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# USING RADAR DATA QUALITY IN COMPUTING COMPOSITES AND NOWCASTING PRODUCTS

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## 1. INTRODUCTION

Although data quality has been a recognized problem since the early days of radar, utilizing numerical quality information in actual processing has been rare until the recent years.

In Europe, extensive common efforts in describing, assessing and applying radar data quality have been carried out in COST-717 (Michelson et al., 2005) and EUMETNET/OPERA projects (Divjak et al., 1999; Holleman et al., 2006). Likewise in the United States, the state-of-art seems to be towards incorporating quality information in national radar composites (mosaics) (Langston et al., 2007).

In this paper, we continue the discussion on radar data quality information, focusing on data quality in terms of both accuracy (in measurement units) and reliability (in a probabilistic framework). We have already showed how radar data quality can be applied in data visualization, client-specific basic products and radar image composites (Peura et al., 2006). In this study, we review these techniques and focus on using radar data quality also in computing nowcasting products.

Originally, end users of weather radars had much of the responsibility in understanding, recognizing and correcting data quality problems such as those originating from bad calibration, Earth curvature and non-meteorological targets.

Many of these problems still remain, but nevertheless automated quality control is widely used at least in detecting evident or likely errors and then marking (flagging) and/or deleting them. There is also automated corrections that change measured values (dBZ, wind) continuously. Examples of these are corrections based on vertical profiles of reflectivity (VPR) and radar-gauge corrections.

Increased computational power has enabled developing and computing various quality descriptors and indices. In fact, it is slowly starting to be a problem to properly manage and exploit miscellaneous quality information. It is evident that just like bin-resolution radar data undergoes various transformations and interpolations in product generation, quality information should be treated similarly as well, in parallel. Practically, this means combining quality descriptors - some kind of quality algebra.

Of course, within a closed system, one is free to design and use whatsoever combination rules – summing, multiplying, taking averages, maxima, or applying if-then decision trees. However, problems will rise if quality information should be exhanged between separate systems. Then, one needs more conformal notations, scales, semantics and policies.

In this paper, our purpose is no either to re-invent the wheel but to emphasize the usability of standard measurement conventions also in the context of our “difficult” radar data.

In the following sections, we first remind about general measurement issues and address also probabilistic aspects, because not all uncertainty can be characterised with standard error intervals. Then, we embed these concepts in mathematics familiar to radar data users. Finally, we show how the resulting “algebra” can be used in generating quality-weighted composites and motion vectors, for example.

## 2. CONCEPTS

### 2.1 *Measurement accuracy*

The International Organization of Standardization (ISO) defines “uncertainty” as *“a parameter, associated with the result of a measurement, that characterizes the dispersion of the values that could reasonably be attributed to the measurement”* (ISO, 1993; D’Agostini, 2003).

Using the standard notation, a result of measuring $x$ is

$$x = \mu \pm \sigma \tag{1}$$

where $\mu = \frac{1}{N}\sum_{i=1}^{N} x_i$ is the average obtained from repeated measurements $x_i$ and $\sigma$ is an accuracy measure, often called “error interval”, typically defined as a root mean square error (RMSE), from $\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2$. Nevertheless, in weather radar community it seems rare to apply accuracies of this kind although radar measurements are based on repeated sampling. (The only exception in this respect might be the Doppler spectrum width.)

One should keep in mind that there are also other definitions for $\mu$ and $\sigma$; for example maximum-likelihood values and respective peak-widths.

### 2.2 *Probabilistic aspects and beyond*

However, even measurements reported in the standard form (1) do not capture many central quality problems in radar — for example, undesired signals like bird echoes, sea clutter or signals from other electromagnetic devices. Specifically, a radar measurement originating from such a “wrong” target may indeed be *accurate* in terms of (1) but still useless. Hence, we propose extending the scheme

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with a further characterization $P$, the *probability of correct target*:

$$x = \mu \pm \sigma, \text{ with } P \tag{2}$$

This probability may originate from statistical data (frequentist approach), physical models or expert's assumptions (Bayesian-belief approach).

Further on, probabilistic value $P$ can be generalized to a quality descriptor[1] reporting degree of confidence, availability, relevance, or representativeness.

