



Quality information in processing weather radar data for varying user needs

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1 Introduction

In this paper, we continue recent discussion on quality information in radar data, proceeding from error source or quality factor oriented topics (Divjak et al., 1999; Saltikoff et al., 2004) towards the challenge of *applying* obtained quality information. Hence, we extend the findings of COST 717 (Michelson et al., 2004) and OPERA work package 1.2 (Holleman et al., 2006), and proceed towards building blocks of a generally applicable “quality algebra” with direct applications in visualisation, data correction, compositing and products obtained by input weighting.

2 Mathematical aspects

2.1 Behind the plus minus

In general, quality of a measurement is often identified with its *accuracy*, appearing in notations like

$$x = \mu \pm \sigma \quad (1)$$

where $\mu = \frac{1}{N} \sum_{i=1}^N x_i$ is the average obtained from repeated measurements and σ is an accuracy measure, typically a root mean square error (RMSE), from $\sigma^2 = \frac{1}{N} \sum_{i=1}^N (x_i - \mu)^2$. In weather radar measurements, signal processor typically takes care of sampling and sends averaged results to the user. Accuracies are not always available; spectrum width of a Doppler measurement is a perhaps the most available accuracy information. (Spectrum width also reminds of the fact that measurement results and accuracies are not always simple averages and RMSE's; other examples are maximum likelihood and similar peaks with accuracy reported as half-

widths.) Nevertheless, communicating and using the “original” reflectivity measurement accuracies is seldom accomplished in radar data processing,

It may also be that the sixth-power mathematics squeezing data (and users) between logarithmic scales makes further considerations of accuracy mathematically “heretic” or even “impossible”. However, it seems logical that using even a simple quality processing scheme results in better meteorological than not using quality at all. Therein, the “classical” measurement convention (1) is a valid starting point for many tasks: for example, a product based on resampling such as a radar image composite can be seen as a repeated measurement process.

2.2 Questioning the whole measurement

Another aspect of quality involves information on overall validity of a measurement. A radar measurement of a flock of geese can be very *accurate*. Hence, the measurement itself can be accurate in terms of σ_x but it may be uncertain whether the target is of desired type. In weather radar, anomalies such as clutter, birds, ships and external transmitters often interfere with echoes of precipitation (Fig. 1). In this case, the quality information should carry a probabilistic character (as well). For obtained measurement x , one can for example associate a probability $P_i = p(c_i|x)$ of x originating from a target of desired type c_i . Again, while problems related to anomalies have been known and discussed for years, the topic of handling – producing and applying – probabilistic quality information is relatively new in the context of weather radars.

If the origin of the measured values is uncertain, it should be reported too, for example like

$$x = \mu, \text{ with } P \quad (2)$$

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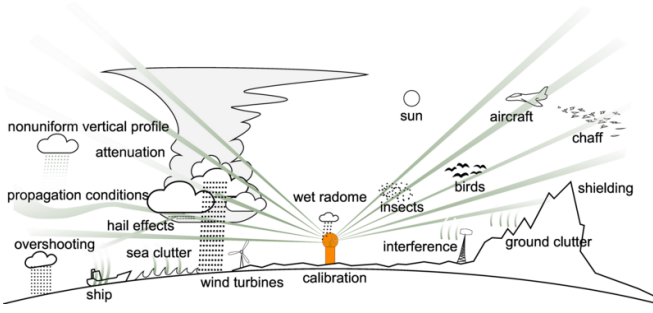


Fig. 1. Error sources

where P' is the probability of a (desired) target.

Also in the case of uncertain sources, we may have an **error interval** available, combining the notations to something like

$$x = \mu \pm \sigma, \text{ with } P \quad (3)$$

As to geometry, one may assign quality information for each pixel, creating separate channels for σ and P . One may also have global (per-volume), sector wise or range wise quality data. Further, quality data may have a dynamic – e.g. diurnal, annual, weather-dependent or constantly decreasing – character. In this paper, we do not concentrate on dynamics but many discussed tools can be extended to the time domain.

2.3 Mixing measurements

Consider multiple remote measurements of a common target – for example precipitation targeted by two radars or by a rain gauge and a radar. Assume that you have been given measurements results in the classical form, (1): $x_1 = \mu_1 \pm \sigma_1$ and $x_1 = \mu_2 \pm \sigma_2$. How do we combine these (or more) observations to single $\mu \pm \sigma$?

