**MAP-MRF Estimation Based Weather Radar Visualization**

**SUMMARY** Real-time weather radar imaging technology is required for generating short-time weather forecasts. Moreover, such technology plays an important role in critical-weather warning systems that are based on vast Doppler weather radar data. In this study, we propose a weather radar imaging method that uses multi-layer contour detection and segmentation based on MAP-MRF estimation. The proposed method consists of three major steps. The first step involves generating reflectivity and velocity data using the Doppler radar in the form of raw data images of sweep unit in the polar coordinate system. Then, contour lines are detected on multi-layers using the adaptive median filter and modified Canny’s detector based on curvature consistency. The second step interpolates contours on the Cartesian coordinate system using 3D scattered data interpolation and then segments the contours based on MAP-MRF prediction and the metropolis algorithm for each layer. The final step involves integrating the segmented contour layers and generating PPI images in sweep units. Experimental results show that the proposed method produces a visually improved PPI image in 45% of the time as compared to that for conventional methods.

**key words:** weather radar image, reflectivity image, contour line retrieval, MRF-MAP estimation, PPI image

1. **Introduction**

The Doppler radar for weather forecasts can not only detect precipitation, but also generate velocity data using the Doppler Effect. Despite significant performance and capability, the long-range radar is unable to detect and identify small tornadoes and other fine-scale weather phenomena. US has already worked on replacing the entire radar from a single polarity to a dual-polar radar with the aim of completing WSR-88D (weather surveillance radar 1988 doppler) of NEXRAD (next generation weather radar system) [1], [2]. To apply the more accurate weather radar numerical analysis and forecasting model, there is an increasing interest in visualization and presentation of radar data based on GIS and real-time coordinate transformation and interpolation of radar and spatial coordinate systems [3].

The visualization process of the Doppler weather radar [4]–[12] involves calculating and estimating considerable dataless parts in the radar image generating step, such as raw file reading, data normalization, coordinate transformation, and data interpolation as shown in Fig. 1 (a). The basic unit of radar data is sampled gates or bins from radar wave, as shown in Fig. 1 (b). A ray consists of a number of gates in the same direction and a sweep consists of a number of rays of a scan. Then, a volume consists of a number of sweeps with different elevations or azimuths.

First, the raw file reading step reads radar data for data structures such as UF file and FORAY netCDF file. Then, the data normalization matches the intensity values of each gate with color scales, and represents a sweep of gates to a raw radar image. Radar emits electromagnetic waves from a radar site with a fixed detecting range and collects the radar data by a spherical coordinate. Thus, the radar data should be transformed into the Cartesian coordinate and interpolates the super-resolution part for generating a radar image. Here, there are description models for radar images; PPI (Plan Position Indicator), RHI (Range Height Indicator), and CAPPI (Constant Altitude Plan Position Indicator). The PPI model is the most common type of radar image. After transforming the coordinate, the sampled gates are mapped to pixels of 2D raw radar image while leaving the remaining space as empty spaces. The interpolation step interpolates the remaining parts using sampled gates.

Main requirement for short-time weather forecasts is to generate high-quality radar image in real-time; image quality and processing time. Firstly, we analyzed the processing time for weather radar image using a number of simulations and found that the data interpolation step requires the most...
 retrieval time as the step involves a number of repetitive computations. However, key information in radar images can be described by the contour lines of different radar layers; using the same can help minimize considerable repetitive calculations in radar retrieval. Secondly, weather radar images may have heavy noise rather than actual precipitation. To generate high-quality radar image, it is important to continuously detect the contour lines of different radar layers while effectively removing noise.

Most of conventional methods apply data interpolation methods that differ with regards to the influence function (estimation function) and weighting scheme. WSR-88D radar [5] uses the nearest neighbor mapping without considering adjacent values at all. The difference of echoes from adjacent beams becomes larger and larger as beams radiate outwards and then the resulting radar images tend to be gridded and discontinuous. The bilinear interpolation is commonly used for real-time radar processing [6], [7], which results in slight blurs on contours. Kriging or Gaussian process regression [8]–[11] which is originally used in geostatistics, models interpolate values by a Gaussian process with prior covariance, as opposed to a piecewise-polynomial spline chosen to optimize smoothness of fitted values. Since Kriging yields the best linear unbiased prediction of the intermediate values under suitable assumptions on priors, it provides more smooth and reliable values than linear interpolation. However, it is computationally expensive and more complicated than linear interpolation. Barnes interpolation [12] interpolates unstructured data points from a set of measurements of an unknown function in two dimensions into an analytic function of two variables. An example situation where the Barnes scheme is important is in weather forecasting, which measures where monitoring stations may be placed given topographical constraints.