In notations, let us use $q$ instead of $P$ to underline this generality:

$$x = \mu \pm \sigma, \text{ with } q \tag{3}$$

Thus, we are including, but not limited to, probabilistic quality indices. Often, it is sufficient to assume that this quantity $q$ be scaled, monotonically increasing with quality and compatible with other corresponding values within a system – a national radar network or international exchange of radar data, for example.

We would like to stress that defining quality indices ($q$-values) as closely as possible to a probabilistic framework is advantageous by facilitating mathematics (in adopting concepts and formulae analogous to established probabilistics) as well by clarifying semantics (eg. in discussing products with end-users).

A simple example of defining and visualizing $q$ is shown in Fig. 1.

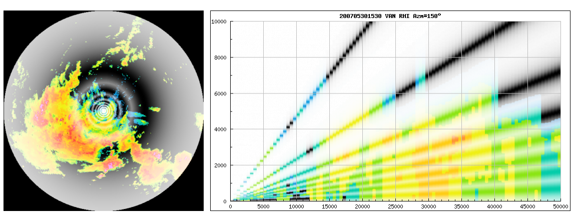

FIG. 1: Visualizing quality: areas of high quality ($q$) are rendered with clear colors. In this example, $q$ is a degree of measurement representativeness motivated by, but not equivalent to, actual (narrower) beam power distributions.

### 2.3 *Towards "quality algebra"*

How should quality information obtained in the form of (1) or (3) be applied in processing data? Before proceeding to examples, we need to define some further ingredients.

Practically, one may think of generating a radar image composite as a "measurement task": it certainly 1) involves multiple samples to be somehow combined into a single measurement (target pixel) and 2) involves multiple sources (radars).

At first for simplicity, assume that one has obtained two measurements of the same event: $x_1 = \mu_1 \pm \sigma_1$ with $q_1$ and $x_2 = \mu_2 \pm \sigma_2$, with $q_2$.

[1] In the OPERA WP1.2 report by Holleman et al. (2006), *quality descriptor* was defined as an expert-oriented, physically meaningful quantity and *quality index* as its end-user oriented, scaled or normalized quantity (possibly simplifying and combining several quality descriptors).

First, assume that $q_1$ and $q_2$ are the sizes – or normalized values of the sizes – of the repeated measurement sets. Then, when combining these measurement sets into one of (normalized) size $q_1 + q_2 = q$, one gets (see Peura et al. (2006))

$$\mu = \frac{q_1\mu_1 + q_2\mu_2}{q} \tag{4}$$

and

$$\sigma^2 = \frac{q_1(\sigma_1 + \mu_1^2) + q_2(\sigma_2 + \mu_2^2)}{q} - \mu^2. \tag{5}$$

These formulae generalize to any number of sets, and can be computed incrementally. One should also relax the strict semantics of "measurement set size", yet treating $q$'s rather analogously. Essentially, our point here is that information of type (3) can be propagated through a production system in a disciplined manner.

Next, let us focus more to $x$ and $q$. Like above, one wishes to combine them to single values. Some general-purpose rules are shown in Table 1. If quality is discarded in decision, one probably takes the AVERAGE or MAXIMUM of $x_i$. If quality is considered essential, one can pick up $x_i$ MAXIMUM-BY-QUALITY. A maximum-expectation-kind of a choice is QUALITY-WEIGHTED AVERAGE. The QUALITY-$(p, r)$-WEIGHTED AVERAGE, tricky at first sight, allows for smooth transitions between the other functions mentioned. For example, with $r \to \infty$ it approaches MAXIMUM-BY-QUALITY. In the following sections, we show how these rules of using "probabilistic accuracy" can be applied in practice.

Table 1: Decision rules (or mixture functions) for obtaining a single value from multiple $x_i$. The $q$ column suggests respective selections of associated quality; notice that quality information may be propagated in the process even though it is not used in the "decisions".

| $x$ | $q$ | |
|---|---|---|
| $\frac{1}{N}\sum_i x_i$ | $\frac{\sum_i q_i}{N}$ | AVERAGE |
| $\frac{\sum_i q_i x_i}{\sum_i q_i}$ | $\frac{\sum_i q_i}{N}$ | QUALITY-WEIGHTED AVG. |
| $\max x_i$ | $q_i$ | MAXIMUM |
| $x_i : q_i = \max$ | $q_i$ | MAXIMUM-BY-QUALITY |
| $\sqrt[p]{\frac{\sum_i {q_i}^r x_i^p}{\sum_i {q_i}^r}}$ | $\sqrt[r]{\frac{\sum_i {q_i}^r}{N}}$ | QUALITY-$(p, r)$-WEIGHTED AVG |

## 3. APPLICATIONS

Most of the rules of Table 1 must be familiar to those dealing with radar composites. Examples their applications have been illustrated in Figs. 2 – 6. Notice that the definition of $q$ is left open in Table 1. If one defines it as a function proportional to the radar proximity, one gets DISTANCE-WEIGHTED AVERAGE, or similarly, nearest-radar algorithm using MAXIMUM-QUALITY algorithm. In software it might be handy to keep selection of quality input and algorithms separated.

