ASSESSING THE 'EXPECTED ERROR' AS A POTENTIAL NEW QUALITY INDICATOR FOR ATMOSPHERIC MOTION VECTORS

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Abstract

The recursive filter (RF) objective analysis has been a significant part of the CIMSS/NESDIS Atmospheric Motion Vector (AMV) post-processing since the algorithm was fully automated in the early 1990s. Although it has proven to be an effective automated quality control module, its mostly undocumented complexity has led CIMSS and NESDIS to pursue alternatives as part of the GOES-R risk reduction program. A promising alternative is the Expected Error (EE), a linear regression algorithm trained against collocated AMV – RAOB differences. Preliminary comparisons show that the EE can lower the AMV – RAOB root-mean squared difference (RMSD) to a similar value as the RF, but at the expense of retaining fewer AMVs, larger speed biases and slower average dataset speeds. Slightly more complex thresholding techniques help to reintroduce some of the faster AMVs without significantly increasing the RMSD. Further investigation is suggested.

INTRODUCTION

AMV quality control is an important prerequisite for NWP data assimilation (DA) applications. This need has led AMV providers to create indices that estimate the quality of each AMV produced. These indices not only provide a measure of quality control, but also can be beneficial to DA if they are related to the AMV's observation error.

Currently, CIMSS/NESDIS uses a sophisticated system of quality control to effectively edit large raw AMV datasets and reduce the average RMSD. This process combines gross error checks along with the quality indicator (QI, Holmlund, 1998) and the RF (Hayden and Purser, 1995). While the RF has been used for many years in this processing, its mostly undocumented complexity is a liability for its transition and use in future operational AMV processing at NESDIS. As a consequence, work is ongoing at CIMSS and NESDIS to examine the EE (LeMarshall et al., 2004). The EE algorithm extends the QI to predict an AMV error in units of ms^{-1}. This paper will describe the current CIMSS/NESDIS AMV processing as well as preliminary investigations of the EE as an alternative QC routine.

CIMSS/NESDIS AMV PROCESSING

THE CIMSS/NESDIS QC process has several steps (for details, see Nieman *et al*. 1997). First, some AMVs are removed through vector consistency checks. After a gross error check against the model background fields to remove highly-spurious vectors, The QI is run. The QI is a weighted average of vector tests in which each wind is assigned a score from 0 to 1 (0 Indicates a poor quality wind, and 1 indicates a high quality wind) (Holmlund, 1998). AMVs with QIs less than 0.5 are not passed on to the final step: the RF analysis. The RF is a 3-dimensional recursive filter objective analysis in which each vector is fit to an analysis of its neighbors (with a model background constraint). The AMV's height is allowed to be re-adjusted based on a level of best fit to this analysis. This fit is optimized by minimizing a vertically oriented penalty function that includes velocity, temperature, pressure, direction and speed. During the RF process, the speed of some upper-level AMVs is increased by 10% to correct known AMV biases (situational). After this process, the wind is assigned a quality flag between 0 and 100 (100 being the highest quality wind; Hayden and Purser 1995, Velden et al. 1997 and 1998). Some high-speed upper-level AMVs that are rejected by the RF can be re-introduced (in strong high-level jet regions) at this stage. Only AMVs with an RF quality flag > 50 are passed on to the user community.

EXPECTED ERROR (EE)

The EE quality indicator is an extension of the previously described QI (LeMarshall et al., 2004). Essentially, it linearly regresses the five QI tests along with other vector information and collocated model information against AMV/RAOB vector differences. The nine predictors are shown in Table 1. The first five predictors are the normalized QI scores as described in the previous section. The sixth and seventh predictors: the AMV speed and pressure level, are derived from the vector itself, while the two gradient predictors are generated from the model. These predictors are generated for several weeks of data and then regressed against the AMV-RAOB vector difference in order to create regression coefficients. The coefficients can then be used to estimate the error for subsequent vectors.

