Comparison of Retrieval Algorithms for the Wet Tropospheric Path Delay
Introduction

Objective :

• Theoretical evaluation of current regression algorithms for the retrieval of the wet tropospheric path delay (dh) :
  • How different are the operational algorithms ?
  • Can we improve those algorithms ?

Outline :

• The wet tropospheric correction
• Algorithms currently used in altimetry missions
• Comparison of two algorithms: log-linear vs neural network
• Correlation analysis of inputs
• Conclusion
The wet tropospheric path delay

- Corresponds to path delay in the radar return signal due to water vapor in the troposphere
- Ranges from 0 to 50 cm.
- Any error in the wet-tropospheric correction directly impacts the sea level determination
- Calculated from radiometer measurements with uncertainty of around 1-cm rms (Ruf et al. 1994)
The wet tropospheric path delay retrieval

- Microwave radiometers measure brightness temperature (natural emission of sea surface and atmosphere)

- $tb$ measured at a given frequency depends on the atmospheric profile and on sea surface conditions

- 3 $tbs$ usually used around:
  - $tb_{24GHz}$: highly sensitive to water vapor ($wv$)
  - $tb_{37GHz}$: sensitive to clouds ($wc$)
  - $tb_{18GHz}$: sensitive to the surface: temperature ($ts$) and roughness.

- Relationship between $dh$ and $tb$ is established through statistical regression
Two families of retrieval algorithms

NASA/CNES/NOAA/Eumetsat:
TOPEX/JASON1/JASON2
• RTM
• Radiosondes and Radiometers
• tb18.7, tb23.8, tb34
• Two-step log-linear regression

Keihm et al. 1995

ESA (+CNES/ISRO ALTIKA):
ERS1/ERS2/ENVISAT/SENTINEL3
• RTM
• ECMWF Fields
• wspd/sigKu, tb23.8, tb36.5
• Neural Network

Eymard et al. 1996/Obligis et al. 2006
Comparison of 2 Algorithms

2012 ECMWF fields + UCL RTM:
20% for learning and 80% for testing

JMR_Reg
Two-step log-linear regression
tb18.7 + tb23.8 + tb34

MWR_NN
Neural Network
sigKu + tb23.8 + tb34

OSTST Meeting, Boulder, October 2013
Results on the test database

**JMR_REG**

\[ \text{RMS} = 4.34 \text{ mm} \]

**MWR_NN**

\[ \text{RMS} = 4.45 \text{ mm} \]
A third Algorithm

2012 ECMWF fields + UCL RTM:

20% for learning and 80% for testing

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Methodology</th>
<th>Equation</th>
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</thead>
<tbody>
<tr>
<td>JMR_Reg</td>
<td>Two-step log-linear regression</td>
<td>$tb_{18.7} + tb_{23.8} + tb_{34}$</td>
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Results on the test database

JMR_NN

RMS = 2.46 mm
Results on the test database

**JMR_REG**

RMS = 4.34 mm

**JMR_NN**

RMS = 2.46 mm

**TWO STEP LOG-LINEAR REGRESSION VS NEURAL NETWORK:**

- dh-dependent bias for JMR_REG
- The two step log-linear regression lacks flexibility to correctly adjust the data compared to neural networks
Results on the test database

SIGKU VS TB18.7:

- sigKu and tb18.7 do not bring equivalent information on the surface

- Use of tb18.7 gives much better performances
Importance of inputs

NN Input Relative Importance : HVS Criteria (YACOUB & BENNANI Y, 1997)

- sigKu is of little importance, compared to tb23.8 and tb34 for the retrieval of dh
- tb18.7 relative importance is much higher than sigKu relative importance
Principal component analysis

- Applied to ts, windsp, wc, wv and dh.
- Best summary of correlation between variables
- Each variable is represented by a vector
- Correlation between two variables is given by cosines of the angle between the two vectors
PCA: Brightness Temperatures

- \( tb_{18.7}, tb_{23.8} \) are highly correlated to \( dh \) and \( wv \) \((cor > 0.90)\).
- \( tb_{23.8} \) is the most correlated to \( dh \), \( wv \) and \( ts \).
- \( tb_{34} \) is the most affected by \( wc \).
PCA: Backscattering coefficients

- sigC and SiKu are highly correlated with windsp:
  \[ \text{cor}(\text{sigKu}, \text{windsp}) = -0.99, \]
  \[ \text{cor}(\text{sigC}, \text{windsp}) = -0.93 \]

- Little correlations are found with dh, wv and tbs (cor < 0.30)
PCA : Conclusions

- sigKu is closer to windsp and lacks information about ts and dh
- tb18.7 is closer to ts and dh
- MWR_NN lacks information about ts?
## Last Comparisons

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<th>Condition</th>
<th>RMS</th>
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<tr>
<td><strong>MWR_NN+ts</strong></td>
<td>ts+sigKu+tb23.8+tb37</td>
<td>2.21 mm</td>
</tr>
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Conclusions

• Only an assessment of the regression quality on a given simulated database and not of the entire radiometric error budget (regression quality, database representativeness, RTM quality, instrumental noise, pixel heterogeneity, antenna pattern...)

  **BUT SUCH ANALYSIS HELPS:**

• Finding an appropriate method of regression:
  
  – **NN are more flexible than log-linear regressions.** NN are black-boxes but tools are being developed to make them more transparent.

• Identifying useful sources of information to improve the retrieval:
  
  – **sigKu** lacks correlation with dh and ts but **provide useful information on windsp** with respect to tb18.7

  – tb18.7 is more important than sigKu in the retrieval of dh : tb18.7 provides additional information on dh and ts => **3-channel radiometers should be preferred**

  – **Lack of 18.7 GHz channel can be compensated by ts for equivalent results.** Reynolds SST could probably be used for near real time dh products

• All these results should be assessed on real measurements using usual metrics (SSH variance at crossovers, radiosonde comparisons...)