Synthetic Aperture Radar (SAR) Image Fusion with Optical Data

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**Remote Sensing imagery**

invaluable to acquire geospatial information about Earth surface for the assessment of land resources and environmental monitoring.

**In most cases**

the information provided by a single sensor is not complete or sufficient. So, the images collected by different sensors are combined to obtain complementary information.

Each remote sensing sensor has its own advantage and disadvantage over other sensors.
Synthetic aperture radar (SAR) imaging is an efficient tool for monitoring and investigation of dynamic phenomena.

It is a feasible alternative or a complement to traditional optical remote sensing techniques because it does not depend on solar illumination and weather conditions.

The high spatial resolution of SAR imagery makes it applicable for high spatial resolution mapping purposes. However, difficulties sometimes exist in the interpretation of SAR images.

Image fusion presents an alternative to improve the interpretability of SAR images by fusing the color information from moderate spatial resolution multispectral (MS) images.
**SAR (Synthetic Aperture Radar) sensors**

*active sensors* capable of collecting images circadian without being affected by weather conditions.

**SAR sensors capable of**

sensing the *geometry & structure* of the features such as terrain *topography, thickness* and *roughness* of surface cover. They can also sense the *moisture* content and presence of *vegetation*.

**Visible-Infrared (VIR) sensors**

*passive sensors* that sense the *electromagnetic energy reflected* from surface.

Information provided by the SAR data alone may not be satisfactory for a detailed analysis of the terrain, since it lacks the capability of collecting *spectral information* about terrain cover types.

**Fusion of VIR and SAR images provides *complementary data***

to increase the amount of information that can be extracted from the individual input images.
For an optimal image fusion, some *criteria* should be defined for algorithmic development.

The success of the fusion strongly depends on the *criteria selected*.

An example, a *pixel based* image fusion algorithm. The method forms the fused images as the *linear combination* of the *input images*. It employs *adaptive windows* to establish statistical relationships between the input images to calculate new fused pixels.

The fused pixels are calculated using two criteria:

1) Variance of the local window in fused image should be equal to the variance of the corresponding window in higher resolution image to transfer spatial detail.

1) Mean of the local window in the fused image should be equal to the mean of the window in the original lower resolution image to retain the color content.
Image fusion is used for many purposes. Very often it is used to produce an image with an improved spatial resolution. The most common situation is represented by a pair of images where the first acquired by a multispectral sensor has a pixel size greater than the pixel size of the second image acquired by a panchromatic sensor. Fusing these images a new multispectral image with a spatial resolution equal to the panchromatic one is produced. Image fusion introduces important distortion on the pixel spectra which in turn improve the information content of remote sensing (RS) images. Different fusion methods have been developed over years for improving spatial and spectral resolutions of RS data sets. It includes: (Karathanassi et al. 2007, Ehlers et al. 2008)

- the intensity-hue-saturation (IHS) transform,
- the Brovey transform,
- the principal components analysis (PCA) method,
- the Gram-Schmidt method,
- the local mean matching method,
- the local mean and variance matching method,
- the least square fusion method,
- the wavelet-based fusion method,
- the multiplicative and
- the Ehlers Fusion.

Most fusion applications use modified approaches or combinations of these methods.

Image fusion is capable of integrating different imagery data creating more information than that from a single sensor.

Many image fusion algorithms and software tools have been developed, such as (Alparone et al. 2004) the IHS (Intensity, Hue, Saturation), PCA (Principal Components Analysis), SVR (Synthetic Variable Ratio) and wavelet based fusion. However, such available algorithms are not efficient for the fusion of SAR and optical images any more. In an urban area, many land cover types/surface materials are spectrally similar. This makes it extremely difficult to analyze an urban scene using a single sensor. Some of these features can be discriminated in a radar image based on their dielectric properties and surface roughness.

In case of RS data sets, three different fusions is possible:

- fusion of optical data with optical data,
- fusion of microwave data with microwave data and
- fusion of optical and microwave data sets

For several decades, fusion of multiresolution optical images has been successfully used for the improvement of information contents of images for visual interpretation as well as for the enhancement of land surface features.