In this paper, we propose a real-time and high-quality weather radar imaging method using contour lines of multi-layers based on MAP-MRF estimation. The proposed method obtains reflectivity and velocity data images from UF files for Doppler weather radar data and then extracts PPI images of sweep unit by multi-layer contour detection, coordinate transformation and contour interpolation, and MAP-MRF prediction based contour segmentation. The main features of our method are as follows. First, we divide a raw radar image into 16 layers of 4-bit units and remove the noise using the adaptive median filter on the reflectance scale, and then detect the contour line by the modified Canny detector based on curvature consistency. A raw radar image of the 3D polar coordinate system is transformed into the 3D Cartesian coordinate system for the PPI image. This coordinate transformation results in empty spaces of pixels and discontinuous contours. Second, we interpolate discontinuous contour lines and empty pixels according to RBF (radial basis function) based 3D scattered data interpolation in a layer image on a Cartesian coordinate system. Looking at the contour distribution in each layer, it is similar to a random field with Markov properties. Third, we segment contour lines by MAP-MRF estimation on the interpolated contour layer, then fill out the contour area by the Flood fill algorithm and then integrate 16 layers. Finally, PPI images of each sweep unit are generated.

We experimented by using UF files from the CASA project and produced final PPI images of reflectivity and velocity with a size of 996×426 and then evaluated the processing time and PPI image quality of our method and conventional methods. Experimental results show that our method generates more enhanced PPI images and in less processing time, about 45% that of conventional methods.

The remainder of this paper is organized as follows. In Sect. 2, we explain the proposed weather radar imaging method using hierarchical contour line MRF-MAP segmentation including UF file reading, contour line abstraction, and MRF segmentation etc. Then, we analyze the performance and computation time of conventional methods and our method in Sect. 3. Finally, we conclude this paper and discuss future works in Sect. 4.

2. Proposed Weather Radar Visualization

We address a weather radar imaging method using contour line retrieval of multi-layers based on MAP-MRF segmentation in this paper. The main features of our method are as follows. 1) We detect contour lines through the adaptive mean filter and modified Canny edge detector as per curvature consistency from a raw radar image for a sweep. It makes a number of contour layers in a sweep. 2) Not all gates correspond to values in the Cartesian coordinate during coordinate transformation. This causes many coordinated values to be estimated and interpolated by using neighboring values. From experiments of the weather radar imaging system [13], we can find that the interpolation process has the most processing time, which is usually 75%–95% of dense repetitive calculation. Thus, our method interpolates the contour line for contour layers using RBF 3D scattered interpolation to reduce the interpolation process. 3) To improve the edge of contour lines, our method segments the interpolated contour lines using MAP-MRF estimation and then integrates all contour layers by filling the area in contour lines using the flood fill algorithm.

Our method reads a raw radar file from Doppler weather radar and processes data normalization and denoising. It then generates a weather radar image by using contour-line retrieval based on MRF-MAP segmentation, as shown in Fig. 2.

2.1 Pre-Process: Reading UF File

The space scanned by the radar is a volume \( V \), the radar scan with a fixed elevation angle is a sweep \( S \), and the radar wave is a ray \( R \). A volume \( V \) has a series of sweeps \( V = \{S_1, \cdots, S_N\} \), and a sweep \( S \) has a series of rays that have the same elevation angles \( S_k = \{R_{k1}, \cdots, R_{kM}\} \). All of the rays are sampled by the fundamental unit of radar data, which is called a gate \( G \). A gate \( G_{kj} = \{G_{kj1}, \cdots, G_{kjN}\} \). A gate \( G_{kj} \) consists of the elevation angle \( \theta_k \) for a sweep \( S_k \), the azimuth
The radar echo intensities for gates $G_{ki}$ and the velocity $V_{ji}$ indicate a gate symbol $G_{ji}$. In general, the intensity of PPI radar image describes the contour lines. Thus, contour line interpolation is computationally less intensive than full-domain interpolation.

