STORM TRACKING IN DOPPLER RADAR IMAGES

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\section*{ABSTRACT}
An automated tracking algorithm for doppler radar storms is presented. Potential storms in Doppler radar images are hypothesized as regions of high water density (high intensity in the radar images) using a merge-and-split region growing algorithm. Potential storms are verified by a relaxation labelling scheme that attempts to find the best tracks based on spatio-temporal storm consistency. Temporal consistency is ensured by requiring temporal coherence of storm properties, which include size, average intensity, radial velocity variance (computed from the Doppler radial velocity images), storm shape and orientation and neighbouring storm disparity. Spatial consistency requires neighbouring storm tracks with common storms to compete with a winner-take-all strategy. The property coherence framework is adaptive, allowing additional properties to be added or deleted as appropriate. The tracking algorithm allows storm merging and splitting via a construction called pseudo-storms. Several tracks for doppler storm radar data supplied by AES are given as examples of the algorithms performance.

\section{1. INTRODUCTION}
Every year extensive damage is caused by severe storms. In southern Ontario, Canada tornadoes alone are reported to have killed 22 people and to have caused more than half a billion dollars in damage from 1979 to 1990. Further damage is caused by the strong winds, lightning, and hail often associated with other kinds of severe storms. For these reasons, the forecasting of severe storms is one of the most important tasks facing meteorologists. Severe storm tracking is a precursor to severe storm forecasting. Knowing the history of the current storm can suggest the future behavior of that storm.

Tracking severe storms in the southern Ontario radar data poses an interesting problem: Since the data is obtained from an operational (as opposed to a research) radar at King City, Ontario, the time between radar images is too great (10 minutes compared to 1 minute for research radar) to allow the use of current correlation-based (matching) techniques found in the literature [7, 2, 4, 3]. Storms move too great a distance and their properties change too much between images. Other problems encountered include aliasing, storm path crossovers, and the birth and death of storms.

\section{2. A SPATIO-TEMPORAL RELAXATION TRACKING ALGORITHM}
Our tracking algorithm uses the hypothesize-and-verify paradigm. We hypothesize storms by detecting regions of high intensity in the Doppler radar intensity images using Horowitz and Pavlidis' [5] merge-and-split region growing algorithm. A pyramid data structure is used to store an image, initially divided into a set of equal-sized square regions (the initial cutset). Each square region can then be split into 4 smaller equal-sized square regions or merged with its three neighboring same-size regions into a larger region. Splitting and merging are based on a threshold of the difference between the smallest ($min$) and largest ($max$) pixel grayvalues in the regions under consideration. If $|max - min| > \tau$ for some region then that region is split into four smaller regions at the next lower level in the pyramid. On the other hand, if $|max - min| \leq \tau$ for a region and its three sibling regions in the pyramid then

\begin{quote}
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\end{quote}
four regions are merged into a new region at the next highest level in the pyramid. Splitting and merging is continued in this fashion until no further splits or merges can be performed (merged regions cannot be split and vice-versa, as merging and splitting are mutually exclusive operations).

Next, a grouping step merges different-sized adjacent regions if the above merging criterion is satisfied. A final editing step then merges large and very small adjacent regions together if the average intensity difference is < threshold \( \tau_z \). This eliminates most small regions and produces the final segmentation (the final cutset). The hypothesized set of storms are these final regions that have an average grayvalue over some threshold \( \tau_z \). Finally, potential disparities are determined. A disparity is the vector displacement formed between all storms in temporally adjacent images that are within a distance of \( \tau_z \). For the results in this paper we use threshold values of \( \tau_1 = 32 \), \( \tau_2 = 8 \), \( \tau_3 = 128 \) and \( \tau_4 = 20 \). An important consideration in tracking storms in Doppler radar images is that storms can split into 2 or more storms or 2 or more storms may merge into a single storm between adjacent images. To allow for this possibility we group all combinations of storms that are close enough together into pseudo-storms. We allow our tracks to contain both storms and pseudo-storms, provided that there is no overlap.

Given these potential storms we verify their correctness by tracking them over time. If a hypothesized storm cannot be tracked over time we conclude it is a valid storm. Untrackable hypothesized storms are rejected. Our tracking algorithm draws from Barnard and Thompson's relaxation algorithm [1] and Sethi et al.'s property coherence ideas [8, 9]. As such, it requires both spatial and temporal storm property consistency. A storm's track must consist of storms with compatible properties in time (temporal consistency) as well as incompatible properties with other potential storm tracks at the same time (spatial consistency).

