Atmospheric Motion Vectors Derived from an Infrared Window Channel of a Geostationary Satellite Using Particle Image Velocimetry

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ABSTRACT

As the new-generation geostationary satellite Himawari-8 provides a greater frequency and more observation channels than its predecessor, the Multifunctional Transport Satellite series (e.g., MTSAT-2), an opportunity arises to generate atmospheric motion vectors (AMVs) with an increased accuracy and extensive distribution over eastern Asia. In this work AMVs were derived from consecutive images of an infrared-window channel (IR1) of the Himawari-8 satellite using particle image velocimetry (PIV) based on the theory of cross-correlation schemes. A multipass scheme and an adaptive interrogation scheme were also employed to increase spatial resolution and accuracy. For height assignment, an infrared-window method was applied for opaque cloud, while an H2O-intercept method was employed for semitransparent cloud. Validation was conducted by comparing the PIV-derived AMVs with wind fields obtained from NWP analysis, radiosonde observations, and the operational system from the Meteorological Satellite Center (MSC) of the Japan Meteorological Agency (JMA) or JMA/MSC. The comparison of wind velocity maps with the NWP data shows that the PIV-derived AMVs are capable of quantitatively depicting full-field wind field maps and strong jets in atmospheric circulation. Through comparisons with radiosonde observations, the root-mean-square error and wind speed bias (4.29 and −1.05 m s⁻¹) of the PIV-derived AMVs are comparable to, although slightly greater than, that of the NWP data (3.88 and −0.26 m s⁻¹). Based on comparison between the PIV-derived AMVs and wind fields obtained from the JMA/MSC operational system, the PIV-derived AMVs are again comparable, producing a slightly lower error but a larger wind speed bias (−1.05 vs 0.20 m s⁻¹). This also implies that a better height assignment algorithm is necessary.

1. Introduction

Atmospheric motion vectors (AMVs) are crucial information not only for the quantitative description of atmospheric circulations, but also for the improvement of weather forecasts through providing wind field data for assimilation. That is especially true in the oceanic region where radiosondes are sparse (Gelaro et al. 2012).

Many researchers have shown that assimilating AMVs has a significant impact on the prediction of a hurricane’s track with different numerical weather prediction (NWP) forecast systems (e.g., Goerss 2009; Langland et al. 2009; Berger et al. 2011). Recently, Velden et al. (2017) conducted a series of experiments on the forecast of track and intensity of tropical cyclones. They concluded that AMVs have a huge positive impact on Hurricane Weather Research and Forecasting Model (HWRF) simulations. Moreover,
Wu et al. (2015) pointed out that AMV data in the interior of a typhoon, defined as 1000-km radius within the typhoon, and at its upper levels (100–350 hPa) significantly improves its forecasts, including those for intensity, initial position, and wind field.

A typical way to derive AMVs is by tracking the cloud or water vapor target in successive images captured by a geostationary satellite. Geostationary satellite images in an infrared-channel window are commonly used in the derivation over the whole troposphere (Nieman et al. 1997). Fujita (1968) pioneered the studies of AMV retrieval. Afterward, with more application potential in weather analysis and forecasts, techniques and algorithms were constantly developed and improved. In general, there are three major approaches for AMV derivations: pattern recognition, optical flow, and cross correlation. The pattern recognition method (Endlich et al. 1971; Wolf et al. 1977; Endlich and Wolf 1981) applies the Lagrangian concept (object orientated) and tracks specific objects in the atmospheric flows. Even though this method may not be suitable for deriving AMVs over a target window, it is an ideal tool for recognizing and tracking deep convective cloud (Dixon and Wiener 1993; Johnson et al. 1998). The optical flow method tracks the motion of brightness patterns relative to the field of view. It then determines the flow motion by solving optical flow constrain equations for every pixels in a small window (Abidi and Gonzalez 1988; Vega-Riveros and Jabbour 1989). In this approach, the displacement field should be slowly varying so that the out-of-window motion and the smooth-out effect can be minimized (Wu et al. 2016). Finally, the cross-correlation method derives AMVs by applying autotracking to tracers within a small window in a successive image pair based on the maximum likelihood in the correlation (Leese et al. 1971; Smith and Phillips 1972; Arking et al. 1978; Menzel 2001).

