LOCALLY ADAPTIVE TEMPLATE SIZES FOR MATCHING REPEAT IMAGES OF MASS MOVEMENTS

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ABSTRACT

This paper presents an algorithm for locally adaptive template sizes in normalized cross-correlation (NCC) based image matching for measuring surface displacement of mass movements. After adaptively identifying candidate templates based on the image signal-to-noise ratio (SNR), the algorithm iteratively looks for the size at which the maximum cross-correlation coefficient attains a local peak and the matching position gets fixed. The algorithm is tested on Landsat7 ETM+ and radar intensity (Radarsat-2) image pairs of glacier flow. It is evaluated in comparison with globally (image-wide) fixed template sizes ranging from 11 to 101 pixels based on the performance of the matching. The adaptive algorithm results in more reliable displacement estimates as it matches the pixels more accurately.

Index Terms— Image matching, Repeat imagery, Normalized cross-correlation, Adaptive template

1. INTRODUCTION

Horizontal displacement of mass movements is measured from repeat remotely sensed images usually by matching image subsets (templates) of certain size and computing the shift in position between the two matching templates [1-4]. This approach, referred to as area-based method, most often uses the normalized cross correlation as the similarity measure between the two templates. The performance of this approach is highly influenced among others by the size of the templates being matched [5-7]. Matching with small templates is ambiguous due to inadequate signal variance or noise, while matching with large templates is affected by projective distortion due to the velocity gradient within the template. When measuring displacements on Earth surface mass movements from repeat images, two major reasons make finding a solution to this conflicting situation even more important and challenging. Firstly, Earth surface masses often move incoherently with spatially variable velocity. Secondly, image pairs or sequences are usually taken with large temporal baseline leading to significant intensity differences and noise. An optimum template size needs to compromise between the influence of ambiguity and projective distortion differently at each location.

Most of the previous attempts to deal with this problem [7-11] are made in machine vision, particularly stereoscopy, where the temporal baseline is often very short, i.e. low level of noise, and the sampling rate (pixel resolution) is very high. None of them targets Earth surface mass movements as its area of application. Most are not tested on NCC but on other similarity measures such as the Sum of Squared Differences. Most of them involve complicated statistical computation and rely on numerous

assumptions. The algorithm presented here aims at locally adaptive optimization of template sizes in NCC-based image matching for displacement measurement of Earth surface mass movements using glacier flow as an example.

2. TEMPLATE SIZE, SNR AND NCC

The SNR of an image subset varies with its size (Fig. 1). Computation made on synthetic and real remote sensing images show that SNR increases with the template size until it attains a peak. The peak is attained when edge is crossed or when new sources of signal cease to appear. If the computation proceeds with larger template sizes other peaks may appear. As the figure shows, such peaks are absent in image subsets that lack signal variance, e.g. shadows, snow-covered areas, and water bodies. The size at which the first peak is attained is the smallest size of a template with optimum SNR which can be considered as the size of smallest distinct feature at that location.

Likewise, template size determines the maximum NCC coefficient that is used in locating true matches. For an image subset with adequate signal variability, the peak of the NCC coefficient is high for small template sizes due to the noise duplicates (Fig. 2). As the template size increases, the noises get suppressed and the NCC peak decreases. After the noise is maximally suppressed the NCC peak increases and attains a peak after which it decreases again. The peak is attained at a size at which the noises are optimally suppressed, and the velocity gradient is still below a pixel. The actual matching position is therefore fixed reliably when this size is used. Larger sizes are affected by velocity gradient within the template while smaller sizes are affected by ambiguity. Image subsets that lack signal variance, or that are occluded, lack such clear peak of the NCC maxima

Therefore, SNR peak can be used to identify matchable templates while the maximization of the NCC peak can be used to unambiguously and accurately match the template. Images lacking adequate signal variability are filtered twice; first based on the maximization of SNR and then based on the maximization of the NCC peak reducing the need for manual filtering and its heuristic impacts.

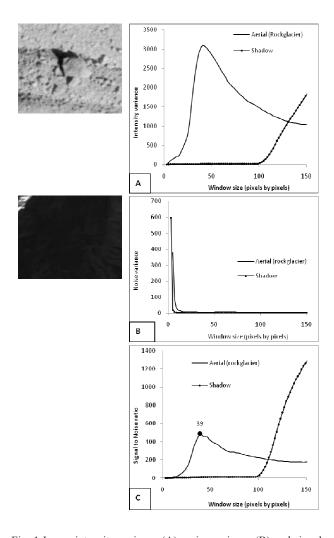


Fig. 1 Image intensity variance (A), noise variance (B) and signal-to-noise ratio together with the first local maximum (D) as plotted against the window size for an aerial image of real rock block (upper left) shadow area (lower left)

