GEOESSENTIAL ERA-PLANET

Essential Variables workflows for resource efficiency and environmental management

Deliverable 1.6
Data fusion guidelines

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Table of Contents

Introduction

The objective of this deliverable is to provide guidelines on methods of “data fusion” that will form the framework of Task 1.6 entitled “Data Fusion” (DF). This task is intimately related to task 1.4 “Modeling and Processing Services” and uses similar approximation techniques albeit for the specific purpose of data fusion. Altogether, these tasks aim at delivering value-added services to Essential Variable (EV) within the premises of WP1 actions on “Knowledge Management Services”. This initial report wants to contribute to the general framework of the modeling services to be developed in WP1 and used by all other WPs for their modeling needs.

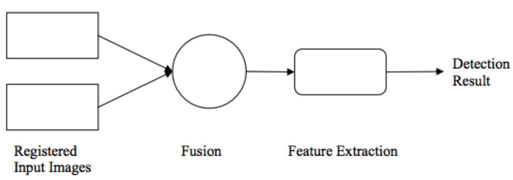
The report addresses a general state of the art with some specific suggestions to be looked at in the two coming project years.

Information (or data) fusion can be defined as the study of efficient methods for automatically or semi-automatically transforming information from different sources and different points in time into a representation which provides effective support for human or automated decision making (Boström et al. 2007).

In the context of multi-sensors imagery, data fusion can be thought of as a process of combining images, obtained by sensors of different wavelengths in order to form a composite and more informative image (Jiang et al. 2009). Images are formed and analyzed with the intent to improve their information content and to make it easier for algorithms to detect, recognize, and identify targets or to analyze the image itself. Multi-sensor data fusion can be performed at three different processing levels, according to the stage at which the fusion takes place (Zhou et al. 2011):

1. **Pixel level fusion**. In pixel level fusion (see Figure 1), the input images are fused pixel by pixel followed by the information extraction step. To implement the pixel level fusion, arithmetic operations are used in time domain, while in the frequency domain frequency transformations are used. The main goal of this kind of fusion is to enhance the raw input images and provide an output image with information content that is more useful for the task at hand. Pixel level fusion is usually effective for high quality raw images, but it is not suitable for images with unbalanced quality level because information from one physical channel might be impeded by the other.

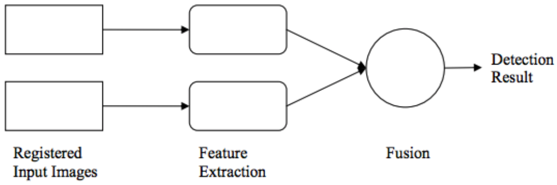
Figure 1: Scheme of pixel level fusion.



2. **Feature level fusion**. In feature level fusion (see Figure 2), the information is extracted from each input image separately and then fused together based on features from input images. The feature detection is typically performed through edge enhancement

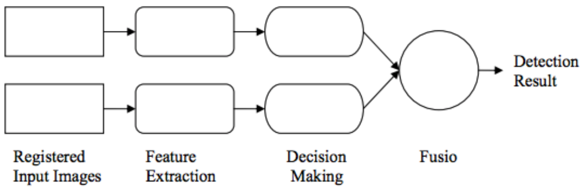
algorithms (if necessary), reduced order modeling (Perracchione et al. 2018), and knowledge-based approaches. Contrary to the pixel level fusion, feature level fusion is effective for raw images with unbalanced quality level.

Figure 2: Scheme of feature level fusion.



3. **Decision level fusion**. In decision level fusion (see Figure 3), the information is extracted from each input image separately and then decisions are made for each input channel. Finally, those decisions are fused together to form the final one. Decision level fusion is effective for very complicated systems with multiple true or false decisions but not suitable for general applications.

Figure 3: Scheme of decision level fusion.



This report is divided into two sections. We will first focus on pixel level data fusion methods, which are mainly used for multispectral imagery enhancement. Subsequently, we provide specific examples for the improvement of EO data for utilization in workflows for the Food-Water-Energy Nexus.

Review: data fusion at pixel level

Besides the grouping described in the previous section, image fusion methods can also be broadly classified into two groups (Jayanth et al. 2011):

1. spatial domain fusion
2. transform domain fusion.