For now, assume that these two measurements originate from N_1 and N_2 original, repeated measurements: x_1, x_2, \dots, x_{N-1} and $x_{N+1}, x_{N+1}, \dots, x_{N+N_2}$. Keep in mind that we have not stored complete sets, but merely the statistics (μ_i, σ_i) and perhaps N_1 and N_2 (or assume $N_1 = N_2$).

The mean is trivially

$$\mu = \frac{1}{N} \sum_{i=1}^N x_i = \frac{1}{N} \left(\sum_{i=1}^{N_1} x_i + \sum_{i=N_1+1}^N x_i \right) = \frac{N_1 \mu_1 + N_2 \mu_2}{N} \quad (4)$$

and the error is

$$\sigma^2 = \frac{1}{N} \sum_{i=1}^N (x_i - \mu)^2 = \frac{1}{N} \sum_{i=1}^N x_i^2 - \mu^2 \quad (5)$$

$$= \frac{1}{N} \sum_{i=1}^{N_1} x_i^2 + \frac{1}{N} \sum_{i=N_1+1}^N x_i^2 - \mu^2 \quad (6)$$

$$= \frac{N_1}{N} (\sigma_1^2 + \mu_1^2) + \frac{N_2}{N} (\sigma_2^2 + \mu_2^2) - \mu^2 \quad (7)$$

Hence, we can derive μ and σ from N_1, μ_1, σ_1 and N_2, μ_2, σ_2 .

However, if one has control over the parameters to be stored in a system, one should cumulate $m = \sum_{i=1}^N x_i$ instead of μ and the squared sum $s = \sum_{i=1}^N x_i^2$ instead of σ . This policy saves computations, provides better accuracy, and requires no extra memory. Then, we can rewrite

$$\mu = \frac{m_1 + m_2}{N} \quad (8)$$

and

$$\sigma^2 = \frac{s_1 + s_2}{N} - \mu^2. \quad (9)$$

These formulae generalise directly to any number of measurement sets – to many radars on a composite image, for example.

2.4 Weighted measurements

In the above formulae, the number of measurements N_j acts as a *weight* of the measurement set $\{x\}_j$: the larger the N_j , the larger contribution in the obtained values of μ and σ . One can generalize this discrete N_j to continuous-valued W_j , the (total) weight of measurements computed as $W_j = \sum w_i$ where w_i is the continuous-valued weight of measurement x_i .

Where does w_i come from? Intuitively, it should describe the confidence on the measurement; its representativeness and reliability. In the context of radar data, it can be the probability of correct (meteorological) measurement source, timeliness of a sample, geometric representativeness or user's confidence on the reliability of a radar site (cf. *Bayesian belief*).

Clearly, there is now a link to notations (2) and (3) involving probabilities: one can think of generalizing also P to a weight. Hence, let us generalize (2) to

$$x = \mu, \text{ with } q \quad (10)$$

where q is a *quality weight*¹ indicating the quality of μ .

Quality weights can be normalized to $[0, 1]$, but that is not often critical. Many concepts from probabilistics can be generalized to these “unscaled probabilities” as well: priors, weighted averages, maxima. With this in mind, we introduce a “general-purpose mixing function”

$$\mathbf{mix}_{r,p}(\{x_i\}, \{q_i\}) = \sqrt[p]{\frac{\sum_i q_i^r x_i^p}{\sum_i q_i^r}} \quad (11)$$

which is actually a weighted L_p norm: large r gives dominance on samples of high quality, and large p gives dominance on samples with large values. With appropriate

¹We use the word *quality weight* here to underline the mathematical feasibility and portability; sometimes *quality index* refers to encoding-related flags and alphabetic categories.

Table 1. Special cases of the mixture function.

p	r	x	
1	0	$\frac{1}{N} \sum_i x_i$	AVERAGE
1	1	$\frac{\sum_i q_i x_i}{\sum_i q_i}$	QUALITY-WEIGHTED AVG.
∞		$\max x$	MAX
	∞	$x_i : q_i = \max$	MAX-BY-QUALITY
	∞	$x_i : q_i = \max$ $1/q_i \propto \text{distance}$	NEAREST-RADAR

p and r , this function generalizes to simpler forms familiar to everybody dealing with radar image compositions; see Table 1. In user interfaces, this enables smooth transitions between different compositing rules.

