refinement was done in follow-up study [14], no reference polygons required, still it seems questionable if this is really transferable
* Different category of studies deals with supervised approaches for field delineation
* Tetteh et al. [9] studied supervised bayesian optimisation of MRS based delineations with semi-automated determination of scale parameter, outperformed ESP tool, similar idea to what is applied here for watershed though in a simpler way with brute-force grid search technique – due to fast performance of watershed not that problematic
* Post-processing with smoothing & merging of small objects common step in workflows [3,5,6,13]

Knowledge explicitly modelled in the approach

* Internal homogeneity & Inter-heterogeneity (does not need to be addressed explicitly as already captured by edge detection & smooth transitions unlikely)
* Sharp boundaries between fields
* Tendency towards linear or only gently curved field boundaries

1. Field mask

* Multi-temporal imagery not only beneficial for boundary delineation but also for classification [15,16]
* NDVI as a common index used to classify crops and/or on a higher hierarchical level distinguish between agricultural and uncultivated land
* Watkins and van Niekerk [14] used min, max, range and std of NDVI through time to establish corresponding rulesets with 2-5 thresholding rules, need to be adjusted depending on the study area
* Pazúr et al. [17] tried several indices characterising either phenology over whole growing season or parts of it, small scale study area (whole Switzerland) and classification problem with three classes (crop, grassland, other LC), thus pretty close to aim in the current case, NDVI std proved to be a valuable feature, generally more meaningful than single bands
* Valero et al. [16] used an extensive set of features engineered based on NDVI time series (n=17) enriched by NDWI & brightness statistics (min, max, sd, mean, median) to derive at an annual cropland/no cropland mask (similar to what is aimed at here), no specific evaluation of feature importance but high accuracy of approx. 90%
* Xiong et al. [18] performed continent-wide binary crop/non-crop classification using NDVI as well as single bands (green, red, blue, NIR)
* Belgiu and Csillik [7] utilised a dynamic time warping approach based on NDVI to classify a variety of crops, including additional indices (NDWI, GNDVI, NDRE, SAVI) in a follow up study only led to small improvements for differentiating between crop types [8]
* only for more specific use cases choosing alternative indices might be reasonable and superior to NDVI, e.g. mapping of maize fields and distinguishing them from soil [19]
* other studies mainly relying on NDVI: van Tricht et al. [20], Jia et al. [21] used min, max, mean & std of timeseries, Solano-Correa et al. [22]
* As primary goal for current application is only to discriminate between fields and non-agricultural uses, a simple set of NDVI & … seemed to be sufficient, no need for including more features, also because providing the possibility of too many features to manually adjust the thresholds can quickly lead to the user being overwhelmed (this may only be sensible in a sample-based classification approach happening behind the scenes)
* To achieve a maximum degree of transferability, the thresholds are not hard-coded but parameter values may be adjusted by the user
* min/max/mean ndvi and std ndvi as adjustable parameters implemented, default values are precalculated based on what is provided as a sample data set (to include at least all fields which have been delineated manually as fields)

1. App ecgonition architect solution: Functionality & Interface
2. App ecgonition architect solution: Implementation details

* speeding up process by performing the parametrisation only on the buffered training samples

1. Performance & Accuracy Assessment

* Important to note the structure of the AoI wrt to field sizes in order to be able to evaluate the obtained accuracies – many studies omit this crucial information
* Studies tend to focus on larger fields by excluding fields of small sizes upfront, e.g. [4] limits analyses to fields > 0.5ha
* Also note that other studies may rely on additional auxiliary data, such as land cover data [4]
* Note that high accuracies were achieved despite complex & heterogenous agricultural structure with huge range of field sizes – especially smaller parcels difficult to except & diminishing the accuracy

1. Summary & Outlook: Further improvements

* Tetteh studied optimal feature sets for delineating fields also with consideration of S1 & S2 features [23]
* Tetteh compared results to what can be achieved with neural network architectures ResUNET & MaskRCNN, MRS optimisation achieved similar results
* Option to create a dockerised solution being able to interact with Python for calculation of statistics & so on -> less user-friendly but probably faster & cumbersome to configure

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