1) Denoising: Before contour line extraction, we perform the denoising process using the adaptive median filter [15] and reflective scale of the radar image to preserve the edge of the contour line. Given the neighborhood $S_{xy}$ of a pixel $g_{ji}$, the minimum, maximum, and median values in $S_{xy}$ are $g_{min}$, $g_{max}$, and $g_{med}$ and the maximum allowed size of $S_{xy}$ is $S_{max}$. The denoising process is as follows:

Level A: $A1 = g_{med} - g_{min}$, $A2 = g_{med} - g_{max}$
If $A1 > 0$ and $A2 < 0$ ($g_{med}$ is not an impulse),
Then go to Level B
Else Increase the window size.
If the window size $< S_{xy}$, Then repeat Level A
Else Output $g_{ji}$
Level B: $B1 = g_{ji} - g_{min}$, $B2 = g_{ji} - g_{max}$
If $B1 > 0$ and $B2 < 0$ ($g_{ji}$ is not an impulse)
Then Output $g_{ji}$
Else ($g_{med}$ is not an impulse), Output $g_{med}$

2) Contour line detection: We split a raw radar image $G_{k}$ into 16 layers $\{CL_{l}\}_{l=1,16}$ for 4bit color space and detect the contour lines by the modified Canny detector according to curvature consistency [16]. This detector aims to adjust the gradient direction estimates of contour line prior to finding the zero crossings in those directions and to provide an empirical improvement over the basic Canny detector in that it gradually removes noisy edges while maintaining strong edges in an image. The basic Canny edge detector can be defined as the solution of

$$\frac{\partial^2 G}{\partial f^2} = f_{xy} \left( \frac{\partial^2 G}{\partial x^2} + \frac{\partial^2 G}{\partial y^2} \right) = 0$$

prior to non-maximal suppression and hysteresis thresholding. Here, $f_{xy}$ is the gradient direction; $f_{xy} = (f_x, f_y)^T = \left( \frac{\partial G}{\partial x}, \frac{\partial G}{\partial y} \right)^T$ and $f_{xy}$ is the scalar distance in that direction.

We firstly formulate the shape index in terms of the gradient by Koenderink et al. [17].

---

Fig. 2 Proposed weather radar imaging technique by using contour-line retrieval of multi-layers based on the MRF.

Fig. 3 A raw radar image $G_i=(G_{ki}=(r_{ki}, a_{ki}))$ with radial resolution by azimuthal resolution (number of rays by number of azimuths). $a_{ki}$ for a ray $R_{ki}$, and the radar range $r_{kj}$ for a gate $G_{kji}=(r_{kji}, a_{kji}, \theta_{k})$ for $k \in [1, Nr]$, $j \in [1, N_r]$, $i \in [1, N_g]$.

First, we read a UF file of raw radar data for Doppler radar data [13]. A UF file has a complete volume scan $V$ of radar and within a file is a series of stand-alone rays $\{R_{ji}\}$. All data are integer words of 16 bits. Header blocks in the beginning of each ray $R_{ki}$ recorder include the organizing information of data and other setting information of radar. The modes of radar scan are indicated by a number and two fields $\{CZ, VE\}$ of the corrected reflectivity factor $CZ$ (dBZ), and the velocity $VE[m/s]$ are indicated by ASCII characters.

2.2 Contour Line Extraction and Interpolation

The radar echo intensities for gates $G_{ki}$ in each ray $R_{ki}$ in a whole sweep $\{S_k\}$ of radar scan results in a raw radar image $G_k=[g_{kji} : i \in [1, N_g], j \in [1, N_r], k \in [1, Nr]]$ with radial resolution $N_r$ by azimuthal resolution $N_r$. Figure 3 shows an example of raw radar image $G_k$. Here, a pixel in a raw radar image indicates a gate $G_{kji}=(r_{kji}, a_{kji})$ in a ray. A radar reflectivity is bordered from $-20$ to $70$ dBZ, which matches an 8-bit pixel value. Hereafter, we denote a pixel value $g_{ji}$ for the radar reflectivity or velocity for a gate as the lowercase of a whole sweep $G_{ji}$. In general, the intensity of PPI radar image describes the contour lines. Thus, contour line interpolation is computationally less intensive than full-domain interpo-
\[
\phi = \frac{2 \tan^{-1}}{\pi} \sqrt{\frac{\frac{\partial f}{\partial x}}{\frac{\partial f}{\partial y}}} + \frac{\partial f}{\partial y} + 4 \frac{\partial f}{\partial x} \frac{\partial f}{\partial y} \tag{2}
\]