The fusion methods such as averaging, principal component analysis (PCA) (Metwalli et al. 2009) and IHS based methods (Al-Wassai et al. 2011) fall under spatial domain approaches. Another important spatial domain fusion method is the high pass filtering based technique (de Béthune et al. 1998). Here the high frequency details are injected into up-sampled version of MS images. The disadvantage of these approaches is that they produce spatial distortion in the fused image. Spectral distortion becomes a negative factor while we go for further processing, such as classification problem. Spatial distortion can be very well handled by frequency domain approaches on image fusion. The multi-resolution analysis has become a very useful tool for analyzing remote sensing images as the discrete wavelet transform has become for fusion. Other well-known fusion methods are also there, such as Laplacian pyramid based (Kaur and Rani 2015), curvelet transform based (Nencini et al 2007). These methods show a better performance in spatial and spectral quality of the fused image compared to other spatial methods of fusion. The approaches at spatial analysis described in D-1.3 (Perracchione et al. 2018) of the present project seem to be highly promising within this context. Ghassemian (2016) provides a review about available methods and groups pixel-based fusion methods into component substitution (IHS, PCA, …), multiresolution analysis (discrete wavelet transform, Laplacian pyramid, …) hybrid methods (curvelet and IHS, …), as well as model-based fusion methods (compressive sensing, hierarchical Bayesian models, …). Most widely-used and accepted methods are presented in the following.

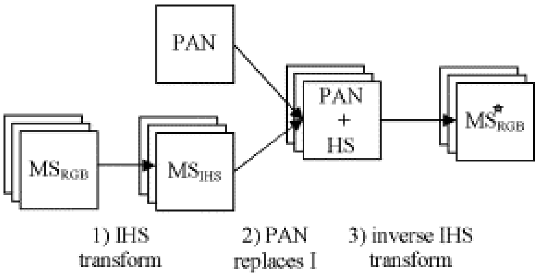
Highpass filtering based fusion

The highpass filtering merging method introduced by (Schowengerdt 1980) extracts edge information of the high resolution (HR) image which is then added to the low resolution (LR) channel on a pixel by pixel basis. The highpass filter of the HR image corresponds to its high frequency component which is mostly related to spatial information. Hence, by adding this filter to the LR channel some of the high spatial information content of the HR image will become apparent in the fused product.

IHS transform based image fusion

The IHS (Intensity, Hue and Saturation) technique is one of the most commonly used fusion techniques for sharpening. It has become a standard procedure in image analysis for color and feature enhancement, improvement of spatial resolution and the fusion of disparate data sets. For the fusion of the high-resolution and multispectral remote sensing images, the goal is ensuring the spectral information and adding the detail information of high spatial resolution, therefore, the fusion is even more adequate for treatment in IHS space. In IHS fusion method the IHS space are converted from the Red, Green and Blue (RGB) space of the Multispectral image. The intensity component I is replaced by the PAN (Panchromatic). Then the reverse transform is applied to get RGB image as an output. A scheme of the procedure is depicted in Figure 4.

Figure 4: IHS based image fusion scheme.



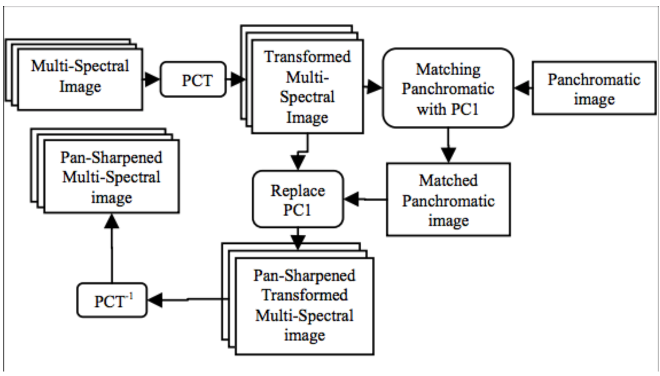
PCA based image fusion

Principal component analysis is a statistical analysis for dimension reduction. It projects data from its original space to its eigenspace to increase the variance and reduce the covariance by retaining the components corresponding to the largest eigenvalues and discarding other components. PCA helps to reduce redundant information and highlight the components with biggest influence so as to increase the signal-to-noise ratio. The information flow diagram of PCA-based image fusion algorithm is shown in Figure 5. The algorithm replacing the spatial component of the multispectral image with the panchromatic image allows the spatial details of the panchromatic image to be incorporated into the multi-spectral one:

1. The resampled bands of the multi-spectral image to the same resolution as the panchromatic image are transformed by the principal component transformation.
2. The panchromatic image is histogram matched to the first principal component. This is done in order to compensate for the spectral differences between the two images, which occurred due to different sensors or different acquisition dates and angles.
3. The first principal component of the multi-spectral image is replaced by the histogram matched panchromatic imagery.
4. The new merged multi-spectral imagery is obtained by computing the inverse of principal component transformation.

Figure 5 schematically summarizes the just described procedure.

