Change Detection in Meteorological Data

Jiang Zhao, Chang-Tien Lu, Yufeng Kou

Department of Computer Science
Virginia Polytechnic Institute and State University
7054 Haycock Road, Falls Church, VA 22043
Tel: 703-538-8373
[jzhao1, ctlu, ykou]@vt.edu

ABSTRACT

Change detection is an important task in signal analysis, data mining, and image processing. In meteorology research, change is frequently associated with severe weather events or climate anomalies. Detecting change is crucial for weather and climate analysis. In this paper, we propose a wavelet based approach to analyze short term changes in the global meteorological data. We design a suite of algorithms to effectively detect the changes considering both spatial and temporal perspectives. The algorithms were implemented and evaluated with a real-world meteorological data set.

1. INTRODUCTION

Over the past decade, spatial database has become a significant area both in academia and in industry. The applications of spatial information promote the development of the Spatial Database Management System(SDBMS). The research on spatial database mainly focuses on spatial data modelling, spatial data access, spatial data query processing, spatial data visualization, and spatial data mining [11, 12]. Spatial data mining [1, 6, 7, 13] is the process of discovering implicit and useful spatial patterns or rules from large spatial data sets. The spatial data mining is attractive to many research works as spatial data tend to be large in size, and it is important to efficiently and effectively extract knowledge embedded in the spatial data sets.

In the research of the atmospheric sciences, huge amount of spatial data have been collected from both observation and modelling. Discovering useful patterns from these data sets would have great practical value and would help weather forecast, and environment monitoring. The temporal and spatial changes of the parameters (especially the prominent change) are frequently associated with the variations of weather phenomena and climate patterns. Consequently, detecting these temporal/spatial changes in the atmospheric parameters is crucial in weather forecast and climate analysis.

In this paper, we propose wavelet based change detection procedures to discover the change in meteorological observation data, which will help retrieve interesting and implicit information from a large volume of spatial data sets. This paper is organized as follows. We provide the literature survey in Section 2. Section 3 discusses the problem and our proposed approach. Section 4 describes the meteorological data set and analyzes the experiment results. Finally, we summarize our work and discuss future directions in Section 5.

2. RELATED WORK

Wavelet analysis is widely used in change detection because of its special advantages such as localization at both time and frequency domains. When time series is analyzed, the results depend on time shifts and scales. While time shifts represent the location of the change, the scales tell the periods of the change. Mallat and Huang uses wavelet analysis to detect the isolated and non-isolated singularities of the signal [10]. In their work, the modulus maximum of the wavelet transform was defined and used to detect singularities in the signal. Extending this application to two dimensional image, the local maxima of the wavelet transform modulus detect the edge of the images. Wang propose a procedure to detect the jumps and sharp cusp in a signal [15]. The method checks the absolute value of the wavelet transform in the fine scales. If significantly large values exist at higher resolution levels, jumps may be located; if significantly large values exist at lower resolution levels, cusp may be detected. Whitcher *et al.* applies wavelet transform to detect and locate multiple variance changes in the presence of long range dependency [16], which helps identify the nonstationary features or change points in a time series.

In the meteorology and climate study, the change in the observation data are of importance to understand the weather events and the environment. Wavelet analysis has been widely used in detecting temporal changes and trends at various ranges from turbulence(minutes) [2, 5] to climate(years) [4, 8, 9, 14]. As meteorological data contain both spatial and temporal information, it is beneficial to take into account the spatial information while detecting the temporal change. For example, the changes could be different from place to place. In this paper, we propose algorithms to detect changes on global data considering both their temporal variation and spatial movement.

