Local motion compensation in image sequences degraded by atmospheric turbulence: a comparative analysis of optical flow vs. block matching methods

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ABSTRACT

As a consequence of fluctuations in the index of refraction of the air, atmospheric turbulence causes scintillation, spatial and temporal blurring as well as global and local image motion creating geometric distortions. To mitigate these effects many different methods have been proposed. Global as well as local motion compensation in some form or other constitutes an integral part of many software-based approaches. For the estimation of motion vectors between consecutive frames simple methods like block matching are preferable to more complex algorithms like optical flow, at least when challenged with near real-time requirements. However, the processing power of commercially available computers continues to increase rapidly and the more powerful optical flow methods have the potential to outperform standard block matching methods. Therefore, in this paper three standard optical flow algorithms, namely Horn-Schunck (HS), Lucas-Kanade (LK) and Farnebäck (FB), are tested for their suitability to be employed for local motion compensation as part of a turbulence mitigation system. Their qualitative performance is evaluated and compared with that of three standard block matching methods, namely Exhaustive Search (ES), Adaptive Rood Pattern Search (ARPS) and Correlation based Search (CS).

Keywords: atmospheric turbulence, turbulence mitigation, optical flow, block matching, motion estimation, local motion compensation, image restoration

1. INTRODUCTION

1.1 Motivation

Imaging through turbulent media results in image degradation which is particularly severe when imaging over an extended propagation path near the surface where conditions often are anisoplanatic. As a consequence of fluctuations in the index of refraction of the air, atmospheric turbulence causes scintillation, spatial as well as temporal blurring and global as well as local image motion including geometric distortions. To mitigate these effects many different methods have been proposed, most of which use either a hardware approach, such as adaptive optics (AO), or a software approach. While AO requires expensive equipment and is usually restricted to applications concerned with the correction of point sources, e.g. astronomy or laser communication, digital image processing can be used for extended objects at low-cost and generally provides more flexibility even regarding real-time applications.

The motivation behind this work is ultimately to enhance image sequences degraded by atmospheric turbulence over a horizontal propagation path that contain one or several moving objects. Global as well as local motion compensation in some form or other constitutes an integral part of many software-based approaches. In order to achieve efficient motion compensation, it is essential to employ suitable methods for motion detection and motion estimation that combine precision and speed. For the estimation of motion vectors between consecutive frames simple methods like block matching are preferable to more complex algorithms like optical flow, at least when challenged with near real-time requirements. However, having worked with block matching in the past, e.g. in [1]-[3], the requirement for more sophisticated methods became evident. Considering that the processing power of commercially available computers continues to increase rapidly, the more complex optical flow methods have become viable options. Being more versatile in terms of their range of application they have the potential to outperform standard block matching methods.

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1.2 Overview

This article is divided into three main parts following this introduction. In the first part the working principles behind the three block matching methods employed here are described, namely Exhaustive Search (ES), Adaptive Rood Pattern Search (ARPS) and Correlation based Search (CS). In the second part the same is done for the three optical flow algorithms that were tested, i.e. Horn-Schunck (HS), Lucas-Kanade (LK) and Farnebäck (FB). In the last part a performance evaluation is given with regard to accuracy and speed of the respective algorithms from which conclusions are drawn concerning the implications for motion compensation for turbulence mitigation.

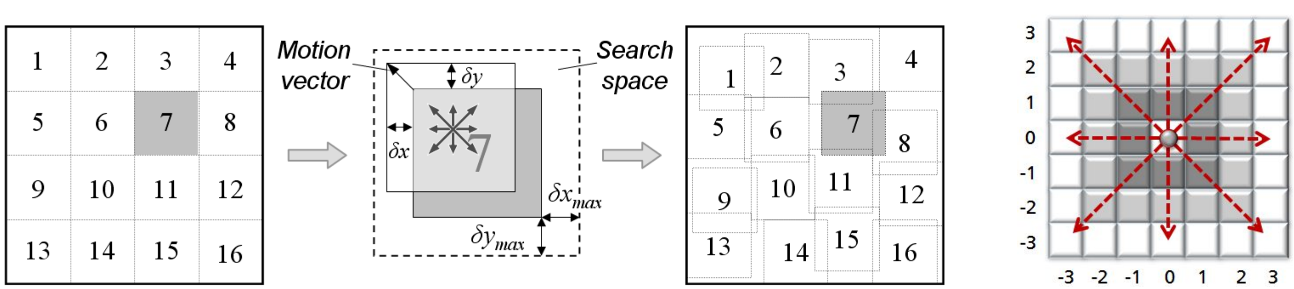
2. BLOCK MATCHING

2.1 Motion Estimation

Motion estimation is concerned with the extraction of motion vectors describing the transformation from one image to another, usually between consecutive frames. Motion vectors can either refer to the whole image (global motion estimation) or only to specific image parts. Block-matching algorithms, for instance, divide images into uniformly sized rectangular pixel blocks. But it is also possible to use arbitrary shaped patches, including single pixels. Motion estimation methods generally can be divided into two categories: feature-based methods and direct methods. In the indirect feature-based approach a sparse set of distinct interest point features are determined separately for a pair of images, e. g. by using the Harris corner detector, and correspondences between frames are found by exploiting statistical properties of these points and their surrounding neighbourhood. An overview over the use of feature-based methods can be found in [4]. Direct motion detection methods generally depend on the differences between two or more consecutive images using pixel-based error measures to determine correspondences for every pixel. Optical flow as presented in [5]-[7] is a closely related concept where motion vectors correspond to the perceived pixel movement. Both the optical flow methods and the block matching employed here can be counted among the direct methods. A general review of direct methods can be found in [8].