to adjust the gradient estimates of \( f_{xy} \) to improve the curvature consistency and reduce the differences of shape index values of neighboring pixels. Then we use the minimization function \( F \) for the process of curvature consistency acting on surface normal estimates; \( F = \int \rho_{\sigma}(||\frac{\partial f}{\partial x}||) + \rho_{\sigma}(||\frac{\partial f}{\partial y}||) \text{d}xdy \), where \( \rho_{\sigma} \) is the robust error kernel of an adaptive kernel width \( \sigma \) and a sigmoidal derivatives; \( \rho_{\sigma}(\eta) = \frac{\eta}{\sigma} \log \cosh(\frac{\eta}{\sigma}) \). The gradient direction \( f_{xy} \) that minimizes the function \( F \) can be obtained by

\[
\begin{align*}
\mathbf{f}_{xy}^{(k+1)} &= H_i(\mathbf{f}_{xy}^{(k)})(\mathbf{f}_{xy}^{(k+1)} + \mathbf{f}_{xy}^{(k-1)}) + \\
Z_i(\mathbf{f}_{xy}^{(k)}) &\left( \frac{\partial f_{xy}^{(k)}}{\partial x} \right)^2 + H_y(\mathbf{f}_{xy}^{(k)})(\mathbf{f}_{xy}^{(k+1)} + \mathbf{f}_{xy}^{(k-1)}) \\
Z_y(\mathbf{f}_{xy}^{(k)}) &\left( \frac{\partial f_{xy}^{(k)}}{\partial y} \right)^2 + H_y(\mathbf{f}_{xy}^{(k)})(\mathbf{f}_{xy}^{(k+1)} + \mathbf{f}_{xy}^{(k-1)})
\end{align*}
\tag{3}
\]

with an adaptive kernel width \( \sigma \) in response to the local shape-index labeling

\[
\sigma = \sigma_0 \exp\left(-\frac{1}{N} \sum_{n \in N} (\phi_i - \phi_j)^2 \right). \tag{4}
\]

Here, \( \phi_i \) is the shape index for the center pixel and \( \Delta \phi_d \) is the difference in shape index between the center pixels of adjacent curvature classes. \( N \) is the neighborhood size and \( \sigma_0 \) is the reference kernel width. \( H_i(\mathbf{f}_{xy}^{(k)}) \) and \( z_i(\mathbf{f}_{xy}^{(k)}) \) are defined as \( H_i(f_{xy}^{(k)}) = \| \frac{\partial f_{xy}^{(k)}}{\partial x} \|^2 \text{tanh}(\frac{\eta}{\sigma} \| \frac{\partial f_{xy}^{(k)}}{\partial x} \|) \) and \( Z_i(f_{xy}^{(k)}) = \| \frac{\partial f_{xy}^{(k)}}{\partial y} \|^2 \text{sech}^2(\| \frac{\partial f_{xy}^{(k)}}{\partial y} \|) - \| \frac{\partial f_{xy}^{(k)}}{\partial x} \|^2 \text{tanh}(\frac{\eta}{\sigma} \| \frac{\partial f_{xy}^{(k)}}{\partial y} \|) \). \( H_y(\mathbf{f}_{xy}^{(k)}) \) and \( Z_y(\mathbf{f}_{xy}^{(k)}) \) are defined as \( \frac{\partial f_{xy}^{(k)}}{\partial y} \) terms in \( H_i(\mathbf{f}_{xy}^{(k)}) \) and \( Z_i(\mathbf{f}_{xy}^{(k)}) \).

We apply the modified Canny’s edge detector to all layers of a raw radar image \( \mathbf{G}_k \) and then obtain the contour lines in each layer, which calls contour layers; \( \{ C_{l}^{\text{th}} = \{ g_{xy}^{(l)} || t \in [1, 16] \} \} \). \( g_{xy}^{(l)} \) is a pixel included in the contour line of the \( l \)-th layer.

3) Coordinate transformation: The coordinate transformation transforms the spherical coordinates of contour lines \( C_{l}^{\text{th}} = \{ g_{xy}^{(l)} \} \) into the Cartesian coordinate \( C_{l}^{\text{th}} = \{ g_{xy} \} \) of the PPI model; \( \mathbf{G}_k = \{ g_{kxy} \} \rightarrow \mathbf{G}_k = \{ g_{kxy} \} \) where \( y = \text{floor}(r_{kxy} \cos(a_{kxy}) \cos(\theta_{kxy})) \) and \( x = \text{floor}(r_{kxy} \sin(a_{kxy}) \cos(\theta_{kxy})) \). Because of the coordinate transformation, a number of pixels in the Cartesian coordinate are discontinuous. However, these sequences identify the relations of pixels in each contour. Detected contour lines are very useful in finding neighbors of each pixel for building the fields for MRF segmentation and also to decide the order in the final layers for the merging step.