Many studies have been conducted on the improvement of spatial resolution of multispectral images by the use of the high frequencies of panchromatic images, while preserving the spectral information. Successful attempts have made fuse the interferometric or multi-frequency SAR images.

Unlike the fusion of optical images, most fusions of the synthetic aperture radar (SAR) data sets aims to increase the spectral variety of the classes.
The fusion of optical and SAR data sets has been widely used for different applications. It has been found that the images acquired at optical and microwave ranges of electromagnetic spectrum provide unique information when they are integrated. Image fusion based on the integration of multispectral optical and multi-frequency microwave data sets is being efficiently used for interpretation, enhancement and analysis of different land surface features.

It is known that optical data contains information on the reflective and emissive characteristics of the Earth surface features, while the SAR data contains information on the surface roughness, texture and dielectric properties of natural and man-made objects.

It is evident that a combined use of the optical and SAR images will have a number of advantages because a specific feature which is not seen on the passive sensor image might be seen on the microwave image and vice versa because of the complementary information provided by the two sources.

Different techniques have proposed and applied to combine optical and SAR images aiming to enhance various features. The results from the fused images is judged to be better than the results obtained from the individual images.

Although, many studies of image fusion have been conducted for derivation of new algorithms for the enhancement of different features, still little research has been done on the influence of image fusions on the automatic extraction of different thematic information within urban environment.
For the extraction of thematic information from multispectral RS images, different supervised and unsupervised classification methods have been applied for many years.

Unlike the single-source data, data sets from multiple sources have proved to offer better potential for discriminating between different land cover types.

The potential of multisource images for the classification of different land cover classes have assessed with promising results.

In RS applications, the most widely used multisource classification techniques are statistical methods, Dempster–Shafer theory of evidence, neural networks, decision tree classifier, and knowledge-based methods.

Proposed image fusion includes two different approaches such as fusion of SAR data with SAR data (ie, SAR/SAR approach) and fusion of optical data with SAR data (ie, optical/SAR approach), while the knowledge-based method includes different rules based on the spectral and spatial thresholds.
Definition

**Data Fusion:**

"...a formal framework in which are expressed means and tools for the alliance of data originating from different sources. It aims at obtaining information of greater quality; the exact definition of greater quality will depend upon the application’”

(Wald 1999)

‘Image fusion is the combination of two or more different images to form a new image by using a certain algorithm’

As a general and popular multi-discipline approach, Data Fusion combines data from multiple sources to improve the potential values and interpretation performances of the source data, and to produce a high-quality visible representation of the data.

Data Fusion techniques useful for a variety of applications, such as object detection, recognition, identification and classification, object tracking, change detection, decision making, etc.

Data Fusion successfully applied in the space and earth observations, computer vision, medical image analysis and defense security, etc.
Remote sensing data fusion aims to *integrate* the information acquired with different spatial and spectral resolutions from sensors mounted on satellites, aircraft and ground platforms to produce fused data that contains more detailed information than each of the sources.

Research on data fusion has a long history in remote sensing since fusion products are the basis for many applications.

Advanced fusion approaches and techniques have been developed to improve performance and accuracy.

Remote Sensing Data Fusing, especially multi-source data, still challenging because of various requirements, the complexity of the landscape, the temporal and spectral variations within the input data set and accurate data co-registration.
**Pohl and van Genderen (1998)** classify remote sensing data fusion techniques into three levels:

- the *pixel/data* level,
- the *feature* level and
- the *decision* level.
Pixel level fusion

the combination of raw data from multiple sources into single resolution data, that is expected to be more informative and synthetic than either of the input data or reveal the changes between data sets acquired at different times.
Feature level fusion

extracts various features, e.g. edges, corners, lines, texture parameters, etc., from different data sources and then combines them into one or more feature maps that may be used instead of the original data for further processing.

This is particularly important when the number of available spectral bands becomes so large that it is impossible to analyze each band separately.

Methods applied to extract features usually depend on the characteristics of the individual source data, and therefore may be different if the data sets used are heterogeneous. Typically, in image processing, such fusion requires a precise (pixel-level) registration of the available images. Feature maps thus obtained are then used as input to pre-processing for image segmentation or change detection.
Decision level fusion combines the results from multiple algorithms to yield a final fused decision. When the results from different algorithms are expressed as confidences (or scores) rather than decisions, it is called soft fusion; otherwise, it is called hard fusion.