2.2 Basic Principle

Block Matching (BM) is generally known as a standard technique for encoding motion in video sequences. Motion between consecutive frames is detected in a block-wise fashion by shifting each (non-overlapping) block from the previous frame to best match the corresponding block in the current frame over a pre-defined search space of a number of N pixels in every direction (with $N \leq .0.5$ block size) The basic idea of rearranging the individual blocks of an image to match a given reference image is illustrated in Figure 1 (a).



(a) (b)

Figure 1. (a) Illustration of the block-wise operation of fitting the blocks from one image to the next image for best match. (b) ES search space of size 3 where the arrows indicate the main search directions.

With block-matching it is also possible to detect moving objects provided that their movements exceed the seeming motion caused by the atmospheric turbulence. Objects in the foreground and the background can then be corrected for turbulence separately. This has the advantage that object movement is not taken into account when averaging, thus effectively reducing motion blurring effects.

2.3 Exhaustive Search (ES)

Exhaustive Search (ES) is quite straightforward and means that BM between frames is executed such that for the current block a given search space around the corresponding block in the next frame is checked exhaustively for every possible shift direction to find the best match for the current block. Figure 1 (b) exemplifies a search space with a radius of 3 pixels. The algorithm as used here has already been detailed in previous work [3] including a discussion on suitable best-match criteria.

As the name suggests, this method is the most thorough and therefore potentially the most precise of all methods employed here, depending on the chosen best match criterion. Unfortunately, it is also the slowest since increasing the search space automatically also increases the computational complexity by $(2*N+1)^2$ where N denotes the maximum pixel shift. To keep calculating time down, the size of the search space usually was limited to only a few pixels in every direction, e.g. 4 or 5 pixels. This of course implies that only small motions can be accounted for unless it is implemented using a pyramidal approach by applying it to subsampled versions of the images first.

2.4 Adaptive Rood Pattern Search (ARPS)

The so-called *Adaptive Rood Pattern Search* (ARPS) suggested in [9] is a fast BM algorithm that uses reduced search patterns with only sparsely spaced search points for detecting small motions. The speed and accuracy of such algorithms strongly depend on the size of the search pattern but is also closely linked to the scale of the targeted motion vector. Therefore the ARPS operates in two stages. In the initial search stage an adaptive rood pattern (ARP), as depicted in Figure 2, is employed which is determined dynamically depending on the predicted motion behaviour of the block under consideration. The prediction is based on available motion vectors of neighbouring blocks exploiting the fact that adjacent blocks belonging to the same object will most likely move in a similar fashion.

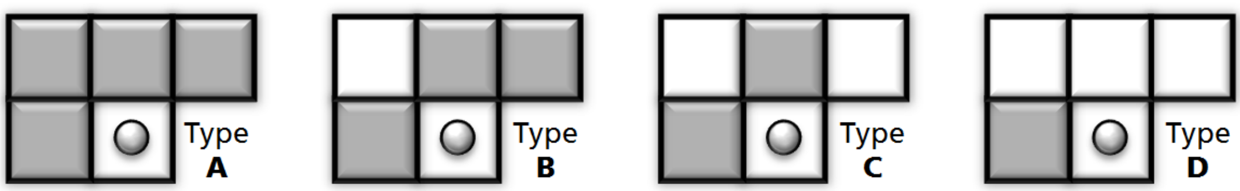


Figure 2. Four possible ARP types for the initial search stage where the current block is marked by a circle and the shaded blocks depict the support of pattern.

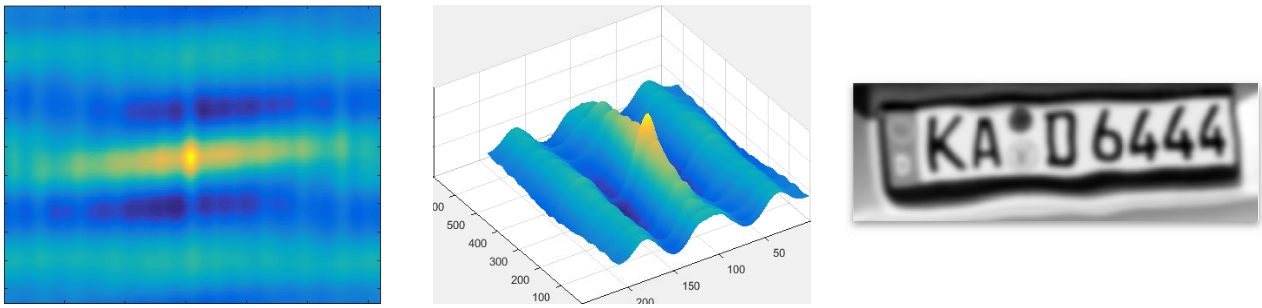
In the second stage a refined local search is executed until the final motion vector is determined. This time a fixed pattern of unit size is used and searched exhaustively, typically either the direct 4- or 8-connected neighbourhood of the pixel under consideration.