Compatibility measures can be computed for temporally adjacent disparities (disparities whose head and tail storms are common) and storm pairs (storms that share a common disparity). Adjacent disparities can be considered compatible if they have similar lengths and directions [10]. These features are captured as the two properties length\(_\text{comp}\) and angle\(_\text{comp}\), respectively, which are defined as:

\[
\text{length}_{\text{comp}}(d_1(s_1, s_2), d_2(s_2, s_3)) = 1 - \left( \frac{\text{Length}(d_1, \text{Length}(d_2))}{\max_{\text{length}}} \right)
\]

\[
\text{angle}_{\text{comp}}(d_1(s_1, s_2), d_2(s_2, s_3)) = 1 - (180 - \text{angle between } d_1\text{ and } d_2)/180
\]

The use of property coherence means that many properties of a potential storm can be tracked. No one property must necessarily be consistent over time but rather overall consistency of a large number of storm features must be maintained over time. We have designed a number of compatibility functions whose values indicate the degree that two storms share a property (values range from 0 (no match) to 1 (perfect match)). We currently use five storm properties:

1. Average Intensity – the average intensity of a storm is expected to vary smoothly over time.
2. Storm Size – although storms do grow and contract rapidly there are limits to this rate of change.
3. Similar Velocity Variance – storms with a high degree of vorticity or turbulence tend to maintain this characteristic over time. This analysis is performed on the Doppler radial velocity data.
4. Storm Shape and Orientation – although storms can change shape rapidly over time, in general certain shapes, for example long thin storms and round storms, generally maintain their shapes and orientation over time. We compute storm shape using the difference between a storm's size and its convex hull and storm orientation using the orientation of the convex hull's minimum and maximum axes.
5. Convexity – although storms can change shape rapidly over time, in general certain shapes, for example long thin storms, round storms, and storms with deep pockets such as the comma-shaped squall line, generally maintain their shapes for some time. We compute storm convexity using the ratio of a storm's size and its convex hull's size.

These storm property functions are given in equations (3) to (6).

\[
\text{int}_{\text{comp}}(d(s_1, s_2)) = 1 - \left( \frac{\max_{\text{int}}(d(s_1, s_2))}{\max_{\text{int}}} \right) \times \frac{\max_{\text{int}}}{\max_{\text{int}}} \tag{3}
\]

\[
\text{area}_{\text{comp}}(d(s_1, s_2)) = 1 - \left( \frac{\max_{\text{area}}(d(s_1, s_2))}{\max_{\text{area}}} \right) \times \frac{\max_{\text{area}}}{\max_{\text{area}}} \tag{4}
\]

\[
\text{var}_{\text{comp}}(d(s_1, s_2)) = 1 - \left( \frac{\max_{\text{var}}(d(s_1, s_2))}{\max_{\text{var}}} \right) \times \frac{\max_{\text{var}}}{\max_{\text{var}}} \tag{5}
\]

\[
\text{shape}_{\text{comp}}(d(s_1, s_2)) = 1 - \left( \frac{\max_{\text{shape}}(d(s_1, s_2))}{\max_{\text{shape}}} \right) \times \frac{\max_{\text{shape}}}{\max_{\text{shape}}} \tag{6}
\]

\[
\text{con}_{\text{comp}}(d(s_1, s_2)) = 1 - \left( \frac{\max_{\text{con}}(d(s_1, s_2))}{\max_{\text{con}}} \right) \times \frac{\max_{\text{con}}}{\max_{\text{con}}} \tag{7}
\]

We obtain an overall compatibility measure for every pair of temporally adjacent disparities by computing a weighted average of all the compatibility values for the storm and disparity properties. The compatibility between two adjacent disparities, \( d_1 \) (between storms \( s_1 \) and \( s_2 \)) and \( d_2 \) (between storms \( s_2 \) and \( s_3 \)) is of the form:

\[
\text{comp}(d_1(s_1, s_2), d_2(s_2, s_3)) = \sum_{i=1}^{n} w_i' \times \text{length}_{\text{comp}}(d_1(s_1, s_2), d_2(s_2, s_3)) + \sum_{i=1}^{n} w_i' \times \text{angle}_{\text{comp}}(d_1(s_1, s_2), d_2(s_2, s_3)) + \ldots
\]

\[
= \sum_{i=1}^{n} \left( \frac{\text{prop}_{\text{comp}}(s_1, s_2) + \text{prop}_{\text{comp}}(s_2, s_3)}{2} \right) + 
\]