Methods of decision fusion include voting methods, statistical methods and fuzzy logic-based methods.

The above categorization does not encompass all possible fusion methods, since input and output of data fusion may be different at different levels of processing. Practically the applied fusion procedure is often a combination of the three levels mentioned previously.
Levels of Data Fusion

Image fusion can be implemented on three different levels.

*Pixel level fusion* refers to the merging of the physically measured entities of an image.

*Feature level fusion* includes a mandatory extraction of non-overlapping adjacent homogeneous objects.

*Decision level fusion* is referred to as *a posteriori* combination of value added data with individual processing and information extraction.

Image fusion can be employed due to many reasons, such as

- enhancement of the spatial resolution of multispectral images,
- improvement of geometric corrections,
- provision of stereo-viewing functionality,
- enhancement of feature visibility,
- complementation of data sets for improved classification,
- multi-temporal change detection,
- substitution of missing information, and
- replacement of defective data.
Levels of Data Fusion

Data Fusion Levels

(reproduced from Pohl & Van Genderen 1998)
Levels of Data Fusion

Pixel level fusion
merging the physically measured entities of an image
Levels of Data Fusion

- **Feature level fusion**
  - a mandatory extraction of non-overlapping adjacent homogeneous objects

(reproduced from Pohl & Van Genderen 1998)
Levels of Data Fusion

Decision level fusion

a posteriori combination of value added data with individual processing and information extraction

Data Fusion Levels

(reproduced from Pohl & Van Genderen 1998)
Levels of Data Fusion

Data Fusion Levels

(reproduced from Pohl & Van Genderen 1998)
General Workflow

Optical-SAR data fusion workflow

- Radar Imagery
- Multispectral Imagery
- System Correction
- Speckle Reduction
- Atmospheric Correction
- Coregistration
  - Orthorectification
  - Geocoding
  - Resampling to common grid
- Fusion Techniques
- Image Map
General Workflow

- It comprises multiple steps.
- Sometimes processing chain of an optical–SAR data fusion differs from conventional approaches, where a high resolution panchromatic image and a lower resolution multispectral dataset are being merged.
- After the correction of system-specific errors, the fusion inputs undergo radiometric processing.
- Speckle filtering is an important and essential precaution to be careful of the impact of an unfiltered Radar image on the fusion results.
- The quality of multispectral data frequently suffers from atmospheric effects during data acquisition and can be improved by means of radiometric calibration.
- In the next stage of data preprocessing, the geometric correction of the multi-source imagery is required.
- Datasets need at least to be resampled to a common grid, but are preferably geocoded, ortho-rectified and most desirably co-registered to each other.
- High resolution SAR scene is used to sharpen the optical inputs employing one of the presented data fusion techniques.
- Considering the type of applications, the synthesized imagery is finally subject to further analysis.
Optical and SAR Image Geometry

Optical and SAR sensors geometry

(reproduced from Wegner et al. 2008)
Optical and SAR Image Geometry

Optical Sensor Model
- For optical imagery, the inverse 3D collinearity equations (object to image) are used in order to project the image to the ground.
- An indirect geometric image transformation for each pixel of the ortho-image is conducted.
- The pixel size of the ortho-image is selected corresponding to the ground resolution of the sensor.
- For all raster points of the ortho-image on the ground, the corresponding height values have to be interpolated within the DEM.
- The entire geometric modelling process is conducted in physical coordinates.
- The interpolation of the grey value within the original image in sensor geometry is a simple bilinear interpolation.