2.5 Correlation-based Search (CS)

Correlation-based Search (CS) means straightforward BM quite like ES only that normalized cross-correlation is employed to determine the closest match between corresponding blocks as described by Eq. 1:

$$\gamma_{xcorr}(u,v) = \frac{\sum_{x,y}\left[f(x,y)-\bar{f}_{u,v}\right]\left[g(x-u,y-v)-\bar{g}\right]}{\left[\sum_{x,y}\left[f(x,y)-\bar{f}_{u,v}\right]^2\sum_{x,y}\left[g(x-u,y-v)-\bar{g}\right]^2\right]^{\frac{1}{2}}} \qquad \text{(Eq. 1)}$$

Here, f denotes the image where the sum over x, y is over the window containing the template g, i.e. the block to be matched which is centred at u, v. Furthermore, $\bar{g}$ denotes the mean of the template g while $\bar{f}_{u,v}$ denotes the mean of the area in the image f under the template. The deviation of the maximum peak of the correlation coefficient γ_{xcorr} from the centre position then yields the relative local shift between $f(x, y)$ and $g(u, v)$. Figure 3 exemplarily shows such a correlation peak for the (global) shift between two frames of the simulated license plate sequence.



(a) (b) (c)

Figure 3. Exemplary (a) 2-D and (b) 3-D visualization of correlation peak for two frames of simulated license plate sequence, e.g. (c).

Normalizing is important in case of intensity variations, e.g. due to illumination changes. According to Eq. 1 the correlation coefficient γ_{xcorr} is undefined in regions of no variance, i.e. homogeneous areas, and therefore is set to 0. Given the loss of high frequencies and consequent loss of information from atmospheric blurring this becomes significant in the context of turbulence mitigation since the degree of homogeneity increases while image contrast decreases. This also affects the accuracy of the CS which strongly relies on the existence of structures in $f(x, y)$ and $g(u, v)$ in order to determine any displacement between them. For this very reason the size of the template (i.e. the block size) must be chosen large enough so as to still contain discernible structures. While this, of course, mainly depends on the quality of the data in question, a block size of ≥16 pixels generally yields reasonable results. Contingent upon the size of the image, the CS is likely executed more efficiently in the frequency than in the spatial domain.

2.6 Remarks

The block size and the search space constitute the main parameters in the baseline ES algorithm and need to be given some consideration. On the one hand, choosing a bigger block size may remedy the "aperture problem" caused by homogeneous areas that are larger than the block size, but on the other hand, choosing smaller blocks will improve the object contours.

The accuracy of most BM methods can be improved upon by additionally exploiting local image variance, indicating the local degree of homogeneity, and by forcing estimated displacements to be 0 where the variance falls below a certain threshold. The assumption that the error of supposing no displacement between near homogeneous image parts is likely not greater than from any estimation results is well in keeping with the aperture problem.

3. OPTICAL FLOW

3.1 Basic Principle

Optical flow (OF) refers to the apparent visual motion that an observer experiences when moving through the (3-D) world. Static objects appear to move as the observer passes them and the closer such objects are, the faster they appear to be moving. In image processing terms, OF describes the perceived motion between successive frames of an image sequence. In practice this means OF describes the transformation of one frame into the next frame of an image sequence. In computer vision applications OF estimation is often used in motion-based object detection and tracking systems for quantitatively describing the motion of objects in a video stream.

When estimating object motion it is necessary to distinguish between the motion that is perceived in the 2-D image and the theoretical projection of the actual 3-D motion into the image. More specifically, the motion between objects in the observed (3-D) scene relative to an imaging optics is described by means of a vector field, containing the velocities and directions for all visible points in the object space as projected onto the (2-D) image plane.