Also the standard deviation ie. RMSE as defined in (5) can be computed in each pixel of a radar composite image. An example corresponding to AVERAGE (Fig. 2) is shown in Fig. 3. This accuracy data can be used also as an input to further processing, say a NWP model.

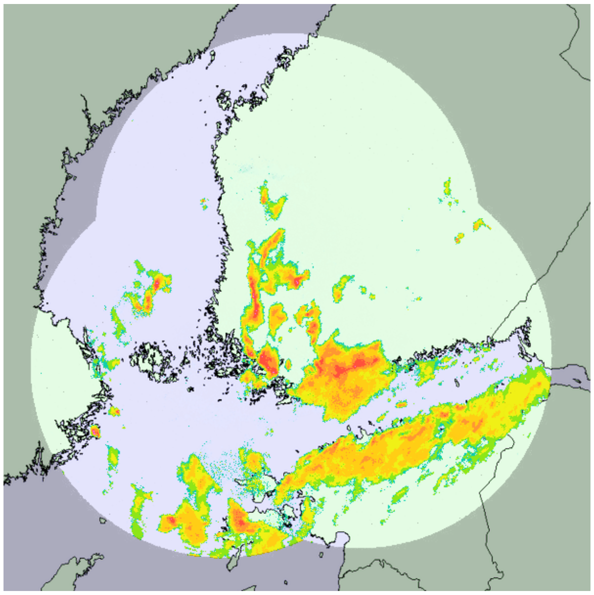

FIG. 2: A three-radar composite applying AVERAGE compositing rule. Korppoo, Vantaa and Ikaalinen radars 9th Aug 2005, 1630 UTC.

### 3.1 *Data correction*

Anomaly detection systems (e.g. Sec. 5.1Michelson et al., 2005; Peura, 2002) provide bin-resolution recognition results. If the anomalies are relatively small in size, the system should not just simply delete them — by assigning zeros or other constant values. Instead, on should try to restore correct values by spatial interpolation ie. propagating values from neighboring pixels. Also that can be done using quality weighting. Modifying WEIGHTED AVERAGE to two dimensions, we can reformulate it as

$$x'(i,j) = \sum_k \sum_l q(i+k, j+l)x(i+k, j+l) \qquad (6)$$

where $(k,j)$ are indices for traversing a local (typically rectangular) neighborhood of image location $(i,j)$. The image can be in polar or Cartesian coordinates. From a source image this operator produces a new blurred image which is dominated by values having high quality. If one makes the effort of blurring the quality field as well, one can reconstruct a third, corrected image by *choosing original* $x(i,j)$ *or blurred* $x'(i,j)$ *— whichever has higher quality at* $(i,j)$. This operation can be repeated recursively, creating spline-like spreading of data and quality fields. An illustration of this **recursive quality-weighted spatial interpolation** is shown in Fig. 7.

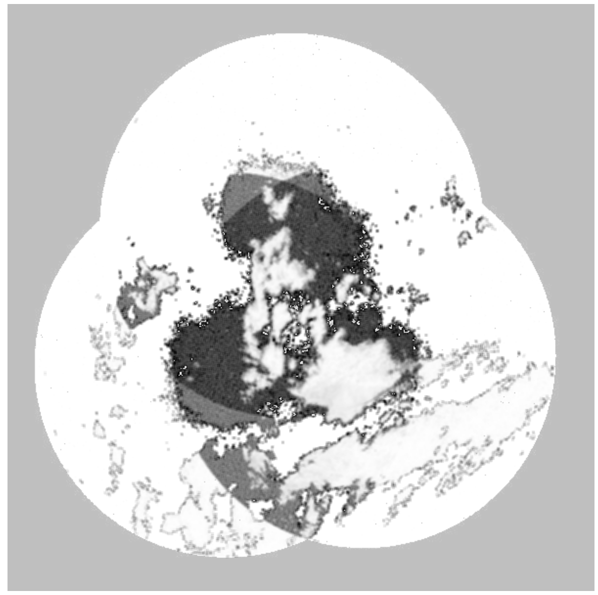

FIG. 3: Deviation (RMSE) of dBZ data originating from three radars. The darkest areas are due to insects which have been removed from the actual product (Fig. 2). Thin contours apparent (also) in single-radar coverage areas originate from bin deviations in subsequent elevations.