Most pixels in the contour line become a series of independent points. Similar to opening an umbrella, the raw image is an unopened umbrella but the PPI image is an opened one. The radar site is the center of the umbrella and each ray is like a rib of the umbrella. Pixels on ‘ribs’ correspond to exact values from a raw image, but pixels on ‘panels’ are unknown values that need to be estimated. Thus, we build a series of fields based on adjacent pixels of contour line and generate a complete closed contour line by MRF.

4) Contour interpolation: A sweep \( \mathbf{S}_k \) has a sequence of Cartesian contour layers \( \mathbf{G}_k = \{ C_{l}^{\text{th}} = \{ g_{xy}^{(l)} || t \in [1, 16] \} \} \). We interpolate blank pixels in Cartesian contour layers using 3D scattered data interpolation [18] with a neighbor sweep. Thus, the \( l \)-th contour layer \( C_{l}^{\text{th}} = \{ g_{xy}^{(l)} \} \) in the \( k \)-th sweep are interpolated using the nearest layers \( C_{l}^{\text{th}+1} \) and \( C_{l}^{\text{th}+2} \) for two rays.

Assume that \( g_{xy}^{(l)} \notin C_{l}^{\text{th}} \) is interpolated by RBF (radial basis function) based 3D interpolation [18], as shown in Fig. 4. Given neighboring pixels \( \mathbf{P} = \{ p_{xy}^{(l-1)} \in C_{l-1}^{\text{th}} \} \cup \{ p_{xy}^{(l-2)} \in C_{l-2}^{\text{th}} \} \cup \{ p_{xy}^{(l+1)} \in C_{l+1}^{\text{th}} \} \) in a fixed cube rage, we interpolate \( g_{xy}^{(l)} \notin C_{l}^{\text{th}} \) by the function-values RBFs

\[
f(g_{xy}^{(l)}, \mathbf{P}) = \sum_{p_{xy} \in \mathbf{P}} h_i(g_{xy}^{(l)}, \lambda_i) \phi_{\sigma}(\| g_{xy}^{(l)} - p_{xy} \|) \tag{5}
\]

where \( \phi_{\sigma}(z) = (1 - \frac{z}{\sigma})^2 \frac{4}{\pi} + 1 \) is Wendland’s compactly supported RBF and \( \sigma \) is its support size. We choose the function \( h_i(\cdot) \) and coefficients \( \lambda_i \) through the following two-step process;

1) At each pixel \( p_{xy} \in \mathbf{P} \), define a function \( h_i(g_{xy}^{(l)}, \theta_i) \) such that its zero level-set approximates the contour shape of \( \mathbf{P} \) in a small vicinity of \( p_{xy} \).

2) Determine the coefficients \( \lambda_i \) from the condition; \( f(p_{xy}) = \sum_{p_{xy} \in \mathbf{P}} h_i(p_{xy}, \lambda_i) \phi_{\sigma}(\| p_{xy} - p_{xy} \|) = 0 \) where \( h(p_{xy}, \lambda_i) = h_i(p_{xy}) + \lambda_i \).

2.3 MAP-MRF Estimation Based Contour Line Segmentation

The distribution of contour lines corresponds to the Markov Random Field (MRF), which is a set of random variables having a Markov property described by an undirected graph. Our method finds edges in interpolated contour layers \( \mathbf{G}_k = \{ C_{l}^{\text{th}} = \{ g_{xy}^{(l)} || t \in [1, 16] \} \} \) using MAP-MRF estimation [19] and the metropolis algorithm.

1) MRF Definition for Radar Layer: Each layer \( \mathbf{G}_k \) in
a raw radar image has a series of fields \( F = \{ f_1, f_2, \cdots, f_N \} \). Let us associate a layer with a stochastic process based on a set of lattice points \( R = \{ y \} \) as a field \( f_y \). We attempt to estimate the corresponding classification for each pixel. Let a field \( f_y \) be a rectangle sub-image \( X = \{ x \} \), then \( x \) is a value in \( X_y \) at a lattice point \( y \). Here, the neighboring points \( \delta_y \) of \( y \) must be symmetric, for which \( s \in \delta_y \Rightarrow y \in \delta_s \) and \( y \in \delta_y \). A clique \( c \) is a set of points that are all neighbors of each other.