Differential (i.e. gradient-based) methods such as introduced by Horn and Schunck in [5] or developed by Lucas and Kanade [11] are based on local Taylor series approximations, that is on using partial derivatives of the intensity image $I(x, y, t)$ with spatial and temporal coordinates (x, y) and t, respectively. It is assumed that for part of a moving object the intensity at corresponding positions of successive frames in an image sequence will remain constant such that the intensity at a point a small distance away, i.e. at a position $(x + \Delta x, y + \Delta y)$, and a small time later, i.e. at a time $(t + \Delta t)$, will coincide. This gives the so-called "brightness constancy constraint:

$$I(x, y, t) = I(x + \Delta x, y + \Delta y, t + \Delta t) \qquad \text{(Eq. 2)}$$

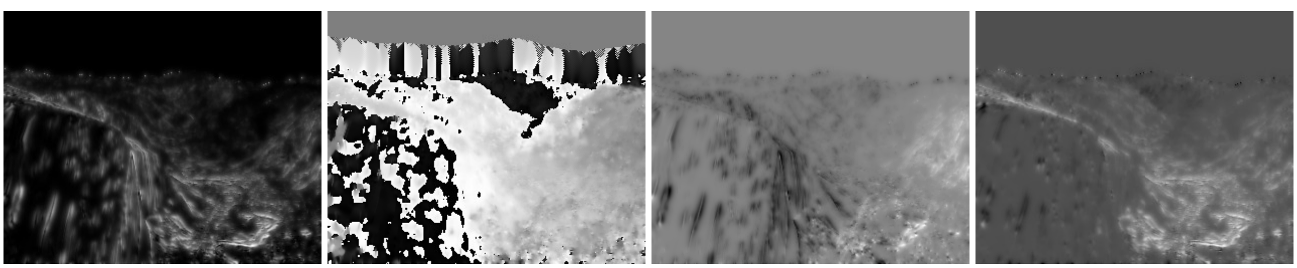
The shifted intensity can be expressed by local Taylor series approximation:

$$I(x + \Delta x, y + \Delta y, t + \Delta t) = I(x, y, t) + \frac{\partial I}{\partial x}\Delta x + \frac{\partial I}{\partial y}\Delta \mathrm{y} + \frac{\partial I}{\partial t}\Delta t + R \qquad \text{(Eq. 3)}$$

where R denotes the remaining higher order terms. Assuming linear motion, i.e. $R \cong 0$, yields the following constraint:

$$\frac{\partial I}{\partial x}\Delta x + \frac{\partial I}{\partial y}\Delta \mathrm{y} + \frac{\partial I}{\partial t}\Delta t = 0 \qquad \text{(Eq. 4)}$$

Unfortunately, the solution to this equation, i.e. the velocity field $[u, v]^T$, is ill-posed necessitating additional smoothness constraints. Therefore, all OF algorithms require additional constraints for estimating the actual flow. A performance review of the most commonly used techniques is given in [10].



Flow magnitude | Flow orientation | Horizontal velocity | Vertical velocity

Figure 4. Exemplary visualizations of OF magnitude, orientation as well as horizontal and vertical velocity components for Horn-Schunck algorithm on Yosemite test images[1].

3.2 Horn-Schunck (HS)

The *Horn–Schunck* (HS) method [5] uses the differential approach for estimating optical flow. It is a global method since it assumes smoothness in the flow over the whole image, introducing a global smoothness constraint in order to deal with the aperture problem. Distortions in the flow field are minimized by the algorithm while solutions which exhibit more smoothness are favoured. The flow field can be expressed as a global energy functional which is minimized and solved for the velocity field $[u, v]^T$:

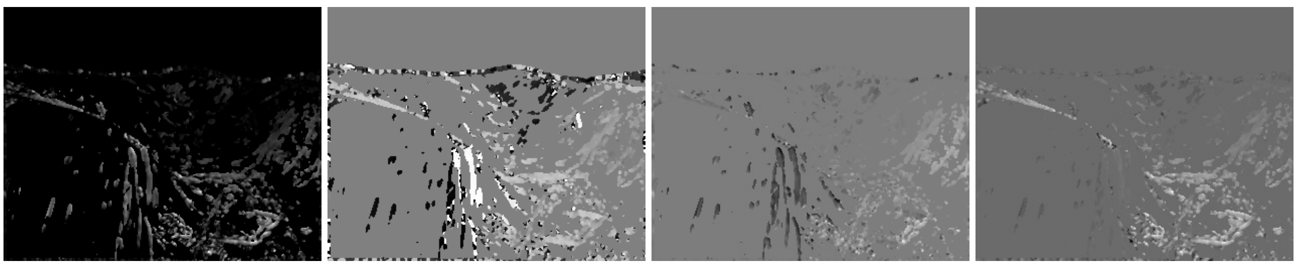
$$E = \iint \left[\left(I_x u + I_y v + I_t \right)^2 + \alpha^2 (\|\nabla u\|^2 + \|\nabla v\|^2) \right] \mathrm{d}x\mathrm{d}y \qquad \text{(Eq. 5)}$$

[1] Middlebury Optical Flow Evaluation Datasets <http://vision.middlebury.edu/flow/data>

where I_x, I_y , I_t denote the respective derivatives of intensity values in the image along the dimensions x, y and time t.The HS algorithm yields a high density flow field where the missing information from homogeneous regions is supplied by the vectors at motion boundaries. Unfortunately, this also makes it more sensitive to noise than local methods. Figure 4 shows an exemplary visualization of the OF for the Yosemite test sequence estimated with the HS algorithm. Depicted from left to right are the estimated flow magnitude, its orientation (i.e. phase angle) and its horizontal as well as vertical shift components (i.e. velocity).