As may be apparent by now, we believe that one can use quantities derived from physical models but also knowledge collected otherwise. For example, many anomalies may be relatively easy to detect and remove (Peura, 2002) while deriving the respective physical models would be much more difficult or impossible.

3 Applications

3.1 Visualisation

In many environments applying radar data, the concept of quality information is new, if not unknown. When quality data is available, it is natural to search for means for displaying it in some way compatible with the actual data. For example, in a meteorological workstation, the quality information could simply be displayed on a separate image with equal geometry, conveniently clickable on/off over the main product image. One can likewise consider mixing the data and quality field by applying markers or marker patterns, color saturation or transparency as in Fig. 2.

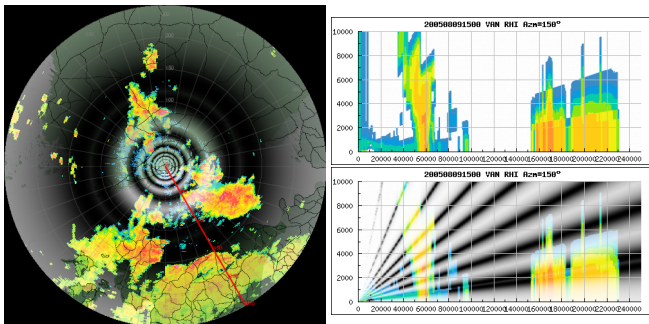


Fig. 2. Using quality data in visualising intersection products: 1500m CAPPI (left) and pseudo RHI 135° (bottom right). Beam proximity has been used as quality data.

Anyway, we believe that the main potential of quality information lies in appropriate mathematical processing outlined above and discussed further in the following.

3.2 Compositing

Examples of applying (11) are shown in Fig. 3 and Fig. 4.

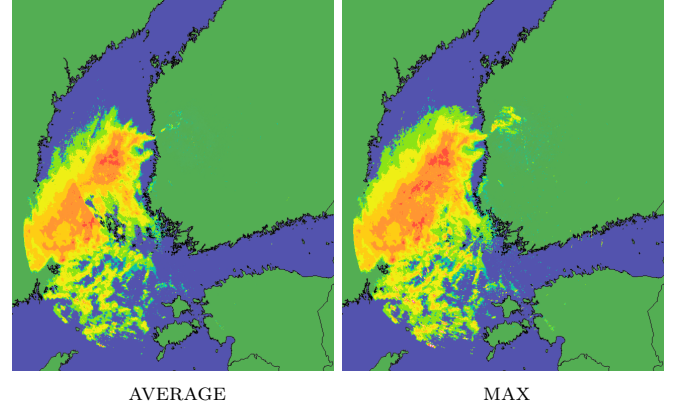


Fig. 3. CAPPI composites of Korppoo (Southern) and Ikaalinen (Northern) radars. The input data suffers from sea clutter (South) and beam overshooting (in the range-overlap region).

As a compositing rule, AVERAGE is recommended if one wants to see contribution of all the radars. However, MAX behaves better for a “conservative” user that is afraid of missing any (dangerous) phenomenon.

Sometimes, the decreased operational quality of a radar should be taken into account. This suggests using global weighting and WEIGHTED AVERAGE principle. The weights can be obtained by hand or by artificial intelligence (say, probability of wet radome from recent precipitation at the site).

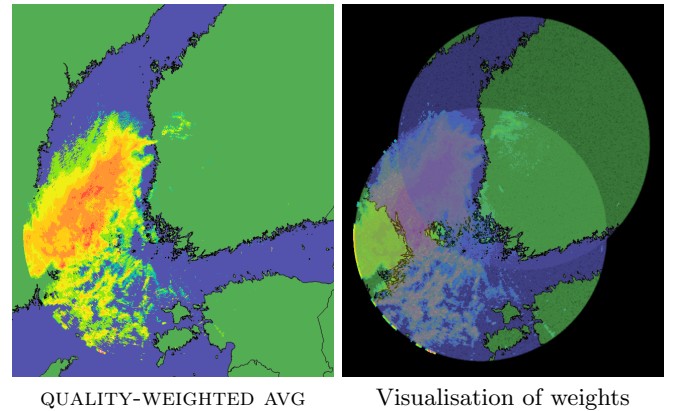


Fig. 4. CAPPI composites with global weights $Q_{KOR} = 5.0$ and $Q_{IKA} = 0.5$.