SAR Sensor Model
- The SAR image is projected to the ground with the inverse equations originally derived from the collinearity equations.
- They incorporate three different models: the motion model, the sensor model and the earth model. Hence, three coordinate systems are used: the image coordinate system, the intermediate coordinate system and the ground cartographic coordinate system.
- The first step is a transformation of the ground coordinates to the intermediate coordinate system.
- It simply applies one translation and one rotation.
- Furthermore, the coordinates of the intermediate system are transformed to the image coordinates.
Fusion techniques
Fusion techniques in Pixel Level

- Color related:
  - IHS (Intensity-Hue-Saturation) Transformation
  - HSV (Hue-Saturation-Value) Transformation

- Statistical/Numerical:
  - Statistical:
    - Principal Component Substitution (PCS)
    - Gram-Schmidt Transformation
  - Numerical:
    - Brovey Transform
    - Color Normalized algorithm
    - High Pass Filter method
    - Wavelets
Color related Fusion techniques

- Not very useful for Optical - SAR data fusion
- Usually applied in Multi-spectral – PAN fusion (PAN sharpening)

Simplified processing scheme of the Intensity Hue Saturation (IHS) transform (up) and the Hue Saturation Value (HSV) transform (down)
Color related Fusion techniques

- Multispectral imagery is usually displayed as a color composite of three bands utilizing the Red Green Blue (RGB) color space.
- Another way of representation comes with the Intensity Hue Saturation (IHS) domain.
- In chromatics, Intensity refers to the total brightness of a color, Hue describes the average wavelength of the light contributing to the color and Saturation corresponds to its purity.
- The IHS transform makes use of this concept in order to sharpen multispectral remote sensing data.
- In a first step, the multispectral input is transformed from the RGB domain to the IHS color space.
- This enables the separation of spatial (Intensity) and spectral (Hue and Saturation) information.
- Following, the Intensity component is replaced by the panchromatic input.
- To achieve higher quality fusion results, the panchromatic image is matched to the Intensity histogram prior to the replacement procedure.
- The final step comprises the reverse transformation of the replaced Intensity component and the original Hue and Saturation components to the RGB domain.
- First applications of the IHS transform in the field of remote sensing are reported by Haydn *et al.* in 1982 and Carper *et al.* in 1990.
- A potential disadvantage is that only three spectral bands can be processed at once. *(continued)*
Color related Fusion techniques (ctd.)

- Hence, if a multispectral dataset features more than three channels, the whole procedure has to be repeated for each desired band combination.

- Using the IHS transform, the best results are to be expected when the high resolution panchromatic image and the lower resolution multispectral dataset are highly correlated – a preliminary that is hard to fulfill when a SAR scene is used as panchromatic input.

- In order to obtain a better fit between the fused and the original data, a modified version of the IHS transform is developed.

- The HSV transform (Hue Saturation Value transform) follows the same principle as the IHS method.

- In fact, the only difference is the HSV color space to which the multispectral data are transferred to. Instead of the Intensity component, as in the case of the IHS fusion, the Value component is replaced by the high resolution panchromatic image using the HSV transform.

- Afterwards, the substituted Value component and the original Hue and Saturation components are subject to back transformation from the HSV into the RGB domain.

- Gillespie et al. (1986) and Kruse & Raines (1984) are amongst the first authors to describe the application of the HSV fusion method to digital imagery.
Statistical Fusion techniques

Principal Component Substitution

Processing scheme of the Principal Component Substitution (PCS) method

(reproduced from Zhang 2002)
Principal Component Substitution

- Principal component analysis (PCA) is a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components.

- The Principal Component Substitution (PCS) is a statistical method that transforms a correlated multivariate dataset into a dataset of uncorrelated images.

- For this purpose, the covariance matrix, eigenvalues as well as eigenvectors are calculated in order to transfer the multispectral fusion inputs into eigen-space.

- This results in a set of principal components of which the first one (PC1) is replaced by the high resolution panchromatic image because it contains the spatial details that are common to all bands.

- In analogy to the IHS transform, the substitution is carried out after the panchromatic input is matched to the histogram of PC1.

- Subsequently, an inverse PC transform takes the fused layer stack back into multispectral feature space.

- The PCS is a well-established method in the field of pixel level fusion.

Processing scheme of the Principal Component Substitution (PCS) method
Statistical Fusion techniques

Gram-Schmidt transformation

Processing scheme of the Gram-Schmidt (GS) transform

(reproduced from Laben & Brower 2000)
Statistical Fusion techniques

**Gram-Schmidt transformation**

- Another statistical method to sharpen digital images is the Gram-Schmidt (GS) transform.