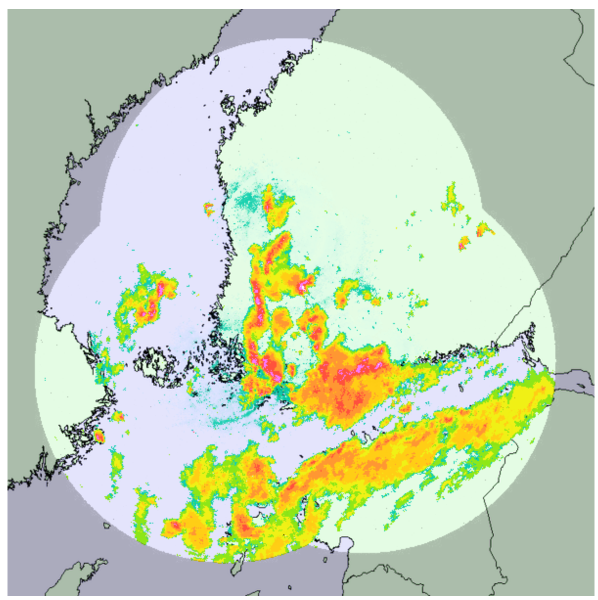

FIG. 4: Composite using MAXIMUM is often preferred in aviation branch; no echo is removed.

This technique can be used not only for intensities but also for vector data.

Current operational numerical weather prediction (NWP) models are not capable of predicting the closest hours. Hence, as far as precipitation is considered, it has

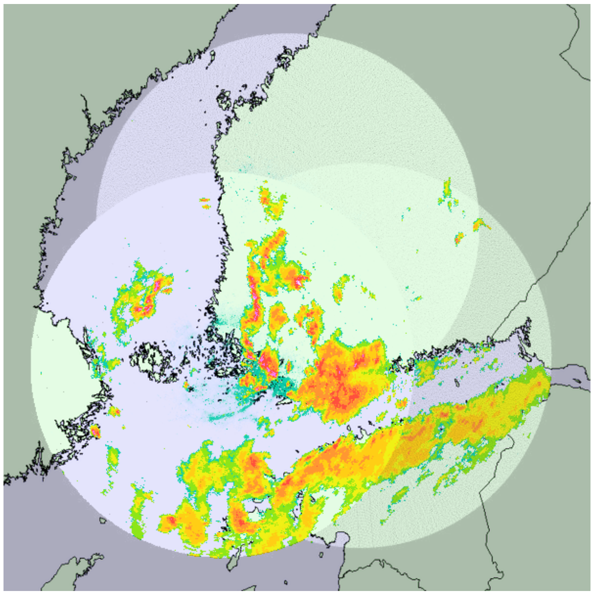

FIG. 5: If radars have varying performance, their contribution in composites can be set accordingly with (quality-) WEIGHTED-AVERAGE. Weighting can be performed at the single-bin level if quality data is available from e.g. anomaly detection.

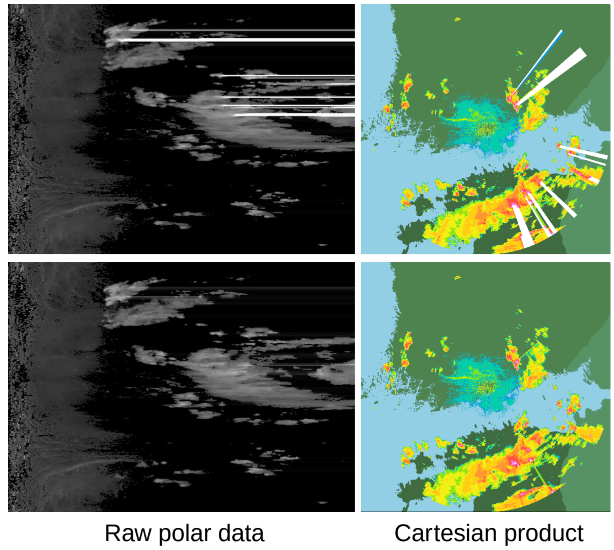


FIG. 7: Correcting attenuation by means of quality-weighted spatial interpolation. Top: attenuation marked; bottom: corrected. Notice that when using this technique it is not that critical *how much* data has been distorted but *where*. (Attenuation has been exaggerated for illustration purpose.)