To the authors’ knowledge, the cross-correlation method has not been significantly updated for AMV derivations after year 2000. On the contrary, the particle image velocimetry (PIV) method (Raffel et al. 2018), based on the cross-correlation method, has been continuously developed and updated since the 1990s. Indeed, PIV has become the method of choice for many experimentalists studying fluid mechanics for flow quantification and visualization. Furthermore, new schemes, such as adaptive PIV (Theunissen et al. 2007; Wieneke and Pfeiffer 2010) and volumetric PIV (Laskari et al. 2016), have been constantly proposed to improve accuracy and broaden applicability. Numerous PIV applications in fluid mechanics (e.g., Chang and Liu 1998, 1999; Adrian 2005; Ryu et al. 2005; Wereley and Meinhart 2010; Belden and Techet 2011; Sudhakar et al. 2017) have proven its robustness and reliability. Although there were numerous successful applications in deriving AMVs using cross correlation (e.g., Velden et al. 1997; Nieman et al. 1997; Bedka and Mecikalski 2005; Bresky et al. 2012; Borde et al. 2014; Velden et al. 2017), the derived vector fields still have much room for improvement. That need inspires the present study to apply a more sophisticated, correlation-based PIV technique to AMV derivations and validate the results using observed data.

In addition to finding velocities through cross correlation, the height assignment of satellite-imagery-based AMV retrieval remains a constant challenge. Several approaches have been introduced for various cloud conditions, such as the carbon dioxide (CO2) slicing algorithm (Menzel et al. 1983), the water vapor (H2O) intercept method (Szejwach 1982), the cloud-based technique (Jung et al. 2010), and the infrared-window method (Fritz and Winston 1962). Both the CO2-slicing method and the H2O-intercept method were proposed for upper-level semitransparent cloud, utilizing the characteristics where differences between the measured radiance and the clear-sky radiance are greater than the instrument noise. For lower-level cloud, it is suitable to apply the cloud-based method. For opaque cloud, the infrared-window method is a robust approach. In that method, a blackbody assumption is applied to the cloud of interest. Subsequently, the height of the cloud is determined by referencing the colocated vertical temperature profile calculated by a NWP model.

It is worth pointing out that most AMV-deriving algorithms operate under the following three assumptions: 1) a tracer is maintained at the same height between two consecutive images, 2) a tracer travels at a constant speed and its shape remains the same in each interrogation window, and 3) the velocity of a tracer represents the velocity of the wind (Bedka et al. 2009). The first two assumptions may be violated if the time interval between two consecutive images is too long to allow significant vertical development of the cloud and the velocity and shape change due to velocity gradients. To avoid such issues, a new-generation geostationary satellite, such as Himawari-8, may be employed. Himawari-8 is capable of capturing and transmitting images every 10 min, which is 3 times faster than its predecessor, the Multifunctional Transport Satellite-2 (MTSAT-2). Launched on 7 October 2014, Himawari-8 has been operational since 7 July 2015 (Bessho et al. 2016). Given the advantages that Himawari-8 has in deriving AMVs, constraints on large displacements and velocity gradients affecting cross correlation can be relaxed, and the derived AMVs would be more reliable (Le Marshall et al. 2017).
The objective of this study is to apply the PIV technique for AMV derivations, and to validate the derived AMVs by comparing results from NWP and radiosonde observations. The concept of PIV, including the multipass scheme and the adaptive interrogation scheme, will be briefly described. Both schemes have been well-established methods in many fluid mechanics studies, although not in the study of atmospheric flows. Two AMV height assignment methods will be applied to assign the height of the derived AMVs within opaque and semitransparent clouds. Finally, validation and discussion will be presented, and conclusions and future work will be addressed.