3.3 Lucas-Kanade (LK)

The widely used *Lucas–Kanade* (LK) method for estimating optical flow as introduced and detailed in [11] equally follows the differential approach and was introduced as early as 1981. It is a local method assuming image displacements between frames to be small, i.e. smaller than 1 pixel) and the flow, i.e. velocity field $[u, v]^T$, to be approximately constant within a local neighbourhood of a given pixel position (x, y). The basic optical flow equation can then be solved for all the pixels in this neighbourhood making use of the least squares method. Figure 5 shows a visualization of the OF for the Yosemite test sequence estimated using the LK algorithm.



Flow magnitude | Flow orientation | Horizontal velocity | Vertical velocity

Figure 5. Exemplary visualizations of OF magnitude, orientation as well as horizontal and vertical velocity components for Lucas-Kanade algorithm on Yosemite test images[1].

The result from the least squares method can be improved by introducing weights. Instead of attributing the same significance to all pixels within the neighbourhood, those pixels are attributed weights decreasing radially with increasing distance to the centre pixel.

A common approach to account for larger motions that would violate the small motion assumption is to use a pyramidal implementation approach reduce the resolution of images by down sampling before applying the algorithm.

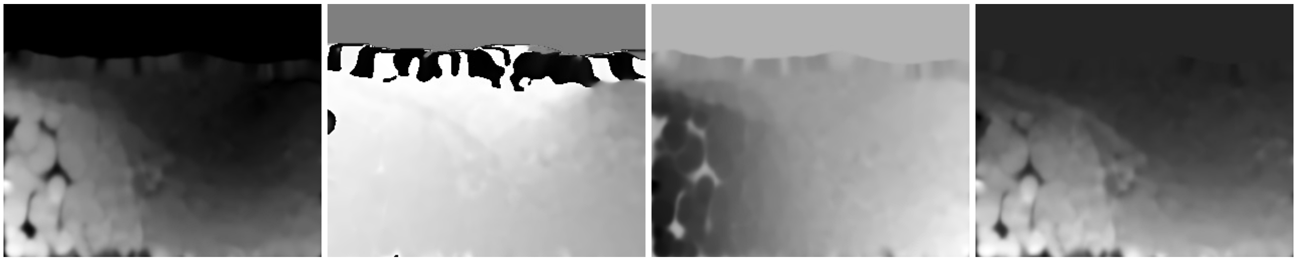
Optionally, temporal and/or spatial Gaussian filtering of the input can be used to smooth the estimated (primarily global) motion field at the cost of suppressing abrupt (local) movements.

3.4 Farnebäck (FB)

The OF estimation method developed by *Farnebäck* (FB) as first presented in [12] estimates motion between two successive frames by using polynomial expansion which is based on normalized convolution. First, a predefined neighbourhood of each pixel is approximated with a polynomial by utilizing the quadratic expansion transform. The corresponding expansion coefficients are estimated by a least squares fit using a similar weighting scheme to that mentioned in the previous section for the LK algorithm. Then a multi-scale approach from coarse to finer scales is employed using down sampled versions of the original images for the estimation of the actual displacement (flow) field. Displacements are assumed to be varying only slowly thus enabling the use of a priori information over a neighbourhood of each pixel. Furthermore, the displacement field can be parameterized according to a linear motion model for velocity field $[u, v]^T$ in order to improve the algorithm's robustness. Figure 6 shows a visualization of the OF for the Yosemite test sequence estimated with the FB algorithm.

FB yields a flow field of an even higher density than the HS algorithm while giving more accurate results, particularly for global observer motion.

Subsampling between scales keeps the computational cost down of having to recalculate the polynomial expansion coefficients for each scale. An efficient implementation becomes possible by using a hierarchical scheme of separable convolutions.



Flow magnitude | Flow orientation | Horizontal velocity | Vertical velocity

Figure 6. Exemplary visualizations of OF magnitude, orientation as well as horizontal and vertical velocity components for Farnebäck algorithm on Yosemite test images[1].

3.5 Remarks

In realistic situations there are a number of complexities that can cause problems not only for OF estimation but also for evaluating OF algorithms. A popular example is a rotating Lambertian sphere under constant illumination from a static light source for which it is impossible to discern the rotary motion from visual information alone [5]. On the other hand, moving a light source around a stationary sphere will create the appearance of motion due to drifting intensities.

Other issues may arise, e.g. from shadows, changing illumination, transparency, motion discontinuities, objects moving out of the field of view, moving camera, complex structured surfaces, specular highlights, camera noise and last, but certainly not least, atmospheric effects as well.

The commonly used Yosemite test sequence was artificially generated in order to make the ground truth for the corresponding flow field available. A digital terrain map containing different depth ranges and motion discontinuities at occluding boundaries was used as template[2].