- It first simulates a low resolution panchromatic image either by using the multispectral fusion inputs or by degrading the high resolution panchromatic band.

- Next, a GS transformation is applied to the simulated panchromatic image (as the first band) and the multispectral fusion inputs (as the remaining bands).

- Mean and standard deviation of the high resolution panchromatic band are matched to the histogram statistics of the first Gram-Schmidt component (GS1), which arises from the simulated low resolution panchromatic image.

- GS1 is then replaced by the high resolution panchromatic band.

- Finally, a reverse GS transform is conducted to generate the multispectral imagery at high resolution.
Numerical Fusion techniques

**Brovey transformation**

\[ DN_f = \frac{DN_{b1}}{DN_{b1} + DN_{b2} + DN_{b3}} \cdot DN_{hr} \]

- **\(DN_f\)** → Digital Numbers of the fusion result
- **\(DN_{1...3}\)** → Digital numbers of the spectral input bands
- **\(DN_{hr}\)** → Digital Numbers of the Data to fuse with (PAN, SAR...)

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Numerical Fusion techniques

*Brovey transformation*

\[ DN_f = \frac{DN_{b1}}{DN_{b1} + DN_{b2} + DN_{b3}} \cdot DN_{hr} \]

- **DN**\(_f\) \(\rightarrow\) Digital Numbers of the fusion result
- **DN**\(_{b1}\) \(\rightarrow\) Digital numbers of the spectral input bands
- **DN**\(_{hr}\) \(\rightarrow\) Digital Numbers of the Data to fuse with (PAN, SAR…)

- There is a large number of arithmetic fusion techniques that base upon addition or multiplication and may incorporate different scaling factors and weighting parameters.
- The Brovey transform is a numerical method that employs mathematical combinations in order to sharpen color images with the help of high resolution data.
- According to Pohl & Van Genderen (1998:835), its formula basically normalizes the multispectral bands of an RGB display before they are multiplied with the panchromatic imagery where **DN**\(_f\), **DN**\(_b\) and **DN**\(_{hr}\) refers to the Digital Numbers (DNs) of the fusion result \(f\), the three spectral input bands \(b\) and the high resolution data \(hr\), respectively. Thanks to the normalization step, the Brovey transform overcomes the disadvantages of the multiplicative method.
- One of the first authors that make use of this fusion technique are Hallada & Cox (1983). In the software Environment for Visualizing Images (Envi), a modification of the Brovey transform is implemented.
Numerical Fusion techniques

**Color Normalized (spectral sharpening)**

\[
CN_i = \frac{(MSI_i + 1) \cdot (PAN + 1) \cdot 3}{\sum_i MSI_i + 3} - 1
\]

\[
CN_i = \frac{MSI_i \cdot PAN \cdot N_{\text{segment}}}{S_{\text{segment}} + N_{\text{segment}}}
\]

- \(CN_i\) → \(i\)th Band of the fusion result
- \(MSI_i\) → \(i\)th Band of the multispectral input
- \(PAN\) → Band of the Data to fuse with (PAN, SAR...)
- \(N_{\text{segment}}\) → # of bands belonging to one spectral segment
- \(S_{\text{segment}}\) → Sum of bands belonging to one spectral segment
Numerical Fusion techniques

**Color Normalized (spectral sharpening)** [energy subdivision transform]

\[
CN_i = \frac{(MSI_i + 1) \cdot (PAN + 1) \cdot 3}{\sum_i MSI_i + 3} - 1
\]

- \( CN_i \) \( \rightarrow \) \( i \)th Band of the fusion result
- \( MSI_i \) \( \rightarrow \) \( i \)th Band of the multispectral input
- \( PAN \) \( \rightarrow \) Band of the Data to fuse with (PAN, SAR...)