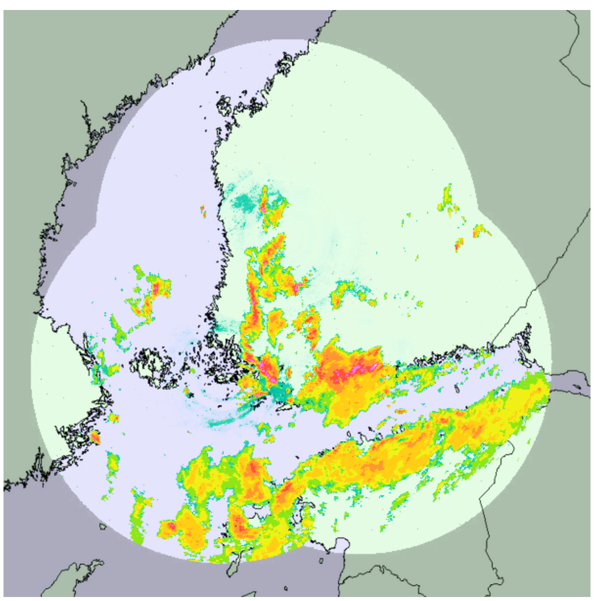

FIG. 6: MAX-BY-QUALITY is not yet widely in use but should be more exploited in systems where quality data streams are routinely available.

been natural to develop nowcasting methods based on radar data – extrapolating measured precipitation fields with atmospheric motion vectors (AMV's) computed from changes in subsequent frames.

In extracting the motion, a common problem has been that the obtained vector field contains also many erroneous vectors - typically appearing as discontinuities and other discrepancies in the motion field. While discontinuity is an apparently promising feature to be monitored in automated quality control, there always remains the risk of deleting or smoothing too many true discontinuous details in data.

Hence, we suggest that motion field discontinuity should be used cautiously, if at all. Instead, we believe that there is still undiscovered quality information available in the underlying motion detection algorithms.

An example of moving precipitation area is shown in Fig. 8. The 30 minutes earlier location is shown as a red contour. Raw motion vectors extracted using *optical flow* (Barron et al., 1994) is shown in Fig. 9. The green and red vectors are of high and low quality, respectively. The quality field as such is shown in Fig. 10. In this case, the quality index has been derived from the determinant of an involved matrix inversion (measuring the ambiguity of the motion vectors, see e.g. Peura and Hohti (2004)).

The vector field corrected with spatial interpolation (**??**) is shown in Fig. 11. Clearly, the quality of the resulting field is better as low-quality vectors and empty areas have been taken over by high-quality vectors.

It should be pointed out that this technique is independent of the motion vector extraction method. However, as mentioned, one must recognize a sensible source of quality information within the selected method.

Many motion vectors methods are based on autocor-

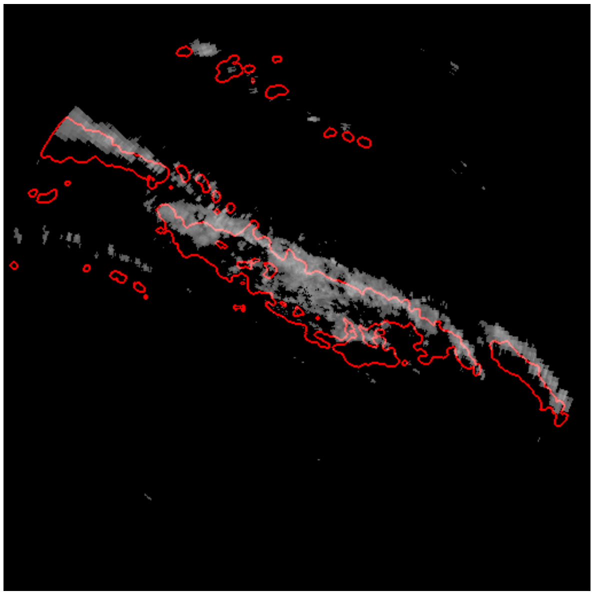

FIG. 8: Example of a moving precipitation. (Vantaa radar, 15th Aug 2006, 11:30 UTC.)