If all \( y \in R \), then MRF can be expressed as a stochastic process of \( X \) on the lattice \( R \) with neighboring points \( \delta_y \).

\[
P(x_y|x_s, y \neq s) = P(x_y|x_s)
\]

(6)

Each field in a contour layer can be described by the conditional distribution of the “local” property, which does not nearly describe the whole random field. MRF depicts the statistical property of the local image while Gibbs distribution depicts it by extending it to the global. The association between them is based on a fundamental theorem of random fields, Hammersley-Clifford theorem [20]. It states that MRF can be represented as a Gibbs distribution. Given a value \( x_c \) of \( X_c \) at the points in a clique \( c \), the potential function of \( x_c \) is \( V_c(x_c) \). Then, we can express the Gibbs distribution as follows;

\[
P(x) = \frac{1}{Z} \exp\left[ -\sum_{c \in C} V_c(x_c) \right]
\]

(7)

where \( C \) is the set of all cliques and \( Z \) is the partition function. In addition, we can express the exponent parts based on the energy function, for which, the smaller the value, the lower the energy; \( U(x) = \sum_{c \in C} V_c(x_c) \). It is usually more stable to be low energy.

2) MAP-MRF Model for Contour Line: MAP-MRF is a model combining MRF model with the MAP(Maximum a posteriori) criterion. Let \( F = \{ f \} \) denote the image fields of contour layers \( \{ G_k \} \) and \( X = \{ x \} \) denotes the labeling fields. Then, the solution of MAP is the maximum of the following function.

\[
\hat{x} = \arg \min_{x \in X} \{ P(x|f) \}
\]

(8)

According to the Bayes formula, we can write the object function as \( \hat{x} = \arg \max_{x \in X} \{ P(f|x) \cdot F(x) \} \). By inserting the Gibbs function into the object function, \( \hat{x} = \arg \min_{x \in X} \{ U(f|X) + U(x) \} \), we obtain the following relation.

\[
P(f|x) \cdot P(x) \propto \exp[-(U(f|x) + U(x))]
\]

(9)

The potential function can be described by the Ising model [21] for convenient calculation. The spin of interacting particles that have two states “up” and “down” denoted by “+1” and “−1” determines their energies. It looks like a binary image. If there are more reverse spins, the system has more energy and it is more unstable. Thus, the MAP-MRF model can be described by the length of edges between reverse spins.

\[
P(x) = \frac{1}{Z} \exp[-\frac{E(x)}{K\cdot T}] = \frac{1}{Z} \exp[-\frac{w_{ij} \sum_{i,j} x_i x_j}{K\cdot T}]
\]

(10)

Here, \( x_i \) and \( x_j \) is the spin of particle but \( w_{ij} \) is the spin otherwise. \( E \) is the sum of all neighbor pairs of particles, \( K \) is the Boltzmann constant, and \( T \) is the temperature.

In a field of \( N \times N \) size, the vertical and horizontal boundary edges of particle-pair are the same as \( N \times (N-1) \). Then, the total edges are \( 2N \times (N-1) \). Given the length of edges of reverse spins as \( dx \), then \( \sum_{x_i=x_j} = 2N \times (N-1) \). Considering \( K \) and \( T \) are constants, the MAP-MRF model function can be rewritten as follows:

\[
P(x) = \frac{1}{Z} \exp[-2w_{ij} \cdot dx]
\]

(11)

3) Metropolis algorithm for Radar Image: Since the MRF-MAP estimation reduces to simply minimizing the posterior energy function, we find a global minima on a radar image using the Metropolis algorithm [22], which is the special case of simulated annealing with a fixed temperature. The brief procedure is as follows:

1) Start with any state, \( X = (x_1, x_2, \cdots, x_N), X \in C \).
2) Select a pixel \( x_n \) in \( X \) randomly and change the sign of \( x_n \).
3) Set the new configuration: \( x' = (\cdots, x_{n+1}, -x_n, x_{n+1}, \cdots) \).
4) Then, accept the new value \( x' \) for the probability as follows:

\[
\alpha(x'|x) = \min\{1, \frac{p(x')}{p(x)}\}
\]

(12)

If \( \frac{p(x')}{p(x)} > 1 \), then the acceptance probability is \( \alpha(x'|x) = 1 \). Otherwise, then it is \( \alpha(x'|x) = \frac{p(x')}{p(x)} \).

