Auto-sorting scheme for image ordering applications in image mosaicing

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The problem of automated image ordering as a precursor and/or assistant process to full image mosaicing is considered. A simple but rapid auto-sorting scheme based on phase correlation is presented which can automatically and robustly provide a good ordering of a disorganised collection of images without human input, *a priori* information or restrictions.

Introduction: The requirement to construct a large, composite mosaic image from a set of smaller images arises in a large number of applications. These depend on image mosaicing techniques [1, 2] which attempt to 'stitch' a set of overlapped images together in an optimal fashion. Sometimes, there is no guarantee either that the source image set is ordered in any predictable fashion, or that any support information is available regarding imaging positions. Aiming to this problem, [3] proposed a comprehensive multi-stage approach which uses image patches and multi-view matching, in order to deliver estimates of camera positions and corrected image clusters that can be embedded in a VRML model. But such an 'all-in-one' technique may be overkill for many applications. Furthermore, because it is a feature-based method, the process will be time-consuming while dealing with high-resolution images and it needs large overlaps between images to offer sufficient correspondences. Here, we report a simpler and faster automated image ordering scheme based on phase correlation, taking the attitude that the aim of this process is merely to produce an approximate arrangement of the image collection and that the production of a full mosaic would be a later, separate process involving more advanced matching techniques.

Phase correlation: Phase correlation techniques are less robust than some feature-based approaches in mosaicing, but when only an approximate answer is required it can offer exactly what is needed for automated image ordering – rapid answers to the questions 'Are these two images overlapping with each other?' and 'Is the degree of overlap large or small?'.

Fig. 1 *Ten input images obtained from aerial imaging system used within Wells Cathedral, UK*

First row: images 1 to 5; second row: images 6 to 10
With thanks to J. Jones of Skycell, UK

Given that there is a translation parameter x between image I_1 and I_2, the value of the point r in I_2 is:

$$I_2(r) = I_1(r + x) = I_1(r) * \delta(r - x) \tag{1}$$

After a Fourier transform ψ, the phase correlation of I_1 and I_2 is:

$$\psi(I_1) = \psi(I_2)e^{j2\pi fx} \tag{2}$$

so,

$$e^{j(\varphi_1 - \varphi_2)} = e^{j2\pi fx} \tag{3}$$

By performing an inverse Fourier transform ψ^{-1} on (3), we obtain

$$d(r) = \delta(r - x) = \psi^{-1}[e^{j(\varphi_1 - \varphi_2)}] \tag{4}$$

Therefore, according to (4), we can derive the translation x by looking for the peak of the impulse function δ. In practice, when the two input images suffer from noise, pseudo-periodic structures, and/or any other unknown transformations, there will be multiple peaks, but there will normally be a single principle peak if the images do overlap. Fig. 1 shows an example. A stained glass window was imaged from multiple positions using a digital camera carried by a remote-controlled airborne vehicle operated by Skycell Ltd. An intervening beam and hanging cable obscure some views – owing to parallax effects they do not appear in image 1, but both objects appear in image 2, while image 3 includes just the beam, but in a different position. These are serious sources of misinformation and could confuse feature-based approaches. However, as shown in Fig. 2, using the phase correlation technique produces a principle peak which is still quite obvious and which has an impressively high relative contrast. In general, the larger the principle peak, the larger the size and quality of the overlap region.

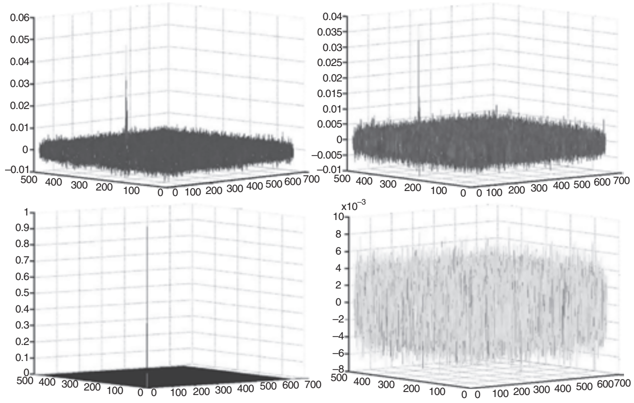

Fig. 2 *Principle peak of pair image 1 and image 2 is 0.0521 (top left); principle peak of image 1 and image 3 is 0.0398 (top right); principle peak of image 1 correlated with itself is 1 (bottom right); there is no obvious principle peak for pair image 1 and image 8, maximum is only 0.0085*