2. Methodology for AMV retrieval

a. Particle image velocimetry

A brief description of the PIV method is given in this section. PIV is an image-based technique for displacement and velocity determination. For more than two decades, this approach has been applied to various disciplines, such as hydrodynamics, aerodynamics, and microfluids, to quantify flow motion. A typical PIV setup involves an imaging system for tracking seeded particles illuminated by a thin laser light sheet. To properly represent the flow motion, a careful selection of the seeding is necessary. In fluid flows, using tiny artificial seeding with its density similar to that of the fluid is a common practice. However, the same approach for atmospheric flows is impractical, if not impossible. In reality not all applications using PIV allow artificial seeding. For example, owing to light reflection off air bubble surfaces, difficulties arise from finding proper artificial seeding in aerated flows such as wave breaking and hydraulic jumps. To conquer the problem, Ryu et al. (2005) proposed to directly use the contrast (differences in grayscale) created by air–water interfaces as tracers. In fact, similar features can also be found in infrared-window channel satellite images. In such images, the thickness of cloud at different heights results in brightness temperature differences that provide contrast for possible PIV velocity measurements. Furthermore, a high contrast (i.e., high dynamic range or bit depth) would be beneficial to tracer detection and correlation in corresponding image processing. From our preliminary tests, it was found that 30 counts or more in grayscale intensity variations are required for obtaining proper tracer detection. For the particular satellite imagery used in the present study, a dynamic range of more than 4000 counts (12 bits) is featured.

In PIV image processing, once tracers are identifiable, each image is then divided into numerous small interrogation windows. Subsequently, a cross-correlation algorithm is applied to each interrogation window from an image pair with a small time interval (\(\Delta t\)). A typical discrete form of cross-correlation function \(R\) for a square interrogation window can be expressed as (Mori and Chang 2003)

\[
R(\Delta x, \Delta y) = \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} [f(x_i, y_j) - \bar{f}][g(x_i + \Delta x, y_j + \Delta y) - \bar{g}]}{\sqrt{\sum_{i=1}^{N} \sum_{j=1}^{N} [f(x_i, y_j) - \bar{f}]^2 \sum_{i=1}^{N} \sum_{j=1}^{N} [g(x_i + \Delta x, y_j + \Delta y) - \bar{g}]^2}},
\]

where \(f\) and \(g\) are the small interrogation windows from each image in an image pair, \(N\) is the window size, and the overbar denotes the mean quantity. By means of fast Fourier transform (FFT), the computation time can be greatly reduced (e.g., Raffel et al. 2018). Figure 1 sketches the procedure of the PIV image processing. A sample cross-correlation result based on a pair of satellite images is also demonstrated in Fig. 1, including a prominent correlation peak. The two-dimensional displacement of the tracers in that interrogation window corresponds to the location of the correlation peak. A curve-fitting scheme (typically Gaussian) is then applied to identify the location of the peak to achieve a subpixel (in general about 0.1 of a pixel) accuracy.

Alternatively, the minimum quadratic difference (MQD) algorithm may be applied to obtain the correlation function as (Mori and Chang 2003)

\[
R(\Delta x, \Delta y) = \sum_{i=1}^{N} \sum_{j=1}^{N} |f(x_i, y_j) - g(x_i + \Delta x, y_j + \Delta y)|^2.
\]

The location of the minimum value in \(R\) is used as the tracer displacement. This approach requires tremendous computation time in comparison to the FFT-enabled calculation based on Eq. (1). However, it is more robust, particularly when the image quality is low.