(5) Generate the uniform random number, \( \mu \in U(0,1) \).

Then, accept \( x' \) if \( \mu < \alpha(x'|x) \), or keep \( x \) if not.

If we repeat the above steps continually, the system will converge to a stable status from a random status. For each layer of sweep, the contour line will stabilize at a certain shape. Because the sizes of all fields are relatively small, the convergence procedure can be completed in a short time.

2.4 Layer Integration

After segmenting contour lines of contour layers \( G_k = \{ C^k_{ij} = \{ g_{ij} \} \} \), we integrate contour layers of a radar image by filling the area in the contour lines using the flood fill algorithm [23]. All contours in a radar image should be closed while including the boundary of the radar screen. Our method needs to select many seeds for the foreground of the labeled area but only one or few for the background because most of the labeled areas are disconnected independently of each other, but the background is not. We initially set both the foreground and background as the label color and then fill the background with black color or make it transparent to complete a layer. The merging order follows the sequence of area in the contour to make sure that there is no area covered by the other layer. We can detect the “hole” in the layer by checking the neighbor of the starting point in the sequence of contours. Finally, we obtain a PPI image \( I_k \) for a sweep \( S_k \).
3. Experimental Results

Our experiment tested three stages for evaluating our method: generating raw radar image, generating PPI image, and measuring the processing time. Our experiment used a normal PC of Intel Core2 E7400 CPU and 2GB memory and simulated using VS2012 and OpenCV based on Windows 7 OS. Here, we used the UF raw data files to generate the reflectivity PPI image of the weather radar that come from the CASA project and is generated according to the UF structure. Further, the raw radar data comes from a radar site located in Rush Springs city, Oklahoma US, and the recorded time is 7:44 on May 14th, 2009. This radar utilizes the PPI sweep model with 2 degree elevation and the radar file has two fields of corrected reflectivity factor CZ [dBZ] and velocity thresholded on NC, VE [m/s]. In a CZ field, the number of samples used in a volume is 996.

To generate raw radar image, we described a gate in a radar file as a pixel and matched the image intensity with the normalized echo intensity of radar while following the UF structure. Here, the resolution of raw radar image is the same as the radar resolution of 996×426 (because the elevation is only 2 degree). Figure 5 shows two raw radar images of base reflectivity and base velocity. Since the imaging processes for reflectivity and velocity are the same, we show only the result image for reflectivity in the remaining parts.

3.1 PPI Imaging

Our method initially processes the raw radar image by the denoising algorithm that not only removes noises but also reduces the computation cost in the post process. We tested the denoising algorithm of wavelet domain, mean filter, and adaptive mean filter, and then selected the adaptive mean filter algorithm [24], which removes noises while preserving the contour line, as shown in Fig. 6. After denoising, we split up the raw radar image into 16 layers according to the reflectivity scale and obtained contour lines by specific intensity threshold. Figure 7 shows contour lines using the basic Canny detector and the modified Canny detector in a layer among total 16 layers. Comparing these two images, we can confirm that the modified Canny detection image has better noise reduction and edge continuity due to the curvature consistency. In the absence of data on several layers at either end of the scale, we have shown some samples of 16 layers with reflectivity data.

Next, we transformed all pixels in contour lines to the PPI image of 2000×2000 resolution. The contour lines become a series of independent pixels in the PPI image. As a whole, the contour line is stored as a sequence in OpenCV, the neighbors of each pixel can be easily recognized. We used two adjacent pixels as diagonal points for building a field and filled the fields through bilinear interpolation. Pixels of contour lines and fields make a closed contour that segments a radar image into “inside” and “outside”. Thus, we filled the “inside” part with label color by the flood fill algorithm. Figure 8 shows the filled “inside” parts from the 8th layer to the 13th layer. Observing PPI images on layers,
the labeled areas are not a whole completed piece, and there are some holes in the low intensity parts. To prevent the unidirectional merging process from expanding coverage, we checked the inside and outside pixels filled area using neighboring pixels of the starting points on the contour sequences. After the flood fill process, the closed contour composed by fields is no longer needed. Thus, the MRF-MAP algorithm segments these fields into the inside and outside parts for detecting contour edges. Finally, we merged all of these completed layers and then made a PPI radar image based on the order of contour area.

