HIGH-RESOLUTION IMAGE GENERATION USING WARPING TRANSFORMATIONS

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Abstract: In recent years the emphasis for applications of 3D modelling has shifted from measurement to visualization. New communication and visualization technologies have created an important demand for photo-realistic content in 3D real-time animations, interactive fly-overs and walk-arounds, panoramic images, visualizations and simulations based on real-world data.
These image-based approaches require acquisition procedures that are simple and flexible with the use of consumer photo- or video-cameras. Ideally the user should be able to move freely while acquiring the images with any device ranging from a mobile phone to a video camera. In this context, a device independent algorithm for the estimation of an enhanced resolution image from multiple low-resolution and distorted compressed video images having arbitrary views is proposed in this paper.
This process of spatial image enhancement is demonstrated here in a controlled scenario whereby the different views of the same scene are warped, firstly, to a common orientation so that a rigorous least squares area-based matching technique can then compute the registration parameters needed for their accurate combination. The sequence is acquired using a digital camera in video mode, which samples the image of a static scene from different angles.
The warping is an iterative process relying on manual intervention and is used here to compensate for the different range of scales and orientations of the low-resolution imagery. Once this imagery is brought into registration and complies with pre-established image correlation criteria, they are combined to recover a high-resolution composite. Although the quality and resolution of the sensor arrays used to capture digital data continue to evolve, it is important that any technique used to enhance spatial resolution must be device independent, thus capable of using input from not only low-resolution images but also from higher resolution devices.

1 INTRODUCTION

Off-the-shelf digital video cameras employ low-resolution sensors that sub-sample the original image sequence. The imagery obtained from video sequences is often compressed in a lossy manner, such as by the MPEG (Moving Picture Expert Group) protocol, in order to reduce the storage requirements (Russ, 2007).

Lossy compression means that data is lost during compression so the quality after decoding is less than the original picture. Lossy compression protocols also introduce several distortions that can complicate the enhancement problem. For example, most compression algorithms divide the original image into blocks that are processed independently, thus creating problems of continuity between blocks after decompression (Farsiu et al. 2004).

Moreover, at high compression ratios (>15:1, as suggested in (Reed, 2005 and Bovik, 2005)), the boundaries between the blocks become visible and lead to ‘‘blocking’’ artefacts. The blocking effect is especially obvious in flat areas of an image. In areas with lots of detail, artefacts referred to as ringing or mosquito noise also become noticeable.

Yet, video sequences contain a large overlap between successive frames, and regions in the scene of interest are sampled in several images and often from different perspective. This multiple sampling can be used to reconstruct imagery with a higher spatial resolution if the images in the sequence are accurately registered, one to another (Vandewalle et al, 2005). The result is then similar to using a high-resolution camera.

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On the other hand, video frames cannot be related through global transformations due to arbitrary pixel movements between the images. As a result, images of the same scene taken from slightly different angles and distances to the same object introduce geometric distortions (i.e., parallel lines are not parallel, angles are not correct, distances appear too long or too short, etc.).

Hence, the arbitrary and distorted views of the scene of interest must first be iteratively warped to a common orientation before an accurate registration procedure can compute the parameters needed for a correct sub-pixel registration.

The least squares area based registration method employed here provides for an efficient and reliable scheme designed to match or align low-resolution images of the same scene. The methodology is capable of achieving sub-pixel accuracies of approximately 0.1 pixels. This technique can also overcome difficulties arising from slight radiometric differences, that is, slight differences in grey scale levels due to varying illumination conditions in the images being matched.

Once all the low-resolution images are brought into sub-pixel registration and comply with pre-established image correlation criteria, the images are combined to recover the desired high-resolution composite. In addition to improving the spatial resolution, the method may also attenuate artefacts caused by lossy compression protocols.

In summary, the basic steps of the proposed image enhancement technique are divided into three main tasks:

- Warping transformations
- Image registration to a sub-pixel level and
- Reconstruction via image mapping on a higher resolution and uniformly distributed grid.

Details of how these three problems are solved are presented in the following sections.

2 WARPING AND RESAMPLING

Image warping is a geometric transformation that maps all positions from one image plane to positions in a second plane. It is used to solve many digital image-processing problems such as removing optical distortions introduced by a camera and a particular viewing perspective or registering an image with a map.

Warping is closely related to the popular image metamorphosis, or morphing technique, and is used extensively to produce special effects in the field of computer graphics and the entertainment industry.

In most iterative warping systems, the user specifies the warp in some very general way, for example by moving grid lines or by specifying point-to-point correspondence or control points (Zitova et. al., 2004). A computerised system then automatically interpolates these geometric specifications.

Amongst the diverse warping models available, the use of generic polynomials is often considered appropriate due to the simplicity of application and accuracy requirements (Russ, 2007). Polynomials are widely used as an approximating function in all types of data analysis.

