Tools For Multitemporal Analysis And Classification Of Multisource Satellite Imagery

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Abstract : As acquisition technology progresses, remote sensing data contains an ever increasing amount of information. Future projects in remote sensing will give high repeatability of acquisition like Venμs (CNES) which may provide data every 2 days with a resolution of 5.3 meters on 12 bands (420nm-900nm) and Sentinel-2 (ESA) 13 bands, 10-60m resolution and 5 days. With such data, process automation appears crucial. For that purpose, we develop several algorithms to automate image processing (classification, segmentation, interpretation, etc.). In this paper, we present an algorithm of automatic analysis which selects the best dataset of dates maximizing classification quality indices. We create two indices to evaluate jointly accuracy and precision. We present tests performed on Formosat-2 images which are similar to Venμs and Sentinel-2 for temporal repetitiveness. These tests allow validating the presented process for temporal discrimination improvement.

METHOD FOR CLASSIFICATION IMPROVEMENT

"A great number of tests showed that classification of a large amount of temporal images does not necessarily give the best results for every class "[1].

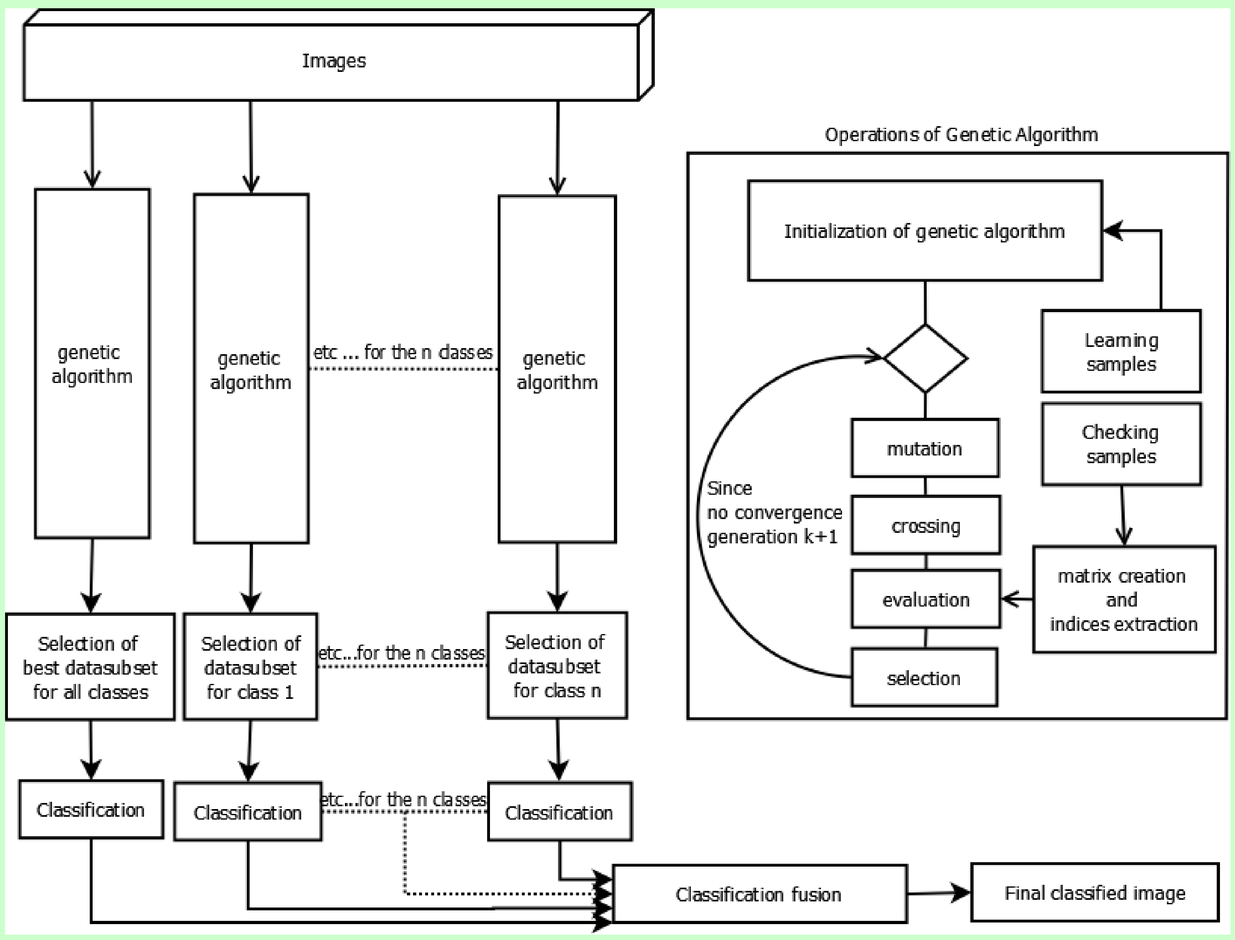
Presented process for classification improvement:

- search of the best dataset with genetic algorithms (for overall and single class evaluation)
- classification of these data sets
- fusion of these classifications [2]

Users want to:

- maximize accuracy and precision of the classification.
- minimize the number of images used (for data price reasons for example).

Diagram of 3-part presented process for n classes with utilization of genetic algorithm [3].

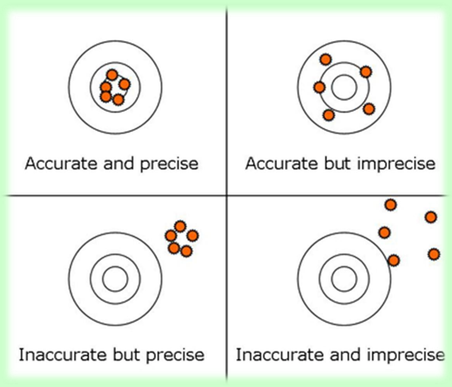


We introduce **new indices** that evaluates classification considering **accuracy and precision.**

We can resume differences between **accuracy** and **precision** with the following figure:

Accuracy

- → Faithful measurement or representation of the truth.
- → Correctness.
- → Degree of agreement between a measured value and the accepted value for that measurement.
- → Diagonal value of confusion matrix.



Precision

- → Faithful measurement of reproduction.
- → Fidelity.
- → Reproducibility or repeatability.
- → Degree to which repeated measurements show the same results.
- → Based on non-diagonal value of confusion matrix.

Several indices exist (such as Overall Accuracy (OA) [3], Kappa index [4]) but they do not take into account all the characteristics which could be extracted from a confusion matrix.

OA index
- ⊕ accuracy index
- ⊖ only considers diagonal terms of the matrix

kappa index
- ⊕ accuracy index and uses sums of rows and columns
- ⊖ no explicit calculation of the precision and combination with accuracy.

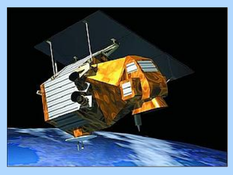
The **new index** Precision and Accuracy Index (**PAI**) for a single class and Overall Precision and Accuracy Index (**OPAI**) for all the classes.

→ stricter index than OA or kappa because OPAI does not express the same nature, which explains different values.

→OA, Kappa and OPAI are complementary.

- ⊕ precision calculation with explicit comparison between columns and rows.
- ⊕ accuracy calculation with diagonal value.
- ⊖ stricter index, high weighting of precision.

APPLICATIONS AND DISCUSSION



Satellite data: Formosat-2 (NSPO, Taiwan) images
high temporal revisit (2 days)
high spatial resolution (8m)
16 dates in **2009** (02/15, 03/17, 03/21, 03/30, 05/03, 06/23, 07/01, 07/12, 07/26, 08/05, 08/14, 08/22, 08/30, 09/06, 09/24 and 10/16).

Ground truth data: Agricultural site located in the South-West of Toulouse, France.