b. Multipass scheme

Generally, the number of tracking particles within an interrogation window \(N_P\) has a significant impact
on the reliability of finding a displacement in the correlation result. While \(N_P\) is not well defined in a cloud image, it may be considered as the “texture” against its background in the image, similar to the bubble image velocimetry method (BIV) introduced by Ryu et al. (2005) that has been successfully employed in many liquid–gas flow studies. In addition, a large velocity gradient in the flow, such as a shear flow or strong vortex, may lead to poor correlations in velocity determination. To minimize the problems caused by low \(N_P\) values and high velocity gradients, a multipass scheme may be employed. The multipass concept involves performing an iterative correlation over a larger interrogation window then applying the resulting displacement to smaller subwindows. For example, a typical dual-pass scheme uses 64 \(\times\) 64 pixels as the first interrogation window and, then, divides that window into four 32 \(\times\) 32 pixel subwindows. The process may be iterated into even smaller subwindows if a finer spatial resolution is preferred, providing that the \(N_P\) value or its equivalent is high enough in each smaller subwindow. Moreover, the displacement determined from a subwindow is used as reference to locate the subwindow in the sequential image (i.e., moving the subwindow in the second image based on the resulting average displacement of the particles or textures). The particles or textures in both subwindows are better correlated when the correlation is iterated, and so as the accuracy of the resulting displacement. The multipass scheme has been applied in the present study.

c. Adaptive interrogation scheme

In addition to the multipass scheme, the adaptive interrogation scheme, also called adaptive PIV (Theunissen et al. 2007; Wieke and Pfeiffer 2010; Yu and Xu 2016), is also employed in the present study. The adaptive PIV scheme is capable of optimizing \(N_P\) by changing the subwindow size and adapting large velocity gradients by changing the subwindow aspect ratio (Wieke and Pfeiffer 2010). The adaptive PIV scheme considers a combination of signal adaptivity and flow adaptivity, while the signal adaptivity weighs about 70% in the correction (Theunissen et al. 2007). The signal adaptivity is associated with \(N_P\), while the flow adaptivity is relevant to the velocity gradient or the local flow fluctuation. The adaptive interrogation scheme is an additional iterative scheme and can be easily inserted into the cross-correlation procedure. Figure 2 illustrates the combination of a multipass scheme and an adaptive interrogation scheme, and the insertion of an adaptive interrogation scheme into the cross-correlation procedure. For details on the
algorithm and applications of adaptive PIV, the reader is referred to Theunissen et al. (2007, 2008, 2010), Wiencke and Pfeiffer (2010), and Yu and Xu (2016).

d. Image data and parameters for PIV processing

The image dataset employed in the present AMV derivations was derived from the infrared-window channel (IR1) data acquired by Himawari-8. The region within 90° and 150° longitude and 0° and 45° latitude was selected with an image spatial resolution of 2 km per pixel for a field of view of 2790 × 2790 pixels. The image dataset, listed as 12 cases in Table 1, contains 12 moments taken from time 0000 UTC 18 June to time 2400 UTC 24 June (note that the original data from 22 June are missing). Each moment has a sequential image pair with a 10-min interval between the two images. Preliminary results showed that consecutive images with a 12-h interval have poor correlations. Accordingly, only the 10-min interval image pairs were processed, employing the PIV method with a multipass scheme and an adaptive interrogation scheme.

Commercial software from LaVision Inc. and in-house developed software package called MPIV (Mori and Chang 2003) were used to perform the PIV image processing. In the process, the initial subwindow size and the final subwindow size were set at 64 × 64 pixels (equivalent to 128 × 128 km²) and 32 × 32 pixels (64 × 64 km²), respectively. With 50% overlap, the final vector resolution is 16 × 16 pixels (32 × 32 km²). The PIV image processing also includes postprocessing to remove spurious vectors using a median filter, and fill the usually small number of missing vectors using the Kriging interpolation method. See Mori and Chang (2003) for details.

3. Cloud-height assignment and AMV quality control

Each AMV determined by PIV is a measure of tracer motion (i.e., cloud in the present study) on a horizontal plane at a certain elevation within that particular interrogation window. Since cloud may exist over a vast range of elevations and the atmospheric motion is known to be a function of elevation, it is necessary to assign a height for each AMV. The height assignment is also necessary when performing AMV validation. Following Nieman et al. (1993) and Deb et al. (2014), the present study adopts the infrared-window method for opaque cloud and the H₂O-intercept method for semitransparent cloud.