Figure 5: PCA-based image fusion scheme.



Wavelet transform image fusion

Wavelet-based fusion (Amolins et al. 2007) schemes are extensions of the high-pass filter method, which makes use of the idea that spatial detail is contained in high frequencies. In the wavelet-based fusion schemes, detail information is extracted from the PAN image using wavelet transforms and injected into the multispectral (MS) image. Distortion of the spectral information is minimized. However, there may be other negative effects. Some of these effects result from the type of wavelet transform that is used while others result from the method of injecting detail information into the MS image. Various models exist for injection information, with the simplest model being by substitution. Another simple model is by addition, while more complex methods apply mathematical models to the detail images. Regardless of the model, the images to which it is applied must be at the same resolution. Depending on the ratio of the original image resolutions, this could necessitate multiple levels of decomposition for the higher resolution image.

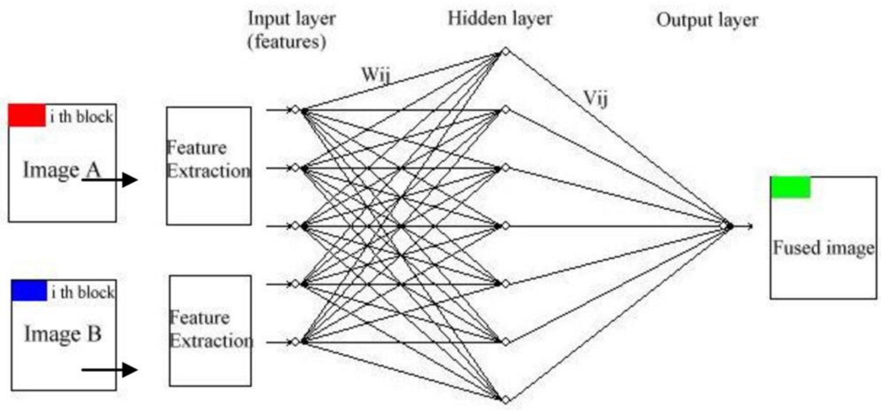
The wavelets-based approach is appropriate for performing fusion tasks for the following reasons (Pajares and Manuel de la Cruz 2004):

- It is a multiscale (multiresolution) approach well suited to manage the different image resolutions;
- The discrete wavelets transform (DWT) allows the image decomposition in different kinds of coefficients preserving the image information;
- Such coefficients coming from different images can be appropriately combined to obtain new coefficients, so that the information in the original images is collected appropriately;
- Once the coefficients are merged, the final fused image is achieved through the inverse discrete wavelets transform (IDWT), where the information in the merged coefficients is also preserved.

ANN-based image fusion

Artificial Neural Networks (ANN) are computing systems vaguely inspired by the biological neural networks. An ANN is characterized by stacked layers of neurons (node) which are connected to each other via a weighted link. The core idea behind ANN is to learn the values of these weights in order to be able to map the given input to the desired output.
The General schematic diagram of the ANN-based image fusion method can be seen in Figure 6. The input layer has several neurons, which represent the feature factors extracted and normalized from image A and image B. The hidden layer (the one in the middle) has several neurons and the output layer has one neuron (or more neurons). The *i*-th neuron of the input layer connects with the *j*-th neuron of the hidden layer by weight W_{ij}, and weight between the *j*-th neuron of the hidden layer and the *t*-th neuron of output layer is V_{jt}. The weighting function is used to simulate and recognize the response relationship between features of fused image and corresponding feature from original images (image A and image B).

Figure 6: Diagram of a general Neural Network-based image fusion technique.



As the first step of ANN-based data fusion, two images are decomposed into several blocks. Then, features of the corresponding blocks in the two original images are extracted, and the normalized feature vector incident to neural networks can be constructed. The features used to evaluate the fusion effect are usually spatial frequency, visibility, and edge. An ANN is a universal approximant that directly adapts to any nonlinear function defined by a representative set of training data. Once trained, the ANN model can remember a functional map which can be used for further calculations.

EV-specific fusion methods

In addition to the methods introduced before, specific methods exist for EO data fusion recorded at wavelengths beyond the infrared spectrum. These can partly be categorized into feature-based fusion methods. In order to provide example workflows in the Food-Water-Energy (FWE) Nexus domain within GEOEssential, specific fusion methods for water applications with focus on soil moisture are presented in the following.