The level of detail in the data that can be approximated depends directly on the order of the polynomial. The polynomial models are determined by first defining a set of control points (CPs) on each image (source and target) which correspond to pixel locations that must align together. This is necessary to constrain the polynomial coefficients. Ideally the control points should have the following characteristics:

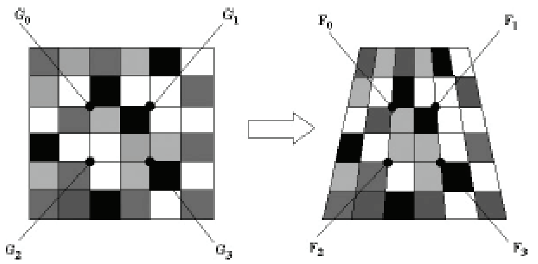
- High contrast in all images of interest
- Small feature size
- Unchanging over time
- Coplanar

Choosing the optimal warping procedure is problematic, with the approach taken here to use a warping process to stretch and pull the source images about defined CPs. This yields images that conform to particular geometric and scene requirements. The pixels are then repositioned, by way of interpolation techniques, from their original locations in the data array, into a specified reference grid dictated by the selected CPs.

Finding corresponding CPs in an image is the most tedious aspect of warping transformations, since it usually requires manual intervention to determine their optimal location. Determining optimal CPs automatically (i.e. without human participation) is desirable and is a subject of further research by the author.

An illustration of the warping process used in the experimental part of the proposed image enhancement process is given in Figure 1, showing a distorted grid on the right that has undergone a geometric transformation from an original grid (on the left) making it appear trapezoidal in shape. Located in the centre of the rectangular grid are four points that can be related to the corresponding points in the distorted grid

The geometric association between these eight points describes the geometric distortion between the trapezoidal and the rectangular grids. It is also due to this geometric relationship that these eight points are referred to as the CPs.



$G_0 \rightarrow F_0$; $G_1 \rightarrow F_1$; $G_2 \rightarrow F_2$; $G_2 \rightarrow F_2$

Figure 1: An example of a trapezoidal distortion of a rectangular grid.

If G(*r, s*) describes the original grid and F(*x, y*) the trapezoidal grid, then the coordinates of these CPs can be related through a set of bilinear equations as:

$$x = a_1 r + a_2 s + a_3 rs + a_4 \tag{1}$$

$$y = a_5 r + a_6 s + a_7 rs + a_8 \tag{2}$$

where the coefficients a_i (i = 1…8) determine the actual geometric relationship between the original and distorted grids.

Given that there are eight unknown coefficients and four corresponding CPs on each grid, then a unique and simple solution is possible. Equations (1) and (2) can produce only linear geometric transformations, so to correct for arbitrary and complex curvatures or distortions, higher order terms may be needed. Typically, equations (1) and (2) can be expanded to include higher order terms or to construct spline models (Gonzalez, 2007).

The concept of removing the geometric distortions from a grid can be easily transferred to that of a digital image. Indeed, the CPs in the grid example above could be considered as relating four pixels in the undistorted image to four pixels in the geometrically distorted image.

The approach used in this study is to use many closely spaced CPs and model the geometric distortion within the region defined by those points as linear. Each set of CPs corrects the pixels just within the region enclosed by the control points. The results in Figure 2 were achieved using this process.

The disadvantage of using this method is the quantity of CPs needed for very complex geometric distortions. In implementing equations (1) and (2), every pixel in the restored image G(*r,s*) is obtained by using the mapping coordinates *x, y* in the geometrically distorted image F(*x,y*) and the CPs associated with that pixel.

For two given images (distorted and reference) of the same scene, the warping process will usually need to be iterated until the selected distorted image clearly resembles the selected target or reference image. Tests by the author show the warping process is satisfactory when the correlation coefficient between the two registered images is greater or equal to 0.999.

Figure 2: A distorted image (a) is warped to create the image in (b) where proportions are rectified.

Figure 2 shows the results of warping or transforming the image in Figure 2(a) into the image in Figure 2(b) after 14 warping attempts. 45 CPs were used in this process. By way of illustration, only a few of the total number of CPs are shown in the figure.

The use of contiguous triangles between three control points and with linear polynomial transformations in each triangle usually eliminates the discontinuities of the boundaries. The distortion is then modelled by a piecewise set of planes, similar to a faceted surface.

When using a network of CPs, it may not be necessary to warp all the triangle areas with the same number of iterations. For instance, intuitively it could be expected that the ocean areas in Figure 2, which are smooth with low detail features, would require fewer warping iterations than the building regions.

Since the (x,y) pixel coordinates of the warped image will no longer be integer values, new integer pixels must be estimated by an interpolation process. There exist many interpolation methods, the most common being the nearest neighbour, bilinear, cubic convolution and splines techniques.

