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A new methodology for pixel-quantitative precipitation nowcasting using a pyramid Lucas Kanade optical flow approach

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SUMMARY

Short-term high-resolution Quantitative Precipitation Nowcasting (QPN) has important implications for navigation, flood forecasting, and other hydrological and meteorological concerns. This study proposes a new algorithm called Pixel-based QPN using the Pyramid Lucas–Kanade Optical Flow method (PPLK), which comprises three steps: employing a Pyramid Lucas–Kanade Optical Flow method (PLKOF) to estimate precipitation advection, projecting rainy clouds by considering the advection and evolution pixel by pixel, and interpolating QPN imagery based on the space–time continuum of cloud patches. The PPLK methodology was evaluated with 2338 images from the geostationary meteorological satellite Fengyun-2F (FY-2F) of China and compared with two other advection-based methods, i.e., the maximum correlation method and the Horn–Schunck Optical Flow scheme. The data sample covered all intensive observations since the launch of FY-2F, despite covering a total of only approximately 10 days. The results show that the PPLK performed better than the algorithms used for comparison, demonstrating less time expenditure, more effective cloud tracking, and improved QPN accuracy.

1. Introduction

Short-term high-resolution Quantitative Precipitation Forecasting (QPF), which refers to the forecasting of future precipitation within a very short time (i.e., 0–2 h), is important for a number of hydro-meteorological applications such as flash-flood warnings and navigation safety (Ganguly and Bras, 2003; Afshar et al., 2010).

Extrapolation-based Quantitative Precipitation Nowcasting (QPN) algorithms, which extract information from current observations (e.g., radar and satellite images), are reportedly capable of producing reliable forecasts, especially within a few hours of the analysis time (Dixon and Wiener, 1993; Johnson et al., 1998; Germann and Zawadzki, 2002, 2004; 2006; Chiang et al., 2006; Vila et al., 2008; Zahraei et al., 2012, 2013; Sokol and Pesice, 2012). These forecasts can complement the QPF of Numerical Weather Prediction (NWP) models (Golding, 1998; Ganguly and Bras, 2003; Wilson et al., 2004; Sokol, 2006; Sokol and Pesice, 2012; Liang et al., 2010) because a QPF model has the limitation of a short lead time (0–6 h) that stems from the significant computational costs, incomplete data assimilation during initialization, and incompatible scales of precipitation structures (Zahraei et al., 2012, 2013).

Currently, several extrapolation-based nowcasting algorithms have been developed for hydrological applications. For example, the system for Convection Analysis and Nowcasting (SCAN) developed by the Meteorological Development Lab (MDL) (Smith et al., 1998), the Warning Decision Support System Integrated Information (WDSS-II) of the National Severe Storm Laboratory (NSSL) (Lakshmanan et al., 2007), and the Auto-Nowcaster (ANC) of NCAR (the National Center for Atmospheric Research) (Wilson et al., 1998) are three examples in the U.S.A. The Nowcasting and Initialization for Modeling Using Regional Observation Data System (NIMROD) (Golding, 1998) and the Generating Advanced Nowcasts for Deployment in Operational Land surface Flood

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forecasts (GANDOLF) have played critical roles in England (Pierce et al., 2000).

Pixel- and object-based algorithms are two QPN categories. Object-based algorithms, which consider storm events as individual objects (Johnson et al., 1998; Dixon and Wiener, 1993), always have difficulty tracking small-scale thunderstorms and rapidly developing cloud patches that are identified as consistent clouds of some type from satellite images due to their complex and flexible characters. Pixel-based algorithms, which are the main focus of this study, treat clouds from a pixel perspective; they have been used extensively in short-term, high-resolution QPN (Grecu and Krajewski, 2000; Mecklenburg et al., 2000; Germann and Zawadzki, 2002; Montanari et al., 2006; Vant-Hull et al., 2008; Berenguer et al., 2011; Zahraei et al., 2012, 2013).

An extrapolation-based QPN algorithm usually consists of tracking and forecasting (extrapolation) processes, as suggested by Austin and Bellon (1974). Various attempts have been made to estimate advection based on cloud tracking. The Maximum Correlation Method (MCM), which identifies the most matching locations between two successive images to estimate storm velocity (Smythe and Zrnic, 1983; Tuttle and Foote, 1990; Laroche and Zawadzki, 1995), is the most widely used approach. It is simple, but the correlation surfaces frequently display diffuse or multiple optima. The minimum velocity unit obtained by the MCM is one pixel, while the cloud always moves with sub-pixel accuracy. Thus, it may introduce large uncertainty into QPN with a long lead time and coarser spatial resolution scans (e.g., from a geostationary satellite). New sub-pixel approaches have been proposed, such as Variational Echo Tracking (VET) (Germann and Zawadzki, 2002), coupled hierarchical-tracking approaches and mesh-based models of image deformation in Pixel-Based Nowcasting (PBN) (Zahraei et al., 2012). In addition to the accuracy issues, the time expenditure of these methods is another important limiting factor in real-time hydro-meteorological applications.