Soil moisture (SM) is a key state variable in the climate system, which controls the exchange of water, energy, and carbon fluxes between the land surface and the atmosphere. Therefore, it can be used to identify important fluxes within the FWE nexus domain.
Satellite microwave observations from active and passive sensors are best suitable for the retrieval of soil moisture. Microwave remote sensing cannot directly measure soil moisture but makes use of the direct relationship between soil dielectric constant and water content. Active microwave remote sensing techniques measure the energy reflected from the land surface after transmitting a pulse of microwave energy, while passive microwave sensors measure the self-emission of the land surface (Peng et al. 2017). Typical spatial resolutions are in the order of tens of kilometers, a spatial downscaling to several kilometers or even tens of meters is required for many regional hydrological and agricultural applications. Data fusion is therefore mainly used for downscaling.

Active and passive microwave data fusion methods

Passive microwave radiometers can provide near-daily observations but have rather coarse spatial resolutions. Active microwave sensors are capable of providing much higher spatial resolutions than passive radiometers. However, the retrieval of soil moisture from radar is often difficult due to the combined effects of surface roughness, vegetation canopy structure, and water content on the backscattering coefficients. Therefore, three typical methods have been proposed for active and passive microwave data fusion for soil moisture:

- Disaggregation of soil moisture product from passive sensor with backscatter data from an active sensor (Das et al. 2011);
- Disaggregation of brightness temperature from a passive sensor with backscatter data from an active sensor and subsequent inversion to soil moisture (Das et al. 2014);
- Fusion of soil moisture product from a passive and a soil moisture product from an active sensor (Montzka et al. 2016);

Optical/thermal and microwave fusion method

Optical and thermal observations provide high spatial resolution, but are affected by cloud coverage. A number of studies have attempted to downscale microwave soil moisture products with help of vegetation cover and surface temperature information. The general idea of these methods is to obtain a downscaling factor from high-resolution optical/thermal data. This downscaling factor is then used to improve the soil moisture spatial variability of the coarse resolution microwave soil moisture (Peng et al. 2017). On the basis of the widely used surface temperature/vegetation index triangular feature space, an empirical polynomial fitting downscaling method was proposed to express the high-resolution soil moisture as a polynomial function of land surface temperature (LST), vegetation index, and surface albedo derived from optical/thermal data (Petropoulos et al. 2009). The polynomial expression is first applied at coarse resolution to determine regression coefficients, by applying the polynomial expression with the coarse resolution regression coefficients a high resolution soil moisture is finally obtained.

A more theoretically and physically based method than the polynomial fitting approach has been developed by (Merlin et al. 2008) and (Merlin et al. 2012). They proposed the Disaggregation based on Physical And Theoretical scale CHange (DISPATCH) method to utilize soil temperature, evaporative fraction (EF), and evaporative efficiency (EE) as SM proxies at high resolution for the relation to observed soil moisture at coarse resolution. The method is categorized as physical because it is based on the soil evaporation process to link optical and near-surface SM data. It is also qualified as theoretical because the scale change modeling relies on mathematical tools such as partial derivatives, Taylor series expansions, and projection techniques.

Methods using geoinformation data

Further combination of coarse scale soil moisture from EO and geoinformation data has the potential to be utilized for downscaling. (Montzka et al. 2018) developed a method to disaggregate EO soil moisture data by soil texture information, where a model has been established to predict soil moisture sub-grid heterogeneity by global high resolution soil maps. Further candidate geoinformation data is topography and vegetation.

Model-based methods

Model-based method to fuse different data types for soil moisture estimation can require statistical approaches and process models. Statistical approaches have been presented before (wavelet-based methods etc.). By involving a process (hydrological) model, deterministic downscaling, e.g. (Ines et al. 2013), as well as data assimilation methods (Montzka et al. 2012) come into play.

Summary

In this deliverable, Task 1.6 “Data Fusion” (DF), we gave the main guidelines for information fusion issues. At first, many methods have been briefly reviewed presenting which are pro and cons. Then, we focused on specific issues related to EVs. In this context, the optical/thermal and microwave fusion methods seem to be very promising and match the purposes of the GEOEssential project. Indeed, they find very natural applications when dealing with EVs, such as soil moisture. Here, the downscaling factor is used to improve the soil moisture spatial variability of the coarse resolution microwave soil moisture. Such a scheme needs to be compared with the other algorithms presented in the current deliverable. Indeed, the final aim is to select those methods that are efficient and accurate to ensure meaningful analysis of the EVs of interest.

Furthermore, these problems are strictly related to the ones presented in Task 1.4 “Modeling and Processing Services”. Indeed, because of the large amount of available data, Gibbs oscillations might occur for polynomial-based schemes and therefore algorithms such as PCA should be applied to obtain more robust solutions. This and numerical tests with real images involving EVs are actually under our investigation.

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