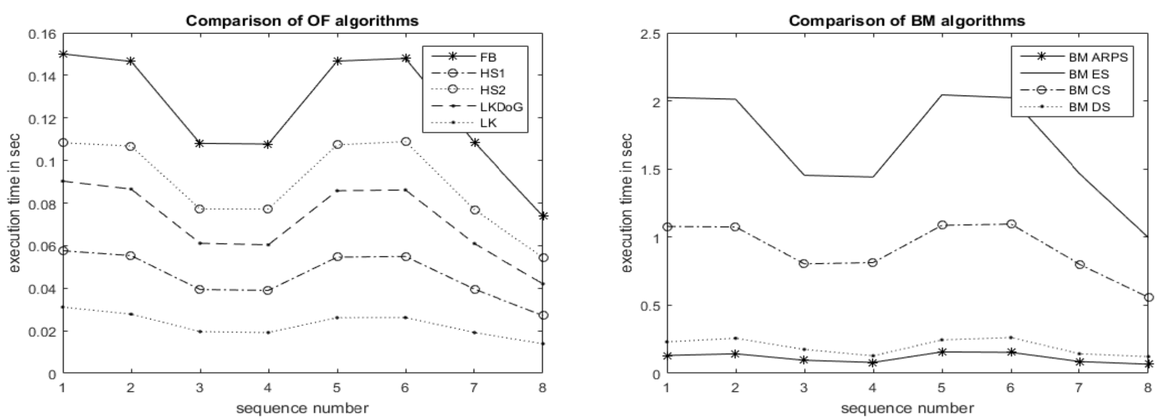


Figure 7. Comparison of OF (left) and BM (right) execution times for Middlebury test sequences[1].

4. PERFORMANCE EVALUATION

4.1 Execution Speed

Figure 7 compares execution times of the OF methods with those of BM algorithms where two parameter sets were used for LK and HS algorithms both. Listed additionally among the BM methods is the so called *Diamond Search* (DS) which

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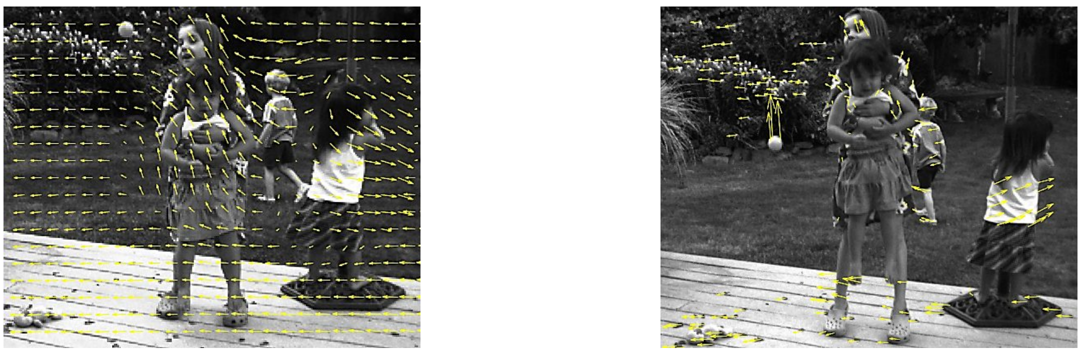
[2] http://cs.brown.edu/~black/Sequences/yosFAQ.html

only differs from the ARPS by using a fixed diamond shaped search pattern. The execution times were only indirectly related to image size as image resolution for most sequences was 480×640 pixels, for sequences 1, 4 and 5 it was 584×388 pixels and for sequence 8 it was 420×380 pixels. For the BM methods a block size of 16 pixels was chosen and a search space size of 7 pixels (search space).

As expected the exhaustive search is slowest of all methods (including OF) while the adaptive rood pattern search executes fastest among the BM methods. The fastest algorithm overall is the Lucas-Kanade algorithm for minimum parameter setting whereas the Farnebäck algorithms is slowest among the OF methods.

It should be noted that the execution times obtained for all the BM methods here are comparatively high is due to the fact that they were implemented purely in software whereas they are normally implemented exploiting hardware acceleration. Nevertheless, the execution times obtained for the slowest of the equally software implemented OF methods, i.e. FB, still lies approximately in the same order of magnitude as the fastest BM method, i.e. ARPS, meaning the main decision will be up to the qualitative performance of the respective algorithms in the following section.



(a) (b)

Figure 8. Exemplary OF visualizations on Middlebury test images[1]. (a) Smooth flow field including homogeneous regions (e.g. for camera movement); (b) estimated flow for moving objects (e.g. for tracking).

4.2 Qualitative Performance

While BM methods only determine motion locally by estimating translations between corresponding blocks of adjacent frames, OF methods are more versatile. OF can either be used to estimate observer motion (e.g. for a camera mounted on a moving platform, a swivelling or panning camera) which can be considered more or less as a global motion or to estimate the specific motion of individual objects (e.g. of vehicles, persons) which needs to be considered on a more local level. However, this means there is always the decision to be made as to which application has higher priority since the choice of parameters is directly related to whether a smooth flow field as for a moving camera is preferable or that potentially abrupt movements of individual objects can be retained. Figure 8 exemplifies the difference in approach.