The optical flow method, a computer vision method, estimates the motion of objects in a visual scene when projected onto a two-dimensional plane (Aubert et al., 1999). It can track objects on a sub-pixel level, and it has been widely applied in many areas for anticipated accuracy improvements, e.g., motion detection, object segmentation, time-to-collision and focus-of-expansion calculations, motion-compensated encoding, and stereo-disparity measurements (Beauchemin and Barron, 1995). The method can be divided into two main categories: local differential and global variational solutions. Since the first introduction by Bowler et al. (2004), the optical flow method has been applied in QPN studies, such as the Multi-scale Optical-flow by Variational Analysis (MOVA) scheme in the Hong Kong Short-range Warning of Intense Rainstorms in Localized System (SWIRLS) (Cheung and Yeung, 2012) and the Horn–Schunck Optical flow (HSOF) in Severe Weather Automatic Nowcast system (SWAN) of China (Han et al., 2008). Most of those studies are based on radar data, which always has challenges when applied to satellites because QPN of satellite tends to demand a higher accuracy in tracking methods on the sub-pixel level for the small movement speed of clouds with coarser spatial resolutions. Further, the smoother spatial characteristics of satellite products tend to make tracking cloud movement more difficult in the overlap region of two consecutive images because of the lack of obvious tracking signs compared with an equivalent terrestrial radar product. In addition, most applied optical flow methods are based on global variational solutions. They have some limitations in real-time QPN applications due to their computationally expensive nature despite the improved accuracy of the advection field. The local variational method is computationally more efficient and has exhibited good accuracy in various applications. However, the only application of the local variational method was the Lucas–Kanade optical flow method (LKOF) in the Cumulonimbus Tracking and Monitoring system (Cb-TRAM) (Zinner et al., 2008), which was only concerned with Cb cloud tracking rather than QPN.

Projection discontinuity is an important problem that is commonly confronted in the forecasting process of pixel-based QPN. A low-pass spatial filter, which averages the advection field of each rainy pixel with its surrounding window, is often used for addressing this problem. However, the method loses some information of the estimated precipitation advection and may also fail to describe the rapidly developing character of rainy cloud patches, especially for small-scale storms and rapidly expanding storms, due to the pre-smoothing process. Therefore, this study proposed to directly conduct an extrapolation process without using a low-pass spatial filter and add a new process of precipitation interpolation to address the projected discrete points produced in the extrapolation process.

The main contributions of this study can be summarized as follows: (1) the introduction of a typical local differential optical flow method, the Pyramid Lucas Kanade Optical Flow method (PLKOF), to track precipitation advection; (2) the projection of rainfall by considering precipitation advection and evolution using a linear pixel extrapolation method; (3) the presentation of a spatial interpolation method based on the spatio-temporal characteristics of cloud patches; (4) the establishment a QPN model using the geostationary meteorological satellite Fengyun-2F (FY-2F) to provide large-scale QPN information; and (5) the estimation of the performance of the proposed method with a comparison of two other advection-based methods, i.e., PMC (pixel-based QPN using MCM and PHS (pixel-based QPN using HSOF). The MCM is the most widely used method in cloud tracking, and HSOF is a newly adopted optical method.

In this study, Section 2 describes the implementation of the proposed model. The applied datasets and cases are shown in Section 3. Their performances are presented in Section 4. Section 5 concludes the results, discusses the limitations of the current implementation, and outlines possible future research.

2. Methodology

A traditional QPN algorithm consists of tracking and forecasting (extrapolation) processes, as suggested by Austin and Bellon (1974). Considering that pixel-based extrapolation methods always produce projection discontinuities, as presented in Fig. 1 (extrapolation), this study suggests adding a new spatial interpolation process to assign data to non-data rainy pixels.

Thus, the proposed PPLK (Pixel-based short-term QPN using PLKOF) comprises three processes, as presented in Fig. 1: pixel-based tracking, rainfall extrapolation, and spatial interpolation. Using the pixels with a black center as a sample to demonstrate the implementation of the PPLK, the steps are as follows: (1) Pixel-based tracking: extracting the pixel advection between $t - \Delta t$ and t on the pixel level using PLKOF; (2) extrapolation: obtaining QPN images with the projection of rainy clouds considering both the precipitation advection and change in rainfall intensity pixel-by-pixel; and (3) interpolation: assigning data to non-data rainy pixels with the inverse distance method on the assumption that the topological relationships between cloud cells do not change between two consecutive times of t and $t + \Delta t$.

2.1. Pixel-based tracking

Advection is a key element in storm movement and QPN. This study compared three advection-extracting methods: MCM, HSOF, and PLKOF. The first method is the most widely used in