The infrared-window method utilizes a threshold value as a proxy to represent the temperature of the top cloud. Based on Nieman et al. (1993), the threshold value is generally assigned as the 25% coldest brightness.
temperature in the target image from an infrared-window channel. As a result, the height of the AMVs at the top cloud can be determined by referencing the collocated temperature profile calculated by NWP model analysis–forecast (Nieman et al. 1993).

For semitransparent cloud, the energy received by satellite is partially emitted from the cloud top and partially from the objects below (e.g., Earth’s surface). Under such conditions, the brightness temperature of the infrared-window channel fails to represent the cloud-top temperature. To address this issue, the H2O-intercept method (Szejwach 1982) is employed to treat the region of semitransparent cloud. The H2O-intercept method utilizes the linear relationship of radiance from a single cloud deck between the infrared-window channel and the water vapor channel (Szejwach 1982; Nieman et al. 1993). Note that the linear relationship is independent of the value of cloud emissivity. In this paper, the scattering effect is neglected whereas only the effects of absorption are considered (Paltridge and Platt 1976). Moreover, absorption by water above the cloud top is assumed to be negligible (Szejwach 1982). As a result, a pair of radiation equations for the water vapor channel and the infrared-window channel can be written as

\[ R_1(T_1) = E_1 R_1(T_N) + (1 - E_1) R_1(T_F) \]  

(3)

\[ R_2(T_2) = E_2 R_2(T_N) + (1 - E_2) R_2(T_G) \]  

(4)

in which \( R \) is the received radiance, \( T \) is the brightness temperature, \( E \) is the effective emissivity, and \( T_N \) is the cloud temperature. In addition, \( T_F \) and \( T_G \) are the brightness temperatures of the incoming upward radiation at the cloud-base level in the water vapor channel and the infrared-window channel, respectively. The subscripts 1 and 2 denote the water vapor channel and the infrared-window channel, respectively.

As suggested by Szejwach (1982), \( E_1 \) and \( E_2 \) are equal to each other so Eqs. (3) and (4) can be deduced and merged into

\[ R_1(T_1) = a R_2(T_2) + b, \]  

(5)

where the coefficients \( a \) and \( b \) are

\[ a = \frac{R_1(T_N) - R_1(T_F)}{R_2(T_N) - R_2(T_G)} \]  

(6)

\[ b = \frac{R_1(T_F) R_1(T_N) - R_1(T_N) R_1(T_G)}{R_2(T_N) - R_2(T_G)}. \]  

(7)

### Table 1. Comparison of AMVs (within 100–1000 hPa) and NWP analysis data (assimilated) with radiosonde wind speeds. Note that columns 3–8 are the mean vector difference (MVD), root-mean-square error (RMSE), standard deviation (SD), wind speed bias (BIAS), mean wind speed (SPEED), and sample number (NUM).

<table>
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<th>Case</th>
<th>Data</th>
<th>MVD (m s(^{-1}))</th>
<th>RMSE (m s(^{-1}))</th>
<th>SD (m s(^{-1}))</th>
<th>BIAS (m s(^{-1}))</th>
<th>SPEED (m s(^{-1}))</th>
<th>NUM</th>
</tr>
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<td>12.40</td>
<td>57</td>
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<tr>
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<td>-0.50</td>
<td>14.65</td>
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</tr>
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The values of \(a\) and \(b\) can be obtained by fitting the observed \(R_1\) and \(R_2\) from a semitransparent cirrus cloud with the disparate emissivity over several areas. Equation (5) is valid for the emissivity ranging from 0 to 1. Once \(a\) and \(b\) are determined, the cloud temperature for the target cirrus cloud under the blackbody conditions can be obtained using Eq. (5) with emissivity equal to 1. The cloud temperature corresponding to the blackbody conditions is essential information for obtaining the cloud height in the H\(_2\)O-intercept method. Szejwach (1982) presented a comparison between the measured data curve and the ideal curve that considers the radiation emitted by blackbodies in both channels. In the graph exhibited by Szejwach, the overlapped curves or \(R_1(T) = f[R_2(T)]\) clearly indicate that the blackbody emission temperature represents the temperature of semitransparent cirrus cloud.