3. PROBLEM AND APPROACH

As it is well known, the weather is always changing, so is the climate. The changes occur on both temporal and spatial domain: temporal change varies from place to place, spatial change evolves as time lapses. The combination of the effect of spatial movement and temporal variation makes the change detection task difficult. What makes it more challenging is that the temporal changes happen at different time scales, ranging from turbulence(minutes) to climate change(years or decades), and the spatial changes occur at different spatial scales as well, varying from tornado (kilometers or less) to El Nino (global). This is a complicated multi-scale problem. Different tasks are interested in particular scales: tornado watches focus on the imminent changes in the atmosphere, whereas global warming research concerns the changes on inter-annual or decades range. The problem is how to find an effective procedure to detect the prominent changes occurred at given scales of interest.

Wavelet analysis is a useful tool to study the subjects from signal analysis to image processing [3,14]. Wavelet analysis has some special attractive features. Wavelet analysis analyzes the signal at different frequencies with different resolutions. The changes of the signal at different scales may be studied with different focuses, they can be separated and recomposed at will. This feature makes wavelet an effective filter to filter the signal and focus on certain scales or split different scales of variation. In the nature world, signals are usually complicated and are non-stationary. Wavelet transform can provide the frequency and the location of a certain variation or the strength of the variation at certain location. In this study, we use continuous wavelet analysis. For a wavelet function $\Psi(t)$, the continuous wavelet transform of a discrete signal $X_i (i = 0, N-1)$ is defined as the convolution of X with scaled and translated Ψ: $W(n,s) = \sum_{i=0}^{N-1} x(i)\Psi^*[\frac{(i-n)\delta t}{s}]$, where (*) indicates the complex conjugate, n is the localization of the wavelet transform and s is the scale. There are many functions that can be used as a base function for wavelet analysis. We chose one of the most widely used bases: *Mexico Hat* base as it provides good localization (spatial/temporal resolution). The base function for the *Mexico Hat* function is: $\Psi_0(\eta) = \frac{(-1)}{\sqrt{\Gamma(21/2)}} \frac{d^2}{d\eta^2}(e^{-\eta^2/2})$. The scales in the wavelet analysis are selected by $S_0 * 2^{j/2} (j = 0, 1, J)$. Here J is the maximum scale index which satisfies : $J \leq 2\log_2(\frac{N}{2})$, where N is the length of the signal.

We use wavelet transform on the real spatial domain and repeat that at different time instances to monitor the change of the spatial anomalies. Then we perform the wavelet transform on time series to detect the temporal changes. We study the detected changes to track where and when the change occurs, and as time lapsing, whether the patterns move or not.

We propose two algorithms, spatial change detection and temporal change detection. Algorithm 1 uses wavelet analysis to track the moving of meteorology objects. Algorithm 2 is used to discover the temporal change of meteorology objects.

Algorithm 1 Spatial Change Detection

Input:
- D_1 is the meteorology data for time t_1;
- D_2 is the meteorology data for time t_2;
- S is a set of selected scales;
- θ_w is the pre-defined threshold of wavelet power;
- α_1 is the beginning latitude/longitude;
- α_n is the ending latitude/longitude;
- $idxSet_1$ is a set of location indices in D_1;
- $idxSet_2$ is a set of location indices in D_2;

Output:
- M is a set of (region, direction) pair;

```
/* wavelet transform along all latitudes or longitudes */
for(i=α_1;i ≤ α_n ;i++)
    wDomain_1 = WaveletTransform(D_1,S,i);
    wDomain_2 = WaveletTransform(D_2,S,i);
/*record points with prominent wavelet power*/
for every point p in wDomain_1
    if ( p > θ_w )
        AddToLocationSet(p,idxSet_1);
/*record points with prominent wavelet power*/
for every point p in wDomain_2
    if ( p > θ_w )
        AddToLocationSet(p,idxSet_2);
/* group points to regions */
R_1 = GroupIndices(idxSet_1)
R_2 = GroupIndices(idxSet_2)
/*output the time and location with prominent changes*/
M=CompareLocation(R_1,R_2)
```