### 3.2 PPI Quality Evaluation

Conventional methods [5]–[12] consist of three main steps: data normalization, coordinate transformation, and data interpolation that the first two steps are general procedures. Thus, conventional methods deal with the first two steps generally and apply differently to the last data interpolation, such as neighbor mapping [5], bilinear [6], [7], kriging [8]–[11] and Barnes [12] interpolations and also evaluate the accuracy of PPI data using RE (relative error) [7], RMAE (relative mean absolute error) [8], and NB (normalized bias)/NSE (normalized standard error) [9] between an interpolated data and an actually observed data. We compared the processing time and PPI quality of our method and Kvasov’s method [7] of bilinear interpolation and Wardah [8] and Moreno [11] methods of kriging interpolation.

We evaluated the quantitative quality using the mean relative error [7] (|I_k – I_k'|/I_k) for all sweeps between an actually observed data I_k and an interpolated data I_k’, which is shown in Table 1. From this table, we confirmed that our method has relative errors as low as 0.5%–1.8% compared to conventional methods and that kriging interpolation methods with relatively low noises have low relative errors with bilinear interpolation method. This reason is that our method based on contour interpolation has better noise reduction and edge continuity than conventional kriging interpolation and bilinear interpolation methods.

Figure 9 shows the PPI images of base reflectivity generated by our method and three methods with the full resolution of 2000×2000 size and the magnified version of middle area of 360×320 size. Kvasov’s method based on bilinear interpolation has a contour line that is not clear due to noise effects. Moreno’s methods based on kriging interpolation cause blurring at all areas due to the Gaussian process with prior covariance. However, our method is more effective in removing noise and edge continuity than conventional method.

### Table 1  Mean relative errors for proposed method and conventional methods.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean RE</td>
<td>2.5%</td>
<td>4.3%</td>
<td>3.2%</td>
<td>3.0%</td>
</tr>
</tbody>
</table>

![PPI Images](image-url)
ods due to contour segmentation and interpolation based on MAP-MRF estimation.

3.3 Processing Time Evaluation

We measured the processing time of our method and the conventional methods for 10 radar samples. Figure 10 (a) shows the results of the processing time. The results show that our method takes 199[s] on average and the conventional methods takes 345[s], 558[s], 464[s] on average; thus, our method is about 1.7–2.8 times faster than the conventional methods. Our method significantly improves the processing time by minimizing the interpolation redundancy.

We analyzed the processing of our method step by step, and found that much time was devoted to field interpolation and MRF-MAP segmentation. Thus, these two steps take about 97% of the total processing time. Through analysis of the processing time for each layer, we found that the number of fields is the factor that determines the processing time of the above two steps. Here, the number of fields is equal to the number of pixels in the contour line. Figure 10 (b) shows the relationship between the number of pixels in the contour line and the processing time of two major steps. Reverting back to the denosing step, our method obtains relatively simple contour lines by using the adaptive mean filter. This affects the reduction of computational complexity in the sequential steps.

4. Conclusion

With growing interest in short-time and fine-scale weather forecasting and weather information in recent years, fast radar imaging technology has become greatly sought after. Although a short-range dense radar network can be a competent hardware-based solution, in this study, we attempt to realize an improvement from a signal processing perspective. Thus, we addressed a radar imaging technique that uses contour line of multi-layers based on MAP-MRF segmentation in this paper. The main feature of our method is to increase the quality of radar image while minimizing the redundancy of the excessive interpolation in the contour line generation step. Our method consists of eight steps in detail: raw file reading, data normalization, denoising, contour line detection, coordinate transformation, field interpolation, MAP-MRF segmentation, and layer merging. Experimental results verified that our method could generate more improved PPI radar images than conventional methods and that our method has a processing time of about 45% compared to the conventional method.

References

Suk-Hwan Lee received a B.S., a M.S., and a Ph. D. degree in Electrical Engineering from Kyungpook National University, Korea in 1999, 2001, and 2004 respectively. He worked at Electronics and Telecommunications Research Institute in 2005. He is currently an associate professor in Department of Information Security at Tongmyong University, which he started in 2005. He works as an editor of Korea multimedia society journal and is a member of IEEE, IEEK, IEICE and also is an officer of IEEE R10 Changwon section. His research interests include multimedia signal processing, multimedia security, digital signal processing, bio security, and computer graphics.