Considering that ground truth is generally unavailable with respect to OF unless created specifically (or charted manually), most of our tests were conducted on test sequences with corresponding ground truths provided by the Middlebury site[1]. The ground truths provided there consist of a two-component velocity vector for each pixel, containing the horizontal and the vertical displacement between the previous and the current frame in sub-pixel precision. All OF methods automatically generate the same information for each pixel. In order to compare the results gained from the tested BM methods, the resulting shift vectors (only one for each block) had to be enlarged to match the original image size. Figure 9 shows a comparison of motion estimation results for all OF and BM methods at the example of the synthetic "Grove" test sequence for which a sample frame (a) and an intensity difference image (b) have been included so as to give some understanding of the observed scene. Images (e)-(l) all contain vertical and horizontal shift components which are visualized as intensity images with white patches indicating big positive displacements between frames while black regions indicate big negative displacements, i.e. shifts in the opposite direction, while medium grey corresponds to zero shifts. Image (e) shows the ground truths for the data, images (f)-(h) show the respective OF estimation results from Farnebäck, Horn-Schunck and Lucas-Kanade algorithms while images (i)-(l) contain the corresponding results from the BM methods exhaustive search, adaptive rood pattern search, diamond search and correlation based search.

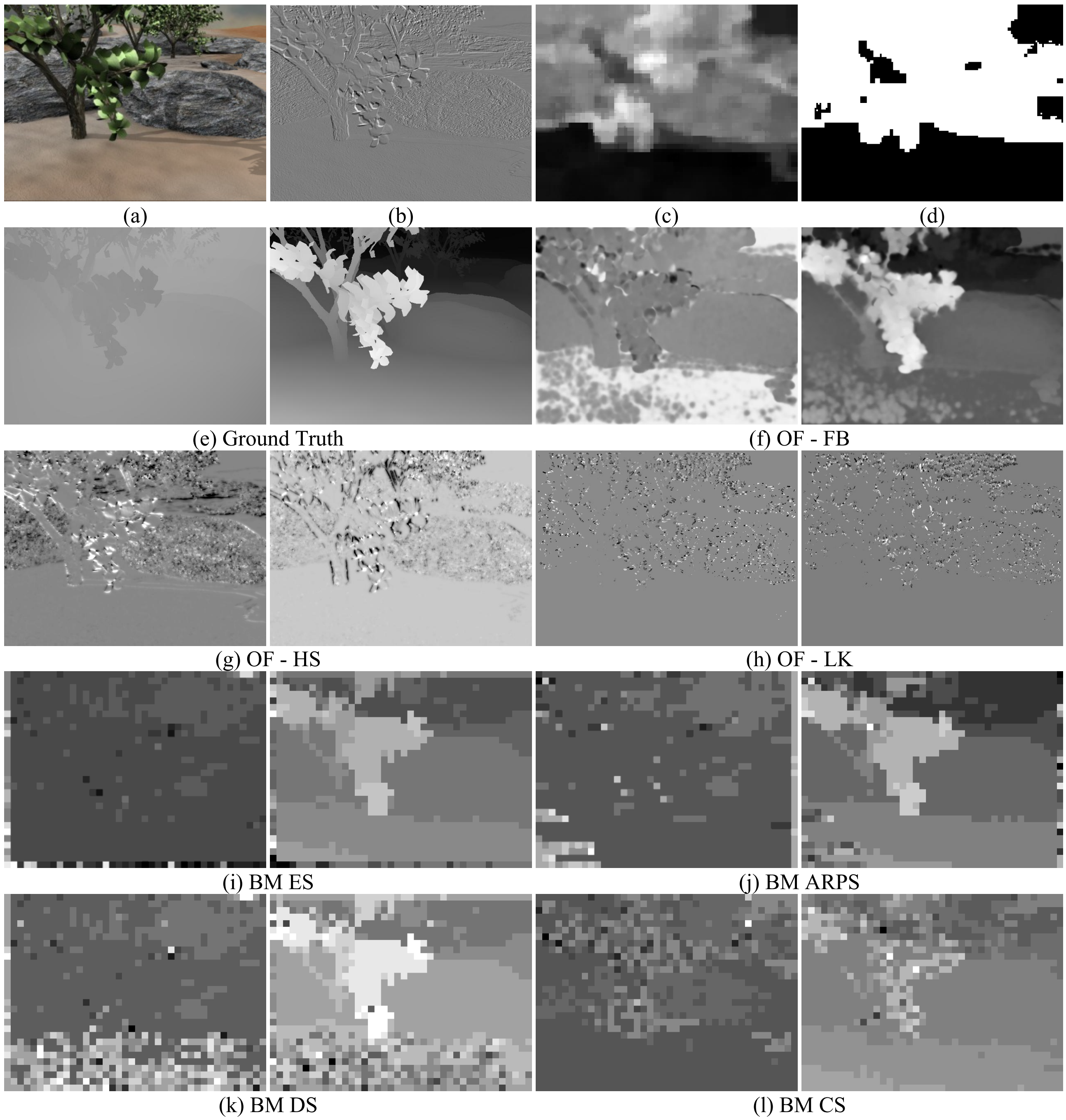
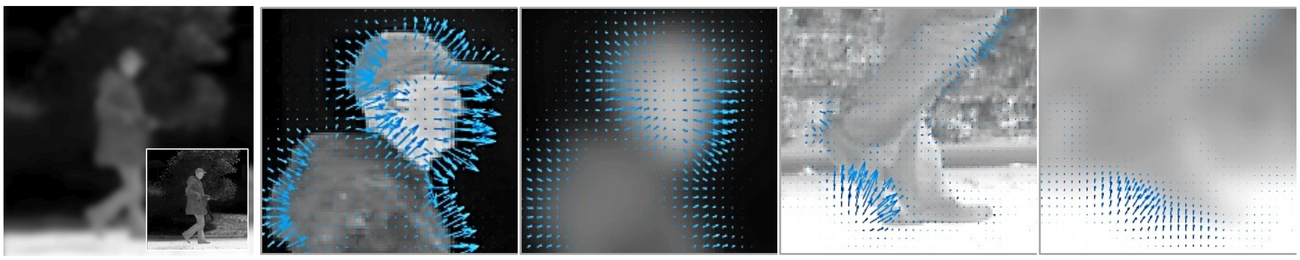