1) QI Speed Test
2) QI Direction Test
3) QI Vector Difference
4) QI Local Consistency Test
5) Qi Forecast Test
6) AMV Speed
7) Assigned Pressure Level
8) Wind Shear (200 hPa Above – 200 hPa below)
9) Temperature Gradient (200 hPa Above – 200 hPa below)

Table 1: **Expected Error predictors. The first 5 are part of the QI, the 6th and 7th are derived from the AMVs, the 8th and 9th are derived from an NWP model.**

APPLICATION TO GOES DATA

To investigate the potential of the EE on the CIMSS/NESDIS AMV quality, we first establish a quality baseline from the performance of the existing RF. Pre- and post-RF GOES-12 IR AMVs were matched against collocated RAOBS from 03 Aug. – 01 Oct, 2007. AMVs with QIs less than 0.5, or those with vector differences from the RAOBs greater than 30 ms^{-1} were excluded from the comparisons (as is done in operationally-produced AMV datasets by NESDIS). Our match criteria dictated that the AMVs be within 150 km in the horizontal and 25 hPa in the vertical from their matching RAOBs. The results of these comparisons are shown in Table 2.

Dataset	Height (hpa)	Pre-RF	Post-RF
Number	100 – 400	41430	35361
	400 – 700	7989	5390
	700 –1000	3419	2221
Spd Bias	100 – 400	-2.02	-0.64
	400 – 700	-1.30	-1.25
	700 - 1000	-0.23	-0.13
RMS Vector Difference	100 – 400	8.89	7.24
	400 – 700	7.46	5.86
	700 - 1000	4.89	4.71
AVG RAOB Speed	100 – 400	19.18	19.80
	400 – 700	14.88	14.66
	700 - 1000	8.68	9.35

Table 2: **Bulk statistics comparing pre-RF AMV-RAOB data to post-RF data. The RF processing effectively lowers RMSD and speed biases compared to RAOBS.**

As the table clearly shows, the post-RF data have a lower RMSD and bias relative to the pre-RF data. Nearly 10,000 AMVs are removed via the quality control, but the average RAOB speed of both datasets is nearly the same. Thus, by effectively removing bad AMVs and making mostly minor speed/height adjustments to some of the AMVs, the RF significantly improves the quality of the GOES AMV dataset as compared to verifying RAOBS.

Having established this AMV quality baseline, the question that this study attempts to address is whether the EE, scheme can provide a similar quality dataset to that of the post-RF dataset? To address this question, EE regression coefficients were generated for the period described previously. Separate coefficients were generated for the pre- and post-RF AMVs. The EE was then used as a threshold maximum in order to select AMVs with the lowest predicted error.

Figure 1 shows the impact of the EE maximum as a function of AMV RMSD. The circled plots are from post-RF AMVs while the hatched marks are for pre-RF AMVs. The colors represent different levels of AMV comparisons. As seen in the plot, lower EE thresholds correspond to lower RMSD values for all levels and both data sets. If the EE maximum for the pre-RF data set is set somewhere between 5 and 6 ms^{-1}, then the RMSD is lower than the bulk statistics for the post-RF dataset. One can also see that for lower EE thresholds, the error reduction is nearly 1-1, a desirable result.