\[
= \sum_{i=1}^{n} \left( \frac{\text{prop}_{\text{comp}}(s_1, s_2) + \text{prop}_{\text{comp}}(s_2, s_3)}{2} \right)
\]
where the \( w_i^d \), \( i = 1, \ldots, n \) are weights that sum to 1, and the \( \text{prop}_{\text{comp}} \), \( i = 3, \ldots, n \) are the \( n - 2 \) compatibility measures in addition to disparity magnitude and direction compatibilities. For the results in this paper we use un-normalized weights \( w_1 = 4, w_2 = 4, w_3 = 1, w_4 = 2, w_5 = 1 \), and \( w_7 = 4 \); we divide each of these by \( \sum_{i=1}^{n} w_i \) to obtain the \( w_i^d \). Each weight, \( w_i \), reflects the relative weight (importance) of each storm property. Note that this framework allows additional storm properties to be added in a straightforward way.

Our relaxation algorithm computes supporting and contradictory evidence for each disparity using the compatibility values. The supporting evidence is the sum of all compatibility values greater than the average compatibility value and the supporting weight is the ratio of supporting disparities to the total number of disparities. We compute contradictory evidence and the contradictory weight in a similar manner. These values are used to compute the certainty of a disparity.

Relaxation is carried out using the following algorithm:

\[
\begin{align*}
    k &= 0 \\
    \text{Repeat} \quad & k++ \\
    \text{ave.comp}_k &= \frac{\text{comp}_k(a,b)}{\text{num} \text{ of pairs of adjacent disparities } a \text{ and } b} \\
    \text{For each disparity } d: & \quad */ \text{Apply temporal continuity} */ \\
    \text{sup.ev.id} &= 0 \\
    \text{num.sup} &= 0 \\
    \text{con.ev.id} &= 0 \\
    \text{num.con} &= 0 \\
    \text{For each adjacent disparity } a \ (i \to d): & \quad */ \text{Apply Temporal Consistency Constraint} */ \\
    \text{sup.ev.id} &= \text{cert}_{k-1}(a) \\
    \text{num.sup} &= \text{num.sup} + 1 \\
    \text{Else} \quad \text{con.ev.id} &= \text{cert}_{k-1}(a) \\
    \text{num.con} &= \text{num.con} + 1 \\
    \text{For each disparity } q \text{ which has the same head storm or tail storm as } d: & \quad */ \text{Apply Spatial Consistency Constraint} */ \\
    \text{sup.ev.id} &= \text{cert}_{k-1}(q) \\
    \text{num.sup} &= \text{num.sup} + 1 \\
    \text{Else} \quad \text{con.ev.id} &= \text{cert}_{k-1}(q) \\
    \text{num.con} &= \text{num.con} + 1 \\
    \text{total.ev.id} &= \text{num.sup} + \text{num.con} \\
    \text{sup.weight} &= \frac{\text{total.ev.id}}{\text{num.con}} \\
    \text{con.weight} &= \frac{\text{total.ev.id}}{\text{num.sup}} \\
    \text{If } (\text{sup.ev.id} \neq 0) \text{ or } (\text{con.ev.id} \neq 0): \text{cert}_k(d) &= \\
    \frac{1}{2} \times \left( \frac{\text{sup.weight} \times \text{con.weight}}{\text{sup.ev.id} \times \text{con.ev.id} \times \text{con.weight}} \right)
\end{align*}
\]

Else

\[
\text{cert}_k(d) = 0
\]

Until \( (\forall a, |\text{cert}_k(a) - \text{cert}_{k-1}(a)| < 0.0001) \) or \( (k > \text{MAX_ITERATIONS}) \)

Given disparity \( d \) connecting storms \( s_1 \) and \( s_2 \), the initial certainty factor for that disparity is based on the storm properties and is calculated as:

\[
\begin{align*}
    \text{cert}_0(d(s_1, s_2)) &= w_5^d \times \text{int.comp}(s_1, s_2) + \\
    w_6^d \times \text{area.comp}(s_1, s_2) + \\
    w_7^d \times \text{var.comp}(s_1, s_2) + \\
    w_8^d \times \text{shape.comp}(s_1, s_2) + \\
    w_9^d \times \text{con.comp}(s_1, s_2)
\end{align*}
\]

where the \( w_i^d \) are renormalized weights such that:

\[
\begin{align*}
    w_i^d &= \frac{w_i}{\sum_{i=1}^{n} w_i} 
\end{align*}
\]