Note, different scales used for each plot

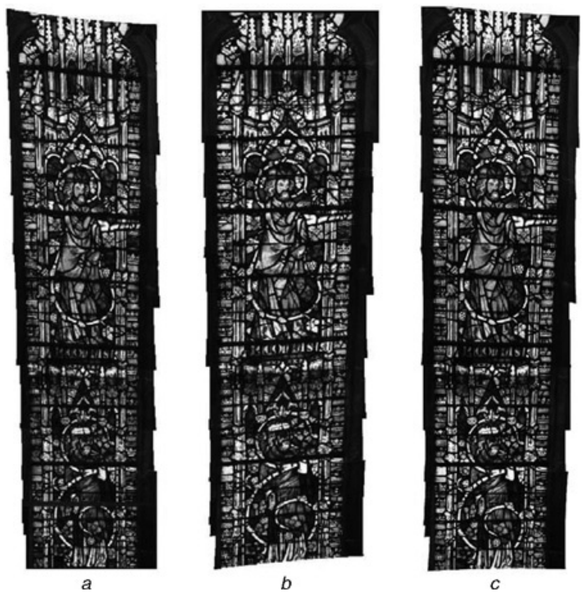

Fig. 3 *Different stitching orders lead to different mosaicing results*

a Stitching order from image 1 to image 10
b Stitching order from image 10 to image 1
c First stitch the five images in first row from image 5 to image 1 and, independently, stitch the five images in second row from image 6 to image 10
Finally stitch two partial mosaics together

Auto-sorting scheme for image ordering: Many mosaicing approaches are based on local misfit measures between pairs of adjacent images and, owing to accumulated errors [4] and unknown/incorrect corrections for lens and positional distortions, the process is highly nonlinear – different stitching orders lead to different mosaiced results (Fig. 3). Further, the use of multiple camera positions means that the exact relationship between any two overlapped images within a multi-row image sequence is effectively random. Essentially, the scheme here is not only to look for realistic positional relationships for the collection of input images but also to try to use the correlation information to define an optimal order in which to later stitch them. The basic principle is hence an iterative approach where the image to be stitched next is chosen as that with the largest/best overlap (correlation) with the images already placed in the current mosaic. Broadly, larger overlaps should offer more information and more matching points for the estimation of positional information. So, constructing the mosaic initially using those images with higher correlations (larger overlaps, and more reliable matching) should produce smaller registration errors. This will minimise the error accumulation early on in the mosaicing process and will reduce the cumulative effect of errors in the final mosaic. Thus we first compute the phase-correlation peaks for all image pairs. Then we can find the largest peak (most reliable matching pair) and stitch the corresponding two images, say m and n, together. Then we seek image k which has the largest sum of peaks with m and n (the next image in the sequence could overlap with several images that have already been placed – it is hence the total correlation with the existing mosaic structure that matters) and also stitch it into the existing mosaic. We keep performing this strategy in an iterative fashion for the remaining images. In effect, we ‘grow’ a composite mosaic by iteratively attaching that image out of the collection which has the largest sum of correlation peaks with those images that have already been stitched into the mosaic at that stage.

Fig. 4 *Twenty images from outer wall of south transept of York Minster, UK*

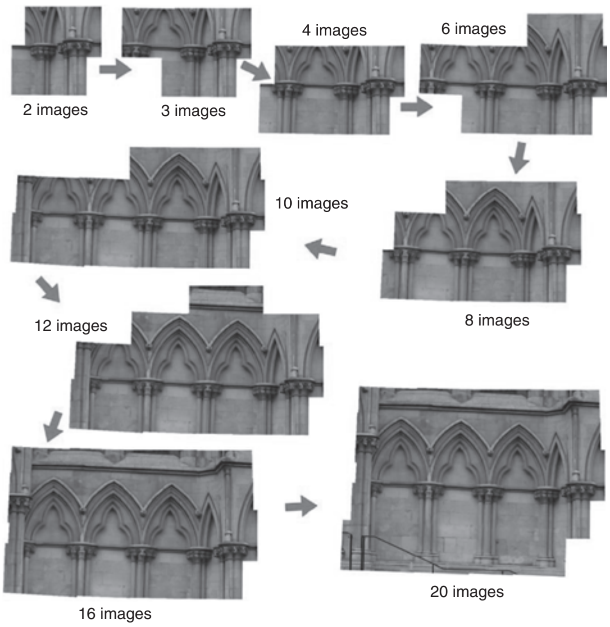

Fig. 5 *Selected stages in process of constructing final mosaic image*

Results: As a practical example, we first load 20 disordered images as shown in Fig. 4. The images contain repeated deceptive objects – without a larger context, some are so similar that is difficult to differentiate them by eye. Number them in terms of their loading order (in Fig. 4, from left to right and top to bottom, the top left image is image 1, the one next to it on the right is image 2 and the bottom right image is image 20). The strongest correlation is found between images 2 and 20, which defines the starting point for the iterative process, and the consequent stitching order is: 2 20 1 5 15 16 4 18 19 7 6 13 17 10 9 14 8 3 12 11. Fig. 5 illustrates this process at various stages of construction.

Conclusion: We report a simple, rapid and complete method for automatic sequencing of a disordered set of images. The method can be used to produce an approximate ordering of images, as just the first stage of a multi-stage mosaicing process, but also provides information that can be used to guide a mosaicing process in order to reduce error accumulation. In the latter case, the image having the largest overlap with the current mosaic is always given priority for stitching. Practical tests indicate that the scheme is robust and can find a good stitching order for multiple images with varying degrees of overlap, multiple deceptive features and occluding objects.

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