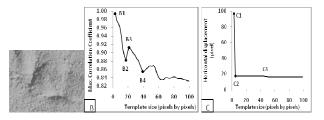


Fig. 2 The relationship between template size and the maximum NCC coefficient (B) and the displacement estimates (C) for an image subset (A) that contains good signal variance

3. METHODS

The algorithm was implemented on Landsat7 ETM+ panchromatic image pair with 15m resolution captured on June 16, 2000 and July

27, 2001 over a part of the Karakoram Mountains of Pakistan. Here, a small section over the Baltoro Glacier is used (lat 35.74°N, lon 76.43°E). A section of synthetic aperture radar (Radarsat-2) intensity images over a section of Kronebreen glacier on Svalbard, Norwegian Arctic (lat 78.87°N, lon 12.5°E; Fig 10) was also used as a second image pair. The first image is taken on April 06, 2009 while the second is taken on April 30, 2009 with a ground resolution of approximately 3 by 3 m.

Image matching is then applied using the NCC algorithm so that displacement is computed as Euclidean distance between the central pixels of the reference and matching templates. First, different globally fixed template sizes ranging from 11 to 101 pixels (with 10 pixels interval) are used. Then, the here-developed locally adaptive algorithm is applied as follows. For a given central pixel, the SNR is computed for each window size around the pixel consecutively. When the SNR attains a certain peak and starts to decrease, the algorithm stops and takes the template as matchable. If the SNR could not attain any peak, the template will be excluded. The SNR is computed as the ratio between the signal variance and noise variance which are computed separately.

Since optimum SNR does not guarantee reliable matching, optimum template size needs to be determined iteratively. The iteration computes peak of the normalized cross correlation coefficient and the matching position for each template size. The algorithm defines optimum template sizes based on the maximization of the peak of the NCC coefficient peak, which is another way of minimization of uncertainty of the matching, and accompanied fixation of the matching point. The optimization is based on the principle that the reliability of a match for a template with optimum size should be greater than not only that of other templates but also that of the same (concentric) templates with other sizes. The same search window size is used for all cases so that the comparison is conducted under the same condition and no manual filtering was conducted in order to mimic full automation.

Subjective evaluation approaches such as visualization of the velocity fields and looking for outliers and illogical displacement vectors can be used at first glance to evaluate the matching. Such approaches can identify most of the mismatches caused by ambiguity as they often result in observable gross errors. However, misrepresentation errors (i.e. errors due to velocity gradient within the template) can hardly be detected visually. Therefore, the global correlation coefficient between the old and new images before matching is computed. After matching the images and reconstructing the new image to the geometry of the old image, the new global correlation coefficient is computed. The correlation is expected to increase after the reconstruction. The method of matching that improved the correlation the most is considered the best matching approach.

4. RESULTS AND DISCUSSIONS

Fig. 3 presents displacement vectors of the Baltoro Glacier as computed using the locally adaptive algorithm. This figure shows both the strengths and the weaknesses of the algorithm. On the one hand, the fact that the algorithm could exclude most of the monotonous (dark and bright) regions from the matching and that the stable areas are mainly correctly identified as stable shows that the algorithm performs well even in such low spatial resolution images of poor quality (i.e. low contrast). On the other hand, one can observe erroneous vectors especially at the transition between shadows and bright regions. These transitions create edge-like

borders which make them pass the candidate selection step. The flowing glacier stream is however very clearly identified without any manual filtering.

Fig. 4 shows that the locally adaptive algorithm results in highest correlation between the old and the reconstructed images implying better accuracy of the image matching. For these images the initial correlation itself is already high due to the large percentage of stable ground and the presence of white monotonous snowy surfaces in the scene. Matching with globally fixed small template sizes (11 pixels) lowered the correlation coefficient of the reconstruction even below the initial due to the high level of noise (sensor and temporal) and the low spatial resolution. Consequently, small template sizes do not correctly match even the stable ground. At large template sizes the reconstruction accuracy is significantly lowered again. Large template sizes translate into large ground areas in such low resolution images, leading to comparably high velocity gradients in the templates. This shows that in such low resolution images, large template sizes significantly distort the image rather than reconstruct it.

The displacement vectors of the Kronebreen glacier have a lot of gaps (Fig. 5). The algorithm manages to exclude much of the low signal areas such as water surfaces at the lower right part of the image. Besides, the stable ground is also clearly identified by the absence of vectors. SAR intensity images are well known to be very noisy due to radar speckle. Unless the template size is very large and temporal baseline is very small, reliable displacement estimates are unlikely to be achieved. If severe deformation is involved, even large templates do not produce reliable estimates. Usually, intensive manual filtering is required to arrive at reliable displacement vectors. The algorithm here however produces very few observable mismatches reducing such manual tasks and its heuristic impact on the reliability.