In Algorithm 1, first, a set S of scales of particular interest should be provided by domain experts. Then wavelet transformation is performed on two data sets D_1 and D_2 along all latitudes or longitudes. Here D_1 and D_2 are meteorology data for time t_1 and time t_2. α_1 denotes the beginning latitude(or longitude) and α_n denotes the ending latitude(or longtitude). $wDomain_1$ *and* $wDomain_2$ are the domain of wavelet power values transformed from the original data D_1 and D_2. The algorithm selects the points with wavelet power greater than threshold θ_w and records their location indices in two sets named $idxSet_1$ and $idxSet_2$. $idxSet_1$ stores the indices of interesting points in D_1 and $idxSet_2$ stores the indices of interesting points in D_2. Then the algorithm groups points with adjacent location indices in $idxSet_1$ and $idxSet_2$ to regions and respectively stores the regions in set R_1 and set R_2. Finally, the locations of the same region in R_1 and R_2 are compared to find the moving direction of this region between time t_1 and time t_2. The comparison is to judge coordinate of the center points of two regions in R_1 and R_2. The output is a set M of (region, direction) pair, which denotes the moving direction of a specific region.

Algorithm 2 Temporal Change Detection

Input:
D is the given dataset;
θ_t is the pre-defined threshold of wavelet power on time series;
β_1 is the beginning time series;
β_2 is the ending time series;
$idxSet$ is a set of location indices;
Output:
O_s is the set of change regions;

/* wavelet transform along all time series */
for(i=β_1;i $\leq$ β_2 ;i++)
  wDomain = WaveletTransform(D,i);
/*record points with prominent wavelet power*/
for every point p in wDomain
  if (p $>$ θ_t)
    AddToLocationSet(p,$idxSet$);
/* group points to regions */
O_s = GroupIndices($idxSet$)
Output(O_s) /* output the time and location with prominent changes

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Algorithm 2 is similar to Algorithm 1, with two major distinctions. First, Algorithm 2 applies wavelet analysis on time domain instead of spatial domain. Second, in algorithm 2, the wavelet analysis picks only one particular scale instead of a set of scales S. The output of Algorithm 2 is a set of regions where prominent changes occur along with time domain. Note that the result of wavelet transform is a 3-dimension array of (time,latitude,longitude). We can observe the temporal change from both latitude and longitude by visualizing this array.

4. EXPERIMENTAL ANALYSIS

In the experiment, we used NOAA/NCEP global reanalysis data sets, this is the multiple parameter data with a horizontal resolution of 1 degree by 1 degree. The data covers the whole earth. We used 40 day water vapor data to study the change of the weather system.

First, we performed wavelet analysis on spatial domain over all latitudes. We mainly focus on the anomalies with subweather scales, that are the variation around 1000 km. The left panel of Figure 1 is the global map of wavelet transform power with scale index 3. As can be seen, there are several areas where the power is extremely high. In these areas the spatial variation is prominent and these areas are possible spatial anomalies (weather system). The locations of strong wavelet power are correspondingly plotted in the right panel using a threshold: one region (a hurricane) over Mexican Gulf (-90^oW,26^oN) and another region (a tropical storm) over south America (-70^oW,-25^oS). Figure 2 shows the spatial wavelet power for another date. Comparing Figure 1 with Figure 2, we can observe the northward moving of the anomaly region (a hurricane) near the Mexican Gulf, while the tropical storm over south America is staying but gradually diminishing. This procedure can be used at consecutive date/time instances to track the change of the weather systems.

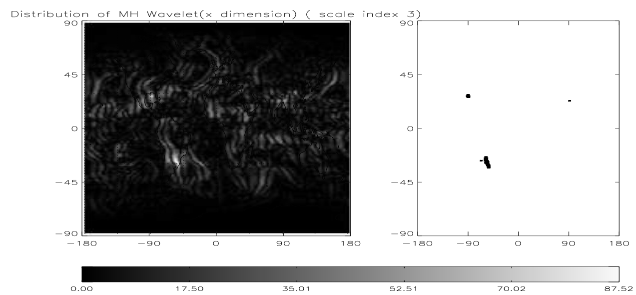

Figure 1: Spatial wavelet power distribution at scale index 3 on day 1.