To increase the accuracy of the height assignment for semitransparency cloud, the initial height obtained by both the infrared-window and H\(_2\)O-intercept methods is further corrected by minimizing the variational cost function (Velden et al. 1997). Both the initial height and the NWP model analysis–forecast are needed to provide necessary input. The variational cost function is defined as

\[
B_{m,k} = \left( \frac{V_m - V_{ij,k}}{F_V} \right)^2 + \left( \frac{T_m - T_{ij,k}}{F_T} \right)^2 + \left( \frac{P_m - P_{ij,k}}{F_P} \right)^2 \\
+ \left( \frac{dd_m - dd_{ij,k}}{F_{dd}} \right)^2 + \left( \frac{S_m - S_{ij,k}}{F_S} \right)^2
\]  

(8)

in which the subscript \(m\) indicates an individual wind measurement that contains \(V\) (velocity), \(T\) (temperature), \(P\) (pressure), \(dd\) (direction), and \(S\) (speed). The subscripts \(i\), \(j\), and \(k\) represent the axes in the coordinate system employed in the NWP regional model.

Fig. 3. AMVs derived from satellite imagery and calculated using NWP. Red, yellow, and cyan vectors represent derived AMVs in ranges from 50 to 250 hPa, 251 to 350 hPa, and 351 to 1050 hPa, respectively. The green vectors represent the analyzed wind vectors at 300 hPa from the NWP regional model. Note that the \(x\) and \(y\) axes represent the longitude and latitude, respectively.
With different subscripts, $F$ denotes the weight of each cost item. The present study follows the suggested values reported by Nieman et al. (1997) and Holmlund et al. (2001). It should be noted that the wind measurement is excluded if the minimum value of the cost function within $\pm 100$ hPa with respect to the initial height is unable to be obtained.

Performing quality control on derived AMVs is a crucial step in its practical use. In the present study, the automatic quality control (AQC) method proposed by Holmlund (1998) was adopted. In this method, five consistency check tests are conducted, including direction consistency, speed consistency, vector consistency, spatial consistency, and forecast consistency, while each test yields a quality indicator (QI). Among the consistency check tests, direction, speed, and vector check tests compare the AMVs derived from two consecutive pairs of images (i.e., image triplet). These tests are equivalent to the temporal filtering and smoothing procedure for the PIV technique at an early stage of development. As the development evolved and more sophisticated and robust schemes were introduced, this postprocessing process applying the temporal consistency check has become unnecessary for the modern PIV technique, provided that the (traditional) post-processing applying spatial filtering has been performed. Note that both the temporal filtering and spatial filtering are not expected to increase the accuracy of the computed displacement vectors but to remove/replace the stray vectors after the cross-correlation computation. As a result, direction, speed, and vector consistency check tests are not performed.

In the present study using PIV, the spatial consistency check is done by applying a median filter and a $3 \times 3$ smoothing kernel to remove spurious vectors and perform spatial smoothing. The removed vectors are then filled, employing Kriging interpolation. The remaining forecast consistency check was done by comparing the PIV-derived AMVs with the NWP-derived wind field. The forecast consistency check is formulated as
where \( S(x, y) \) and \( F(x, y) \) present the AMV and the NWP-derived vector, respectively. Instead of using the cumulative distribution function, Holmlund (1998) applied a hyperbolic tangent-based form to better examine influences due to small deviations as follows:

\[
\Phi = 1 - [\tanh(\xi)]^a.
\]  

For a single consistency check test, QI is equal to Eq. (10), or \( QI = \Phi \). As suggested by Holmlund (1998), \( a = 2 \) was used for a forecast consistency check, and \( QI = 0.5 \) was set as a threshold in the AQC performance on all the derived AMVs.