Figure 9. Comparison of exemplary motion estimation results for OF and BM methods. (a) Original frame of Grove test sequence[1], (b) difference image between two frames, (c)+(d) local standard deviation as homogeneity map where (d) is a binarized version of (c); left & right in each case of (e)-(l) vertical & horizontal shift, resp., (e) ground truth, (f) optical flow Farnebäck algorithm, (g) OF Horn-Schunk algorithm, (h) OF Lucas-Kanade algorithm, (i) block matching exhaustive search, (j) BM adaptive rood pattern search, (k) BM diamond search, (l) BM correlation based search.

The quality of the results varies greatly with the FB algorithm clearly outperforming all other methods. The greatest dissimilarities between ground truth and shift estimations occur in more or less uniformly coloured areas as the homogeneity map in (c) and (d) helps identify for which the local standard deviation of the original image was exploited. As initially mentioned, the flow information from both HS and LK algorithms do not extend into homogeneous areas and are restricted to displacement information along edges which is reflected in the results shown. Among the BM methods, the results from ES and ARPS come closest to the ground truth.



(a) (b) (c) (d) (e)

Figure 10. Exemplary OF estimation results (image details) with HS algorithm showing the influence of turbulence. (a) (Downsized) frame of test sequence with simulated turbulence (L = 3 km, $C_n^2 = 10^{-14}\,\mathrm{m}^{-2/3}$), (b)+(d) OF results without turbulence, (c)+(e) OF results with turbulence.

In order to verify the results gathered from the mostly artificial sequences, further testing was done on sequences with simulated turbulence since there at least the ground truth with regard to moving objects can be extracted. Figure 10 shows a downsized sample frame of one such test sequence with corresponding OF results from HS algorithm with and without turbulence.

4.3 Remarks

Atmospheric blurring acts as a low-pass filter reducing higher spatial frequencies causing a loss of contrast and an increase of (near) uniform image areas where neither BM nor OF algorithms can be estimated reliably.

One main advantage of OF over BM is that the flow field information is available for each pixel. However, the accuracy of OF algorithms is strongly reliant on a suitable choice of parameters whose suitability is in turn highly dependent on data content and quality.

Despite being the slowest of the OF methods, execution time for FB still lies approximately in the same order of magnitude as the fastest BM method, i.e. ARPS, giving the more powerful and versatile OF algorithm a clear advantage over the BM approach.

5. CONCLUSION

Motion compensation plays an integral part in many software-based turbulence mitigation algorithms therefore the robustness, speed and accuracy are rather essential criteria for the motion estimation technique that is employed. Tests were conducted on standard datasets with and without available ground truths, on simulated as well as on real turbulence data. In all cases Farnebäck algorithm performed best among the tested methods without necessitating much "parameter tweaking", giving a smooth high density flow field with reasonable accuracy and sufficient robustness. Given that the goal is ultimately to enhance atmospherically degraded image sequences containing one or more moving objects, maximizing the smoothness of the flow and at the risk of losing information about object motion may not necessarily the best course of action. Then again, turbulence-induced motion will be present on the complete image, including moving objects, and turbulence motion can be expected to change smoothly spatially as well as temporally. In the end any solution will have to be more or less of a compromise with the Farnebäck algorithm offering the best among the methods tested here. However, in applications where specific object motion has to be estimated, possibly for tracking, the faster Horn-Schunck algorithm may be better qualified.

Subject of future work will be combining two or possibly more OF methods that are parameterized for different priorities in order to allow for both, motion on a global level preferring a smooth flow, and motion on a local level permitting abrupt flow changes from moving objects. This approach promises to widen the range of possible applications to include active camera motion which has been neglected so far.

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