Method: genetic algorithm with those parameters:

1/100 probability of mutation	OPAI and PAI indices as evaluation function
6/10 probability of crossing	500 phenotypes and 50 generations

Results

Evaluation of the best dataset for all the classes

ALL CLASSES	Genetic algorithm	Exhaustive research		
Problem	OPAI	OPAI	OA	kappa
No constraints on dates number	56.7 %	56.7 %	74.5 %	71.6 %
Dates number=4	53 %	53.1 %	69.4 %	66.3 %

→ 4 dates and OPAI : 02/15, 05/03, 06/23 and 09/06

Evaluation of the best dataset for "Sunflower" class

SUNFLOWER	Genetic algorithm	Exhaustive research		
Problem	PAI	PAI	Accuracy	kappa
No constraints on dates number	86.1 %	86.7 %	96.2 %	95.3 %
Dates number=4	85.2 %	85.2 %	92.9 %	91.5 %

→ 4 dates and PAI : 03/21, 07/01, 08/14 and 08/30

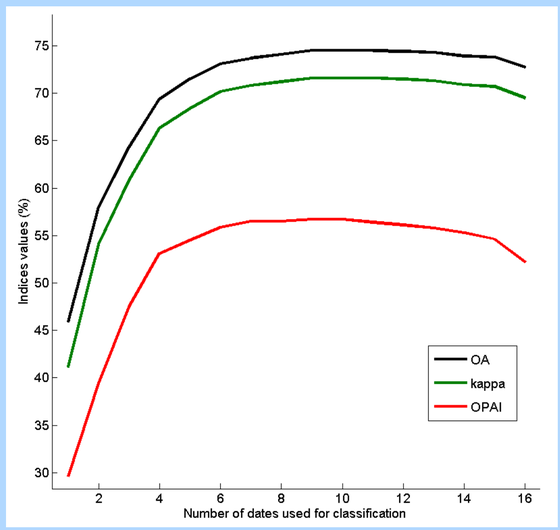
Extracted image from classification of the best dataset for all classes

➢ Over representation of sunflower (brown) to the detriment of built (pink) and trees (green)
➢ Overall Precision and Accuracy is maximum

Extracted image from classification of the best dataset for "Sunflower" class

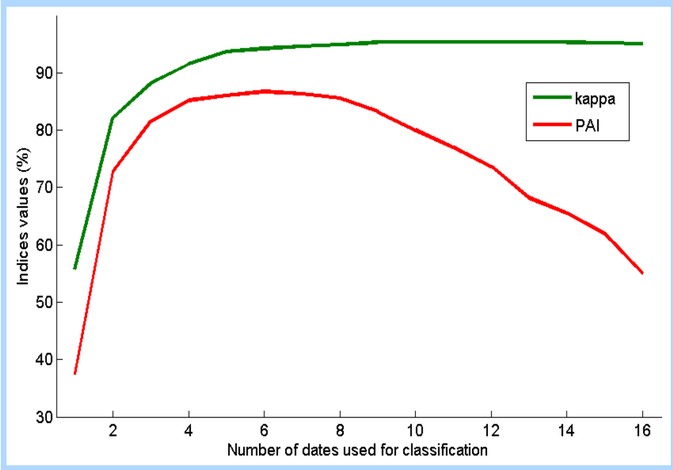
➢ Good representation and precision of sunflower (brown)
➢ Precision and Accuracy is maximum **only** for class Sunflower

Evolution of the best datasets found by overall indices for all classes



➢ classification on a great number of dates gives the best overall accuracy
➢ whereas some classes present confusions with other classes

Evolution of the best datasets found by indices on sunflower class depending on number of dates used



➢ PAI gives information of precision
➢ more dates = possibility of over-weight of non-discriminative information

CONCLUSION AND PROSPECTIVE

➔ A goal of this method is to give information of statistical discrimination to users, to help them to choose the dataset which correspond to their thematic research.

➔ The OPAI and PAI indices are well adapted to select dataset because best overall accuracies do not necessarily mean correct classifications. These two indices are stricter than OA or Kappa but they clear up all the available information that we could extract from a confusion matrix.

➔ A research on other indices extracted from different tools than confusion matrix, will be a future work.

➔ Future work is utilization of the temporal discrimination to **interpret automatically unsupervised** classification. The most important problem is multiannual difference of phenological stage; thus a best dataset is not the same year after year.

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