4. Validation and discussion

a. Comparison of wind velocity maps with NWP

Figure 3 shows comparisons between AMVs derived from Himawari-8 imagery using the PIV method and the corresponding analysis wind vectors obtained by NWP at 0000 UTC 18 June 2017. Note that in the present study the Weather Research and Forecasting (WRF) Model was employed as the NWP model. For a detailed description of the WRF Model, the reader is referred to Skamarock et al. (2005) while its applications in typhoon predictions can be found in Hsiao et al. (2015).

In Fig. 3, the AMVs in three different vertical regions—50–250 hPa, 251–350 hPa, and below 351 hPa—are presented and colored as red, yellow, and cyan, respectively. The background green vectors are the analysis wind vectors at 300 hPa from a NWP regional model. In the comparisons, both the PIV-derived AMVs and the NWP wind field are very similar. Moreover, with some special signatures in the cloud patterns, one can see that the atmospheric circulation is clearly captured by the AMVs. The cloud patterns show two westerly jets: one is along the north of South Korea (from 110° to 130° longitude and from 40° to 45° latitude) and the other is along the south of Japan (from 110° to 140° longitude and from 20° to 35° latitude) with a trough shape, forming a weak cyclone circulating around the Tsushima basin. Furthermore, a weak anticyclone circulation pattern is noticeable around the junction of the Indochina peninsula and China (from 90° to 110° longitude and from 20° to 30° latitude).

Figure 4 presents a comparison between the PIV-derived AMVs and NWP analysis wind field by matching the grids between AMVs and the NWP winds (which have much higher spatial resolution). Good agreement in both magnitude and direction can be found at most grids. Accordingly, Fig. 4 indicates that AMVs obtained using the PIV method are capable of quantitatively depicting the atmospheric circulation. Figure 5 further shows detailed comparisons among the AMVs, NWP analysis vectors, and radiosonde observations at six stations around Taiwan. Overall, the PIV-derived AMVs match the radiosonde wind vectors well.

b. Comparison of errors with NWP winds

To evaluate the uncertainty of PIV-derived AMVs, errors in both AMVs and NWP analysis winds were estimated by comparing to the radiosonde observations. The errors feature the mean vector difference (MVD), the root-mean-square error (RMSE), the standard deviation (SD), and the wind speed bias (BIAS). The mathematical expressions for evaluating these errors can be found in Nieman et al. (1997). To match the radiosonde observations, the NWP data were interpolated to the location of the radiosonde observation stations. For the PIV AMVs, the average value of the data closest to the radiosonde observation station within a horizontal distance of 150 km and a vertical range of 20 hPa was used. The calculated results are listed in Table 1 along with the mean wind speed (SPEED) and the sample number (NUM) for 13 cases, including 12 separated
moments (denoted as date and time) and all of the moments combined (denoted as case All).

The MVD, RMSE, and standard deviation of the PIV-derived AMVs are 3.70, 4.29, and 2.17 m s\(^{-1}\), respectively, which are slightly larger than those of the NWP data (3.35, 3.88, and 1.97 m s\(^{-1}\)). The wind speed bias of the PIV-derived AMVs is \(-1.05\) m s\(^{-1}\), and the slow speed bias is found in each case. Figure 6 further shows a scatterplot of AMVs versus radiosonde data. Many studies (Nieman et al. 1997; Genkova et al. 2008; Bresky et al. 2012) indicate that the slow speed bias is mainly caused by the inaccurate assignment of the tracer height. One source of the bias could be from neglecting the contribution of the coldest pixel (20\%–25\%) brightness temperature in the tracking process (Bresky et al. 2012). Another could be from excessively averaging or smoothing the instantaneous wind field due to the use of a large interrogation window (Bresky et al. 2012). Future work is thus needed to improve the height assignment algorithms or to adopt better options for the PIV AMV derivations. Nevertheless, the wind speed bias of the PIV-derived AMVs is at the level of \(-1\) m s\(^{-1}\) and remains nearly constant in all the cases, indicating that the PIV-AMV approach has shown good potential to be incorporated into the operational system for assisting in weather analysis and providing input for data assimilations.

c. Comparison with JMA/MSC operational AMVs

By comparing to radiosonde data, Table 2 summarizes statistical errors for the AMVs derived by PIV and the operational system from the Meteorological Satellite Center (MSC) of the Japan Meteorological Agency (JMA), or JMA/MSC. All the AMVs derived from the 12 cases listed in Table 1 are included in the comparison. Note that the altitude and location of the two AMV datasets cannot be precisely matched due to differences in the employed tracking methods and height assignment algorithms. Hence, the error estimates were performed independently, while different vertical regions and radiosonde observation stations were assigned to these two AMV datasets.