Note that \( \text{cert}_k \), \( k > 0 \), is calculated in the relaxation. The compatibility between two adjacent disparities, \( d_1 \) and \( d_2 \) at the initial iteration is given by:

\[
\begin{align*}
    \text{comp}_0(d_1(s_1, s_2), d_2(s_2, s_3)) &= \\
    w_1^d \times \text{length.comp}(d_1(s_1, s_2), d_2(s_2, s_3)) + \\
    w_2^d \times \text{angle.comp}(d_1(s_1, s_2), d_2(s_2, s_3)) + \\
    w_3^d \times \text{shape.comp}(d_1(s_1, s_2), d_2(s_2, s_3)) + \\
    w_4^d \times \text{con.comp}(d_1(s_1, s_2), d_2(s_2, s_3)) 
\end{align*}
\]

where the seven weights are again renormalized versions of the \( w \) weights.

\[
\begin{align*}
    w_i^d &= \frac{w_i}{\sum_{i=1}^{7} w_i} 
\end{align*}
\]

If we then calculate a new weight \( w_i^d \) such that:

\[
\begin{align*}
    w_i^d &= \frac{7}{\sum_{i=1}^{7} w_i^d} 
\end{align*}
\]

then equation (11) for disparity compatibility at the \( k \)-th iteration \( (k > 0) \) can be calculated as:

\[
\begin{align*}
    \text{comp}_k(d_1(s_1, s_2), d_2(s_2, s_3)) &= \\
    w_1^d \times \text{length.comp}(d_1(s_1, s_2), d_2(s_2, s_3)) + \\
    w_2^d \times \text{angle.comp}(d_1(s_1, s_2), d_2(s_2, s_3)) + \\
    w_3^d \times \left( \text{cert}_{k-1}(d_1(s_1, s_2)) \times \text{cert}_{k-1}(d_2(s_2, s_3)) \right)
\end{align*}
\]

Once the relaxation process has converged each disparity will have a certainty value in the interval \([0, 1]\). To find all potential tracks we construct the set of all longest tracks such that each disparity has a final certainty over a threshold \( T_1 \) and that the average certainty of all disparities in the track is greater than another, typically larger, threshold \( T_2 \). We choose a subset of these tracks, such that no storm lies upon more than one chosen track. We select tracks containing mutually exclusive storms with the highest average certainty values over a dynamic threshold, \( \text{max.certainty} \), (initial value 0.9) using the following algorithm:
Mark all tracks as unused
While there are still tracks which are marked unused
firstone = TRUE
For all unused tracks j
  If firstone Then
    firstone = FALSE
    maxtrack = j
    maxcertainty = avg certainty(j)
  Else
    If avg certainty(j) > max certainty Then
      maxtrack = j
      maxcertainty = avg certainty(j)
  Mark the track maxtrack as chosen
For each storm s in the track maxtrack
For all unused tracks j
  If s ∈ j
    Mark the track j as deleted

This algorithm does not yield the tracks with the best possible storm covering as that goal is often incompatible with a covering having the highest average certainty value. Once a pseudo-storm or any of its component storms (which may also be pseudo-storms) are accounted for in a track, none of the component storms are acceptable in any other tracks. This prevents storm overlap in the tracks. Full details of the algorithm are in two theses [6, 10].

3. EXPERIMENTAL RESULTS

Here, we present some preliminary tracking results for two image sequences provided by Atmospheric Environment Service. Figure 1 shows the first and last Doppler radar intensity images for a series of 20 sequential images from July 1987 centred just north of Toronto, Canada. We have used the AES naming convention and refer to this series as the “77-series”. Figure 2 shows the first and last Doppler radar intensity images for a series of 30 images from August 1991 centred northwest of Edmonton, Canada. We refer to this series as the “18-series”. Storms are labelled in Figures 1

![Figure 1: The first (top) and last (bottom) Doppler radar intensity images for the 77-series.](image)

![Figure 2: The first (top) and last (bottom) Doppler radar intensity images for the 18-series.](image)
and 2. Figures 3 and 4 show the storm tracks obtained by the tracking method discussed in this paper for the 77-series and the 18-series, respectively. The storm labels are reflected in the labels in Figures 3 and 4, respectively. Each label \( x-y \) in Figures 3 and 4 encodes the image number \( x \) and the storm number \( y \) in image \( x \). Due to lack of space it is impossible to display all of the intermediate images in each sequence. With a few exceptions the tracks coincide with what is expected.

4. CONCLUSIONS

We have shown that we can successfully identify and track storms in Doppler radar images, even when there is a fair amount of storm activity and the data may be significantly aliased. We are currently investigating improved storm hypothesizing algorithms since the quality of the tracks produced depends on the precision in the storm detection phase.

5. REFERENCES