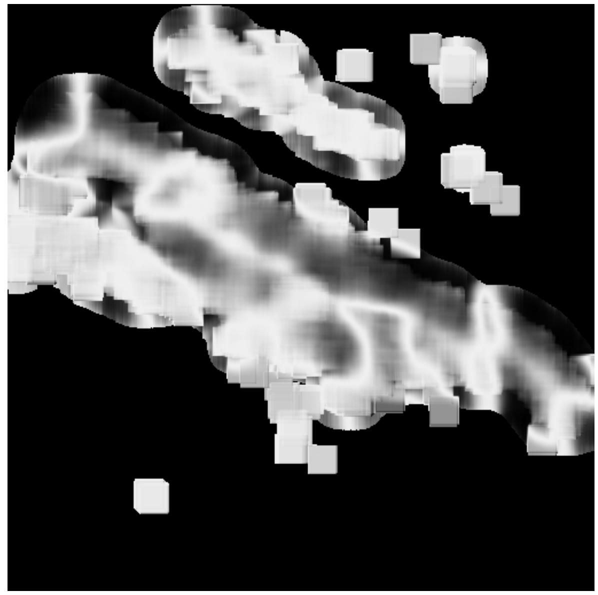

FIG. 10: Quality of the motion field.

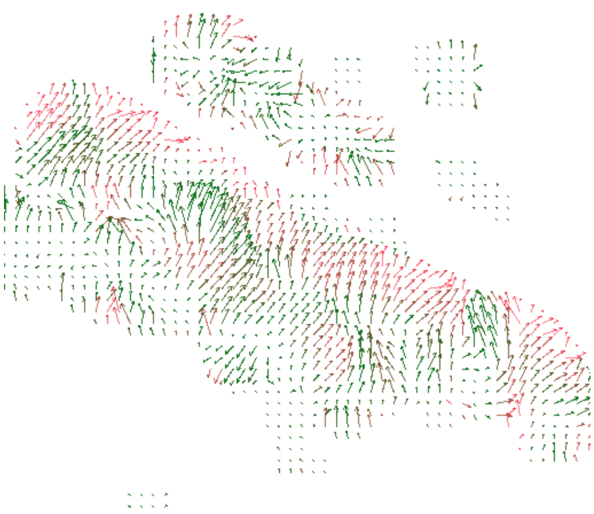

FIG. 9: Motion vectors without quality control.

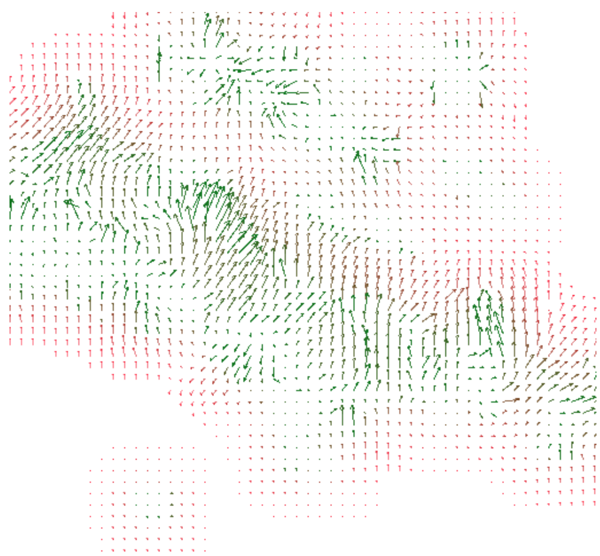

FIG. 11: Motion vectors after recursive quality weighted spatial interpolation.

relation. There, for example, one could (incrementally) keep record of the deviation of the correlation, obtaining a natural characterization of the ambiguity of each motion vector.

## 4. Conclusions

In this paper, we showed how standard concepts of measurement accuracy, extended by quality indices having a probabilistic character, can be used in generating radar products in a disciplined manner. Especially, all the illustrated applications supported both input and output of quality data — one can say that quality information propagated through them — for potential further use of other applications.

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