- The additive constants in the equation are to avoid division by 0.
- A refined version of the CN algorithm is called CN spectral sharpening.
- The method can be used to spatially enhance any number of spectral bands within one step.
- The extended CN resolution merge only sharpens those input channels that fall within the spectral range of the high resolution panchromatic image, as defined by the center wavelength of the spectral bands and their Full Width at Half Maximum (FWHM) value.
- If this precondition is provided for, the color images are grouped into spectral segments that correspond to the spectral range of the high resolution data.
- The resulting band segments are then processed in the following manner.
Numerical Fusion techniques

**Color Normalized (spectral sharpening)** [energy subdivision transform]

\[ CN_i = \frac{MSI_i \cdot PAN \cdot N_{segment}}{S_{segment} + N_{segment}} \]

- Since it takes into account the wavelengths that are covered by the fusion inputs, the CN spectral sharpening is particularly useful to improve the geometric resolution of hyperspectral imagery.
- On the contrary, this technique might be inappropriate for an optical–SAR fusion scheme.
Numerical Fusion techniques

High Pass transformation

\[ W = \frac{\sigma(MS)}{\sigma(HPF)} \cdot M \]

- **W** → Weighting factor
- **σ(MS)** → Std.-Dev. Of multispectral channels
- **σ(HPF)** → Std.-Dev. of high pass filtered PAN/SAR image
- **M** → Modulating factor

\[ DN(output) = DN(input) + (HPF \cdot W) \]
**Numerical Fusion techniques**

*High Pass transformation*

\[ W = \frac{\sigma(MS)}{\sigma(HPF)} \cdot M \]

- **W** → Weighting factor
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- **M** → Modulating factor

\[ DN(output) = DN(input) + (HPF \cdot W) \]

- The High Pass Filter (HPF) method first computes the resolution ratio between the multispectral dataset and the panchromatic image.
- Then a high-pass convolution kernel filters the panchromatic input using a window size that is based upon the ratio.
- After the multispectral imagery is oversampled to fit the pixel spacing of the high resolution data, the HPF image is weighted relative to the global standard deviation of the spectral bands by the factor **W**.
Numerical Fusion techniques

High Pass transformation

\[ W = \frac{\sigma(MS)}{\sigma(HPF)} \cdot M \]

- \( \sigma(MS) \) and \( \sigma(HPF) \) are the standard deviations of the respective multispectral channels and the high-pass filtered panchromatic image.
- \( M \) is a modulating factor used to determine the crispness of the fusion output. Note that \( M \) is user-adjustable, but also depends on the resolution ratio.
- The above equation enables the calculation of band-specific values for \( W \) which are then employed to inject the HPF image into the individual spectral input bands via addition.
**Numerical Fusion techniques**

*High Pass transformation*

\[ DN(\text{output}) = DN(\text{input}) + (HPF \cdot W) \]

As the final step of the HPF resolution merge, the output images are rescaled by linear stretching in order to match the mean and standard deviation of the original multispectral images.
Numerical Fusion Techniques

Wavelets

Processing scheme of Wavelet fusion approach
**Numerical Fusion techniques**

*Wavelets*

- Wavelet transforms are powerful mathematical tools that have their origin in the field of signal processing.
- The technique entered in the image fusion domain when Mallat in 1989 proposed a functional framework for wavelet-based image decomposition and reconstruction called Multiresolution Analysis (MRA).
- Since then, various data fusion techniques have been introduced that rely on this very concept.
- Wavelets are elementary functions in which a given input signal can be decomposed.

**Processing scheme of Wavelet fusion approach**

- In Wavelet fusion, a high resolution panchromatic band (PAN) is first decomposed into four components: A low resolution approximation of the panchromatic image (PAN’) and three images of horizontal (H), vertical (V) and diagonal (D) Wavelet coefficients representing the spatial details in the high resolution panchromatic image.
- Later the individual bands of the multispectral dataset (MS) substitute the low resolution panchromatic image.
- The spatial details of the high resolution data are finally injected into each spectral band (MS*) by applying an inverse Wavelet transformation that makes use of the corresponding Wavelet coefficients for reconstruction.
Fusion techniques in Feature Level

Knowledge based

• Cluster Analysis
• Neural Networks
• Fuzzy Logic
• Expert Systems
• Logical Templates

Data Fusion

Identity Fusion Concepts

• Bayesian Inference
• Dempster-Shafer Method
Fusion techniques in Decision Level

Data Fusion

- Knowledge based
  - Expert Systems
  - Logical Templates
  - Neural Networks
  - Fuzzy Logic
  - Blackboard
  - Contextual Fusion
  - Syntactic Fusion

- Identity Fusion Concepts
  - Classical Inference
  - Bayesian Inference
  - Dempster-Shafer Method
  - Voting Strategies
“A neural network consists of a number of interconnected nodes [...].