<table>
<thead>
<tr>
<th>AMV method</th>
<th>MVD (m s(^{-1}))</th>
<th>RMSE (m s(^{-1}))</th>
<th>SD (m s(^{-1}))</th>
<th>BIAS (m s(^{-1}))</th>
<th>SPEED (m s(^{-1}))</th>
<th>NUM</th>
</tr>
</thead>
<tbody>
<tr>
<td>PIV</td>
<td>3.70</td>
<td>4.29</td>
<td>2.17</td>
<td>(-1.05)</td>
<td>12.40</td>
<td>645</td>
</tr>
<tr>
<td>JMA/MSC</td>
<td>4.29</td>
<td>4.88</td>
<td>2.33</td>
<td>(-0.20)</td>
<td>18.36</td>
<td>589</td>
</tr>
</tbody>
</table>
Based on Table 2, the performance of the PIV-AMV is slightly better than that of JMA/MSC-AMV for almost every error category except for the wind speed bias (BIAS). As previously mentioned, a negative BIAS or a slow wind speed is highly associated with the accuracy of the employed height assignment algorithms. In the JMA/MSC operational AMV system, an advanced method (Borde et al. 2014) that provides a direct link between feature tracking and height assignment is employed in the operational cross correlation. As a result, the negative BIAS issue is significantly alleviated. Since the PIV-AMV and the JMA/MSC operational AMV system apply different schemes in deriving AMVs, the method used by JMA/MSC cannot be readily implemented into the present PIV-AMV. It is anticipated that the PIV-AMV could become a promising AMV derivation approach if a better height assignment operation can be incorporated.

The present study mainly aims to examine the applicability of the PIV method in deriving AMVs from an infrared-window channel (IR1). In fact, there are 12 additional channels (such as visible and water vapor channels) acquired by the Himawari-8 satellite; these channels may be used to derive AMVs at different heights. Improving the PIV-AMV approach, especially in terms of high assignment, and implementing the approach into an operational system seems to be a feasible future task.

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5. Conclusions and future work

This paper presents a successful attempt at applying the PIV technique with a multipass scheme and an adaptive interrogation scheme to the derivation of AMVs from infrared-window satellite images acquired by the new-generation geostationary satellite Himawari-8 over eastern Asia. The use of these schemes in the PIV analysis enhances the accuracy in cross correlating the tracers created by inhomogeneous cloud patterns through brightness temperature differences. Furthermore, the observations with increased frequency by Himawari-8 provide a much needed frame rate (every 10 min) for each image pair, limiting the maximum displacement and velocity gradient to within a range of confidence.

Based on the comparison with the NWP data, the PIV-derived AMVs are capable of quantitatively depicting the full-field winds featuring strong jets in atmospheric circulation. By comparing with the wind speeds of radiosonde observations, the mean vector difference, root-mean-square error, and standard deviation (3.70, 4.29, and 2.17 m s\(^{-1}\)) of the PIV-derived AMVs are comparable to, though slightly larger than, those of the NWP data (3.35, 3.88, and 1.97 m s\(^{-1}\)). On the other hand, the wind speed bias (−1.05 m s\(^{-1}\)) of the PIV-derived AMVs is slightly higher in comparison to the corresponding bias in the JMA/MSC operational system. The higher wind speed bias indicates the need of better height assignment schemes for the PIV-AMV approach. Nevertheless, the validation shows that deriving AMVs by using PIV is a promising approach in determining atmospheric flows and providing input to data assimilation models.

REFERENCES