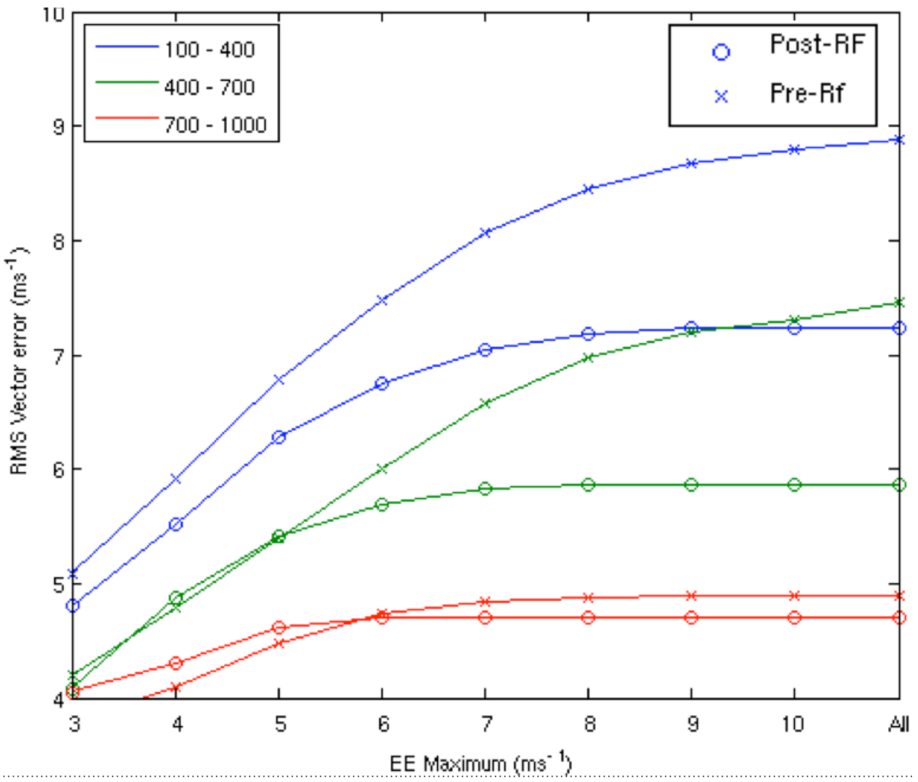

***Figure 1*: AMV-RAOB RMS vector Difference as a function of EE maximum. The circled plots are from post-RF AMVs while the hatched marks are for pre-RF AMVs. The colors represent different levels of AMV comparisons. Lowering the EE threshold lowers the RMSD as compared to collocated verifying RAOBS.**

The impact of an EE threshold of 6 ms^{-1} is shown in Table 3 and compared to the same statistics of the post-RF dataset. As seen in the table, while the RMSD are fairly similar for both datasets, the baseline post-RF dataset retains many more AMVs in the upper-levels, a smaller bias at all levels, and higher average mean RAOB speeds (implying faster AMVs are retained).

Data Set		Pre-RF EE Max 6 ms^{-1}	Post-RF All
Number of matches	100 - 400	27184	35361
	400 - 700	5796	5390
	700-1000	3310	2221
Spd Bias (AMV – RAOB)	100 - 400	-2.12	-0.64
	400 - 700	-1.47	-1.25
	700-1000	-0.27	-0.13
RMS Vector Diff. (vs RAOB)	100 - 400	7.48	7.24
	400 - 700	6.01	5.86
	700-1000	4.74	4.71
Avg RAOB Speed	100 - 400	16.04	19.80
	400 - 700	13.11	14.66
	700-1000	8.60	9.35

***Table 3:* Summary of statistics comparing the post-RF dataset to that of the pre-RF dataset using an EE maximum threshold of 6 ms^{-1}. The EE threshold lowers the RMSD to near post-RF values, but at the cost of high-level AMV quantities, and by lowering the average AMV speed.**

COMPARISON OF THE EE AND QI

As shown previously, the EE can effectively lower the RMSD compared to RAOBS. It is, however, based on the existing QI, so it makes sense to compare the results of the two indicators. Figure 2 is the same as Figure 1, except it bins the data by QI minimum rather than EE maximum. As the plot shows, the RMSD decreases slightly with increasing QI minimums, but the slope is not as large as with the EE. The QI also does not have as much impact with the post-RF data as it does for the pre-RF data. The RF modifies the speed and height of some of the AMVs after the QI has already been calculated. It is possible that this nullifies some of the QI impact.

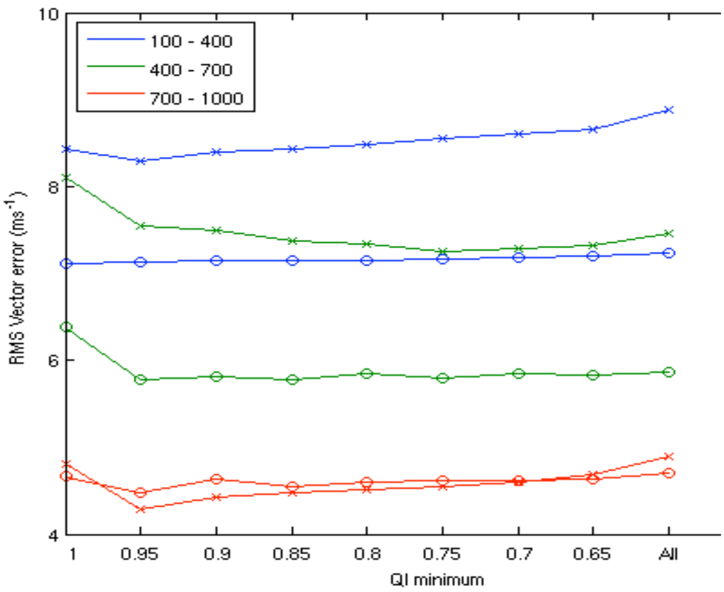

Figure 2: **The same as Figure 1, except using the QI minimum as a threshold rather than the EE maximum. The QI does reduce the RMSD, but not as effectively as the EE.**