Each node is a simple processing element that responds to the weighted inputs it receives from other nodes.

The arrangement of the nodes is referred to as the network architecture.”
Artificial Neural Networks (ANN)

- Neural networks are the systems that seek to emulate the process used in biological nervous systems.

- A neural network consists in layers of processing elements, or nodes, which may be interconnected in a variety of ways.

- The neural network performs a non-linear transformation of an input vector.

- This theory is used when the relation between output and input data is unknown.

- A neural network can be trained using a sample or training data set (supervised or unsupervised depending on the training mode) to perform correct classifications by systematically adjusting the weights in the activation function.

- This activation function defines the processing in a single node.

- The ultimate goal of neural network training is to minimize the cost or error function for all possible examples through the input-output relation.

![Neural Network Diagram]

(Atkinson & Tatnall 1997)
Artificial Neural Networks (ANN)

Image Channels

• The neural networks can be used to transform multi-sensor data into a joint declaration of identity for an entity.

• The Figure illustrates a four-layer network with each layer having multiple processing elements.

• In 1994 A. Chiuderi et al. used a neural network approach for data fusion of land cover classification of remote sensed images on an agricultural area. By using supervised and unsupervised neural network, the optical-infrared data and microwave data were fused for land cover classification.

• In 2001 L. Yiyao et al. adopted a knowledge-based neural network for fusing edge maps of multi-sensor remote sensing images.

• In 2003 He Mingyi and Xia Jiantao proposed DPFNN (Double Parallel Feedforward Neural Networks) used to classify the high dimensional multispectral images.

• Other applications can be found in crop classification, forest type classification, recognition of typhoon clouds etc.
Fuzzy Logic

Principle Concept of Fuzzy Logic

\[
\begin{align*}
\mu \text{ „low“} & = 0.4 \\
\mu \text{ „medium“} & = 0.2 \\
\mu \text{ „high“} & = 0.0
\end{align*}
\]

\[
\begin{align*}
\mu \text{ „low“} & = 0.0 \\
\mu \text{ „medium“} & = 0.0 \\
\mu \text{ „high“} & = 0.8
\end{align*}
\]
Bayesian Fusion
Bayesian Fusion

• The method takes its name from the English clergyman Thomas Bayes.

• It is based on Bayes’ theorem on inequality which was first presented by Bayes in 1763.

• The Bayesian inference technique resolves some of the difficulties with classical inference methodology.

• Bayesian inference allows multi-sensor information to be combined according to the rules of probability theory.

• Bayes’ formula provides a relationship between the *a priori* probability of a hypothesis, the conditional probability of an observation given a hypothesis, and the *a posteriori* probability of the hypothesis.

• It updates the probabilities of alternative hypotheses, based on observational evidence.

• New information is used to update the *a priori* probability of the hypothesis.
Dempster-Shafer fusion

- Sensor #1
  - Observables
  - Classifier
  - Declaration

- Compute or enumerate mass distribution for given declaration

- Sensor #2
  - Etc.

- Sensor #n
  - Etc.

- Transformation from observation space to mass distributions

- Combine/fuse mass distributions via Dempster's rules of combination

- Decision logic

- Select best combined evidential interval

- Fused probability mass for each object hypothesis, Qj

- General level of uncertainty leading to

- Combined evidential intervals

Dempster-Shafer method
The DS method’s theory was proposed by Dempster in 1967 and extended by Shafer.

It is a generalization of Bayesian theory that allows for a general level of uncertainty.

Unlike the Bayesian approach, the DS method provides a means to account explicitly for unknown possible cause of observational data.

DS utilizes probability intervals and uncertainty intervals to determine the likelihood of hypotheses based on multiple evidence.

DS computes a likelihood that any hypothesis is true.

Both DS and Bayesian methods lead to identical results when all of the hypotheses considered are mutually exclusive and the set of hypotheses is exhaustive.
Thank you!

&

any question