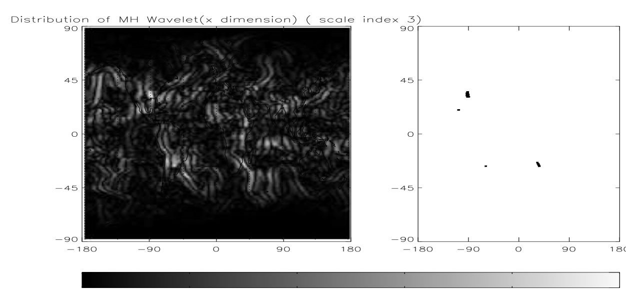

Figure 2: Spatial wavelet power distribution at scale index 3 on day 2.

By applying Algorithm 2, We did the wavelet transform on the time domain to detect the temporal change of the water vapor. As the preliminary tests show that the strongest variations are short-term changes for this data set, we focused on the short temporal scale in our analysis. We performed the wavelet analysis on time series over all 1×1 grids. Figure 3 is the cross section (at 90^oW) of the wavelet power (with temporal scale 0) along date(1-40) and latitude. As can be seen, the changes are mainly located at mid-latitudes, especially around $25^o N$, and the prominent changes happen during days 20-35. The figure also shows that some change signals are moving northward with time lapsing, which is consistent with the pattern observed from Figures 1 and 2. Figure 4 provides the 3 dimension distribution of the high wavelet transform power across latitude, longitude, and date (with threshold 35). We can see some change signals and their spatial-temporal locations. We are interested in the continuous change signals which reveal the development and moving of the weather systems. One of the significant changes happens in the South America($-70^o W$,$-25^o S$), which is a tropical storm. The signals are persistent and moving northward and eastward sometimes. Another one is the Gulf Mexico region($-90^o W$,$26^o N$); a strong change signal arouses around day 20 and moves northward as time lapses. This is a developing hurricane process over Gulf Mexico.

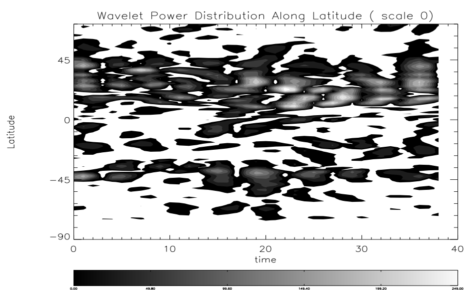

Figure 3: Temporal wavelet power distribution across latitude and date.

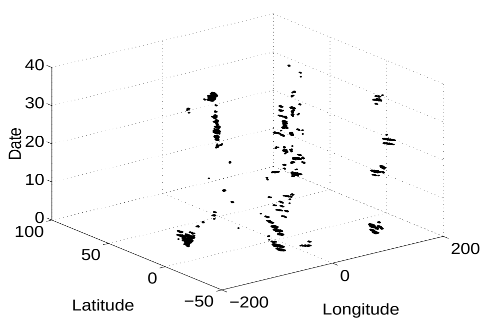

Figure 4: Distribution of high temporal wavelet power (threshold=35) across longitude, latitude, and date.

5. CONCLUSION

In this paper, we propose a wavelet based approach to detect temoral/spatial changes in the meteorological data. Using wavelet analysis on the global meteorological data, we utilize the advantage of the multi-scale capability of the wavelet transform to focus on certain scales of spatial/temporal variation. This will help identify distinct change patterns. Some of those patterns may be visible in the original data set, whereas some of those patterns may be hidden in the original data and might be ignored if not using wavelet analysis. By analyzing the wavelet transform, we identify the location and the timing of the change occurrence. This helps monitor the changing weather and climate. In this work, we focus on short range changes. We are planning to explore other scales of change and extend the proposed algorithms to other meteorology parameters, so that the detected changes will be comprehensive and representative.

6. REFERENCES

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