Fig. 6 shows that at very small template sizes the matching is so noisy that the reconstruction itself becomes random. When globally fixed template sizes are used the quality of the reconstruction improves with the template size. It keeps on increasing up to the 101 pixels maximum pixel size used showing that even large template sizes could not optimally remove the influences of noise. The adaptive algorithm thus produces better reconstruction than all the globally fixed template sizes used. However, the number of discarded templates for lacking an acceptable level of SNR is high as expected in this image pair.

The histogram of the template sizes (not shown here) also shows that this image pairs have highest mean template size (35 pixels) due to the high noise level; compared to that of the Landsat Image of Baltoro glacier (26 pixels). The relatively smaller template size (in pixels) of the Landsat image over Baltoro glacier is ascribed to its low spatial resolution which indicates large ground template size and necessitates minimization of the projective distortion.

The principles followed in the algorithm discussed here are comprehensive of single principles developed in previous studies. Most popularly, intensity and disparity variations are used to model uncertainty of disparity estimation for different template sizes taking the size which produces the lowest uncertainty as the optimum size [7, 9, 12, 13]. In the present algorithm, intensity variation (SNR) is used to identify candidate templates and to limit the iteration. Maximization of the NCC coefficient is used as a measure of the (un)certainty of the matching. Iteration was used to arrive at the peak of the certainty.

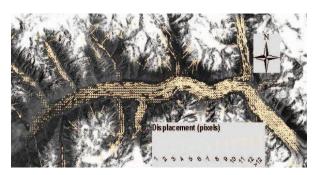


Fig. 3 Displacement vectors on the Baltoro Glacier as computed from the bi-temporal Landsat panchromatic images using the locally adaptive algorithm

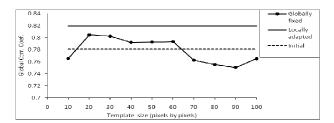


Fig. 4 Global correlation coefficients between the original reference image and the target image before (dashed line), after reconstructing using the globally fixed template sizes (dotted line) and the locally adaptive algorithm (smooth line) for the Landsat image section over the Baltoro glacier

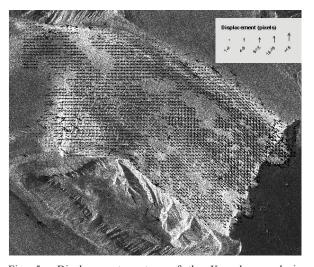


Fig. 5 Displacement vectors of the Kronebreen glacier as computed from the bi-temporal SAR images using the locally adaptive algorithm.

The algorithm is one step forward towards full automation of deformation measurement in Earth surface mass movements, which is increasingly becoming important due to the increasing need for fast and reliable monitoring system of such processes. The necessity is partly increased by the climate change driven hazardous Earth surface mass movements in high mountains

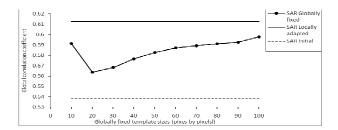


Fig. 6. Global correlation coefficients between the original reference image and the target image before (dashed line), after reconstructing using the globally fixed template sizes (dotted line) and the locally adaptive algorithm (smooth line) for the SAR image pair over Kronebreen, Svalbard.

and cold regions, sometimes with disastrous consequences. Besides, human activities are expanding to such areas enhancing further the need for reliable and fast monitoring of slope stability.

The drawback of the algorithm is that it is computationally expensive as iteration is involved in both the identification of matchable templates and finding their sizes. The process can take up to hours depending on the computer performance, the search window size and the number of templates to be processed.

6. CONCLUSIONS AND OUTLOOK

This paper presented a new algorithm for locally adaptive template sizes in Normalized Cross-Correlation (NCC)-based image matching for displacement measurement of Earth surface mass movements. Implementation of the algorithm shows that it performs better than globally fixed template sizes. The algorithm removes the mismatches due to ambiguity in small templates and reduces the errors due to projective distortion in large templates. How effectively it removes both sources of error depends on the noise content and deformation of the images. Errors due to projective distortion remain only where noise or lack of good signal variance necessitate the use of large template sizes. The algorithm discards most of the templates which lack sufficient SNR and occluded templates (i.e. templates whose matches do not exist).

The algorithm pushes displacement measurement from repeat images one step forward towards full automation. One can also use the two parts of the algorithm separately if one is interested in only either identifying matchable template or locally optimizing the template sizes assuming that the images contain high level of SNR. Further research is needed to deal with the drawbacks of the algorithm.

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