The two indicators, however, have different speed dependences. As the EE is a function of speed, the average RAOB (and AMV speed) decreases as the EE maximum decreases (not shown). The QI (shown below in Figure 3) behaves nearly the opposite. As the QI minimum increases, the average speed increases. Thus, even if the RMSD increases slightly, the normalized RMSD (by mean AMV dataset speed) may decrease. The QI tends to retain faster AMVs, a quality we wish to capture better in the EE scheme.

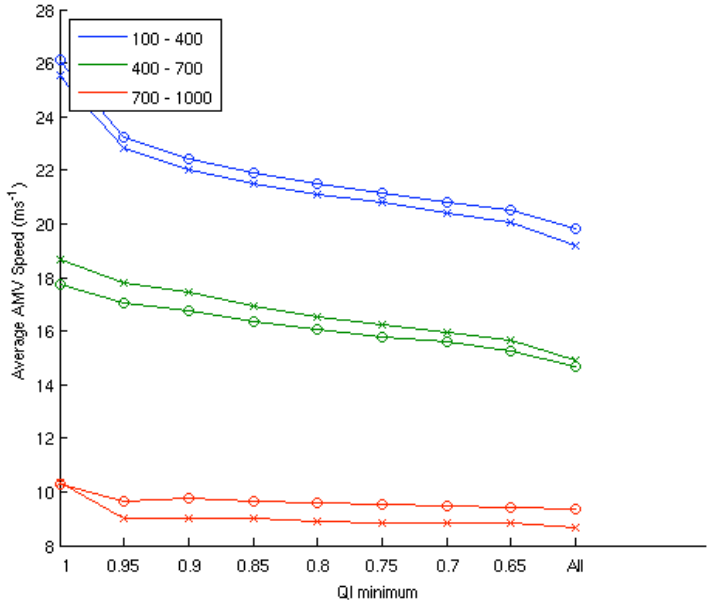

Figure 3: **Average RAOB speed as a function of QI minimum. Unlike the EE (not shown), the average speed increases as the QI increases.**

TWO TECHNIQUES FOR ADDRESSING THE EE SPEED ISSUE

As the previous section alluded, reducing the EE maximum threshold reduces the average AMV speed in the dataset. Thus, some AMVs that have low error are removed from the dataset simply because their speed is high. This section will focus on two techniques to alleviate this issue.

The first technique uses a simple linear EE threshold that is a function of AMV speed. Fitting a simple linear equation between AMV speed and AMV – RAOB vector difference, the following threshold is derived:

$$eem = 5.49 + 0.089 * speed \qquad (1)$$

where eem is the EE maximum and speed is the AMV speed. Thus, AMVs with EEs higher than this fit are considered to be low quality AMVs. From (1), slow AMVs have a threshold of about 5.5 ms^{-1}, a threshold consistent with the results of Figure 1 where the pre-RF matched the post RF between 5 and 6 ms^{-1}. The maximum threshold for fast AMVs is around 12 ms^{-1}, much higher than the simple hard threshold. The results of the speed threshold technique are compared to the hard threshold and post-RF threshold in Table 4. The speed threshold technique does increase the average speed of the dataset as compared to the hard 6 ms^{-1} threshold. The dataset contains more AMVs but has a higher RMSD than either of the other datasets. The speed biases, however, are slightly smaller than the hard threshold, but not as small as the post-RF dataset. This technique is fairly straightforward, but the higher RMSD may limit its use.