3.3 Weighting products for varying user needs

The above example of QUALITY-WEIGHTED AVERAGE applied only global (per-radar) quality information. However, one should use higher resolution quality like clutter maps or dynamic anomaly detection fields. as illustrated in Fig. 6. If pixel-level quality processing scheme detects different quality factors separately, one may weight the intermediate results to obtain different overall quality fields for different users as illustrated in Fig. 6. Just like one can combine weighted quality fields, one can use composite them further in quality weighted composing (Fig. 6).

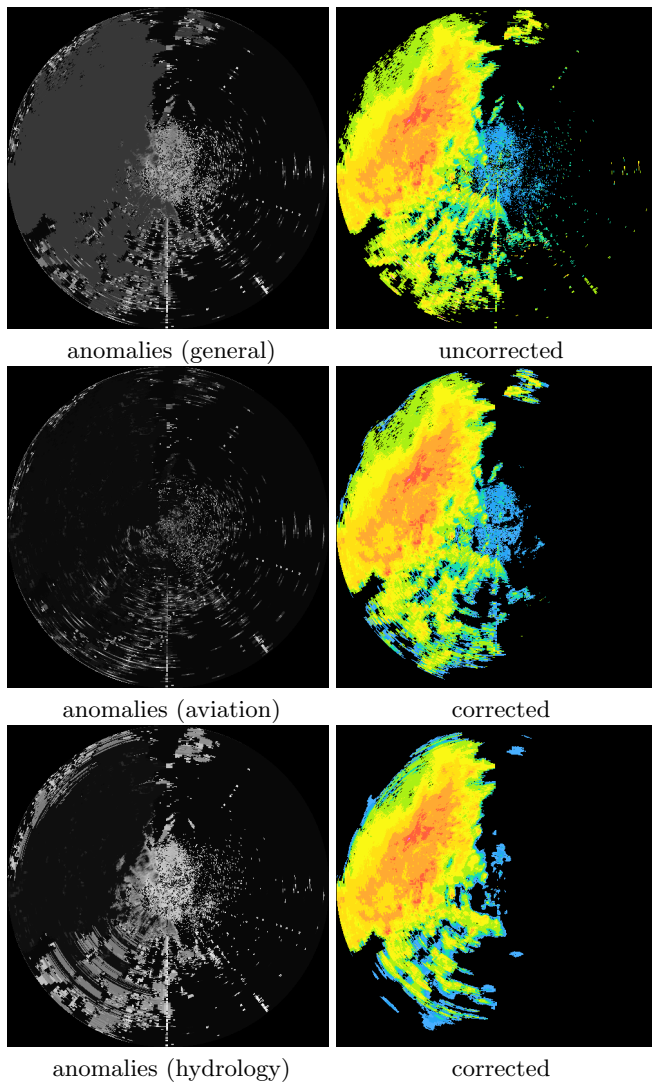


Fig. 5. Quality fields of three end user categories and respectively corrected data. Anomaly fields are weighted combination of elementary anomaly detection fields.

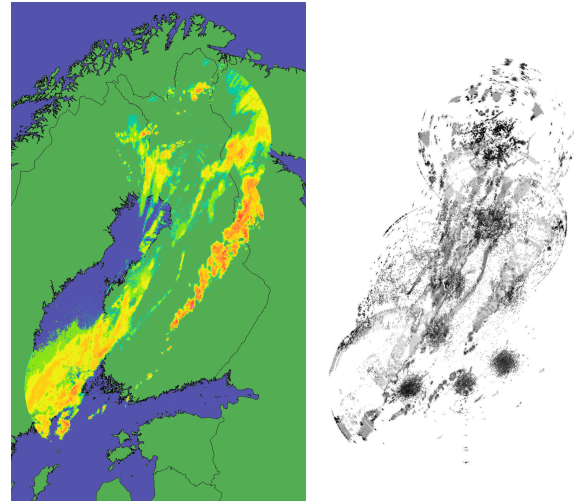


Fig. 6. A composite of the eight FMI radars (left) and the corresponding quality field.

4 Conclusions

Whenever possible, one should use to standard accuracies ($\pm\sigma$) and to hold to native units. Also, if the measurement involves probabilistic character, one should try to approximate it in a disciplined way. If physical information or models are not available, one can apply probabilistics and related tools. The critical point in designing quality weights is that they are mutually comparable and mathematically easy to use.

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