Data Set		Pre-RF Linear Threshold	Pre-RF EE Max 6 ms^{-1}	Post-RF All
Number of matches	100 - 400	35593	27184	35361
	400 - 700	6852	5796	5390
	700-1000	3363	3310	2221
Spd Bias (AMV – RAOB)	100 - 400	-1.93	-2.12	-0.64
	400 - 700	-1.21	-1.47	-1.25
	700-1000	-0.21	-0.27	-0.13
RMS Vector Diff. (vs RAOB)	100 - 400	8.20	7.48	7.24
	400 - 700	6.46	6.01	5.86
	700-1000	4.81	4.74	4.71
Avg RAOB Speed	100 - 400	19.23	16.04	19.80
	400 - 700	14.41	13.11	14.66
	700-1000	8.65	8.60	9.35

Table 4: **Bulk statistical comparison of the linear threshold technique, the hard 6ms^{-1} threshold and the post-RF dataset. The linear threshold technique retains more AMVs than either dataset, but the RMSD is higher than the other two methods. The average RAOB speeds are comparable to the post-RF dataset.**

Another technique we are exploring involves utilizing the QI's property of preferentially retaining higher speed AMVs. The strategy is as follows:

1) For slow AMVs, use a hard EE threshold.
2) For fast AMVs, retain AMVs that have high QI values regardless of their EE value.

The thinking behind this methodology is that the EE is superior at identifying the quality of relatively slow AMVs. The QI appears better with relatively faster AMVs of good quality. Thus, it is conceivable that the two approaches can be used in tandem. The trick is in choosing the appropriate AMV speed thresholds and corresponding QI tolerances.

Examples of two chosen thresholds are shown in Table 5, compared with the post-RF and hard threshold results. Both of these examples use 5 ms^{-1} for the slow AMVs and a "good" QI threshold of 0.95. The difference is that the fast AMV thresholds are set at 20 and 30 ms^{-1}. The trends are as expected. Both of these QI/EE thresholds have lower RMSD than the 6 ms^{-1} threshold as well as fewer AMVs. This makes sense as the slow AMV threshold is lower than the hard threshold. They also, however, have higher average speeds and smaller biases than the 6 ms^{-1} threshold, corresponding to the additional AMVs permitted through the QI tolerance. These preliminary experiments appear promising, but the threshold settings must be tested further to optimize the effectiveness of the approach.

Data Set		Spd >=20ms^{-1} EE > 5 ms^{1} QI >=0.95	Spd >= 30 ms^{1} EE > 5 ms^{-1} QI >=0.95	Pre-RF EE Max 6 ms^{-1}	Post-RF All
Number of matches	100 - 400	20,565	18707	27184	35361
	400 - 700	4346	4155	5796	5390
	700-1000	3077	3075	3310	2221
Spd Bias (AMV – RAOB)	100 - 400	-1.62	-1.69	-2.12	-0.64
	400 - 700	-1.13	-1.23	-1.47	-1.25
	700-1000	-0.33	-0.33	-0.27	-0.13
RMS Vector Diff. (vs RAOB)	100 - 400	7.41	7.20	7.48	7.24
	400 - 700	5.77	5.63	6.01	5.86
	700-1000	4.49	4.48	4.74	4.71
Avg RAOB Speed	100 - 400	18.13	17.36	16.04	19.80
	400 - 700	13.28	12.83	13.11	14.66
	700-1000	8.43	8.43	8.60	9.35

Table 5: Bulk statistics for **two examples of the QI/EE combination technique, compared to the 6ms^{-1} threshold and the post-RF dataset. Both of these examples have smaller RMSD and smaller biases than the two previously described techniques. They have slightly higher average speeds than the straight thresholding technique, however, they keep fewer AMVs.**

CONCLUSIONS AND FUTURE WORK

This research shows the potential of the EE to skillfully select higher quality AMVs as part of a potential post-processing QC module for the future CIMSS/NESDIS AMV processing package. However, while the EE method can reach the level of skill of the existent RF in terms of achieving overall AMV dataset quality, it does so at the expense of vector quantity and higher speed AMVs. The EE threshold technique and the QI/EE combination techniques briefly explored in this study show some promise in retaining high quality, high speed AMVs; a hard EE threshold would have removed them. Optimizing these techniques to produce the best combination of AMV quality and quantity will take further study.

This study focused on the EE as originally described in LeMarshall's 2004 paper. Are there other predictors that may improve on its skill? Can we estimate the height and vector errors separately as requested by some numerical weather predictor centers? These are questions for future study.

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