The spatial and local interpolation technique considered here was the nearest neighbour interpolation. Although bilinear interpolation and cubic convolution may yield more visually pleasing results the nearest neighbour approach is generally used when radiometric fidelity is at a premium (Russ, 2007).

Once all the low-resolution images are processed and warped to a common orientation using the methodology described above, the next step is to register or match all the low resolution images to a common reference frame and thereby determine the value of the sub-pixels shifts existing (if any) among them.

3 IMAGE REGISTRATION

In an idealised scene registration, two different images of the same object are assumed to be essentially identical except for an x and y shift. In practice, with distorted and multi-temporal video frames, the two images will generally exhibit substantial differences beyond this assumption. These differences can be classified as:

- Intensity differences, - e.g. the images are taken at different times or under different lighting conditions;
- Structural differences, - e.g. between the taking of the two images the common objects may have altered; and
- Geometric differences, - e.g. the motion of the camera may cause geometric differences such as rotation, aspect and scale in the object.

Even though two images may both be of the same scene, these differences of intensity, structure, and geometry will often be sufficient to produce erroneous registrations. If the differences of intensity and structures are very small, the reference image can be thought of as an exact map of the object scene and scene matching can be characterised as map matching.

On the other hand, when the differences between two images are large, the reference information may no longer be a map but somewhat like directions given to a lost tourist: 'Turn left at the set of lights, follow the road past the church and then turn right after the park'. With this knowledge, the tourist can effectively perform the scene-matching function and find his way to his intended destination.

Analogously, when there is a considerable difference between two images, simple matching algorithms will not work and so some iterative warping of one image relative to the other must take place before the images can appear similar and be combined into a higher resolution composite.

The registration problem can be stated as finding the transformation T (the warping transform) that, when applied to one image $F(x, y)$, will ultimately bring the object detail into registration with the corresponding detail in another image $G(r, s)$, such that:

$$T * F(x,y) = G(r,s) \tag{3}$$

where the symbol = means equivalence of object detail.

The result of applying the warping transformation T to all the low-resolution images is used to carry out a preliminary alignment of all the low-resolution images. The alignment assumes that there is only a global translation among the images and, as a preliminary step, this alignment is carried out within the integer range. This initial step is referred to as the pixel shift estimator and is based on normalized cross-correlation techniques.

After the low-resolution images are aligned within a pixel, the second step is to compute the real fractional shift between each image. The method for estimating this fractional shift is based on Taylor series and can achieve sub-pixel accuracies of approximately 0.1 pixels. The reader is referred to Pilgrim (1991) for the theory and formulation behind this methodology.

For a correct detection of the shifts or offsets between two images, the images must contain some features that make it possible to register or match them.

Very sharp edges and small details are most affected by aliasing, so they are not reliable to be used to estimate these shifts. Uniform areas are useless, since they are translation invariant

(Hendriks et al. 1999). The best features are slow transitions between two areas of grey values as these areas are generally unaffected by aliasing. Such portions of an image need not be detected specifically, although their presence is very important for an accurate result. Hence, before a given sequence of images of the same scene is registered, a low-pass filter may be applied uniformly to each image. The purpose of a low-pass filter, as shown in Figure 3, is to smooth:

- Sharp edges and small details
- Sudden changes of intensity values and
- The distortions created by the compression process.

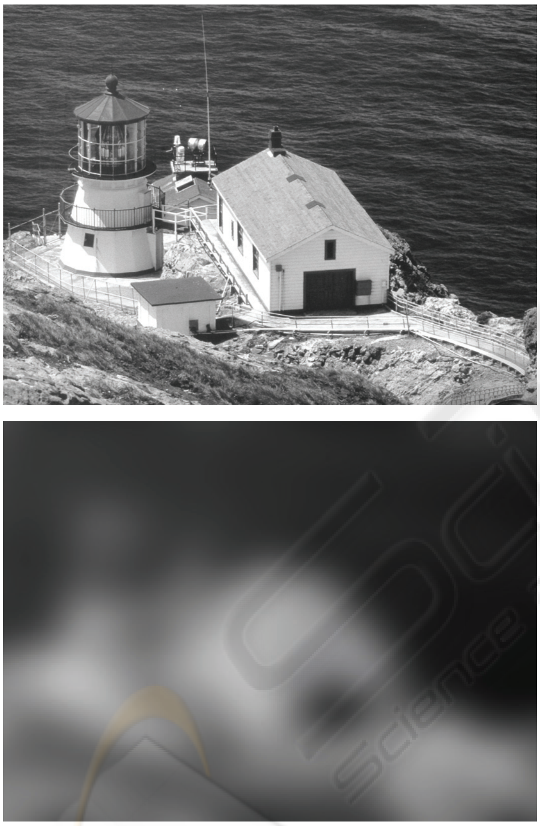


Figure 3: The lighthouse (top) and after applying a low-pass filter (Gaussian, 18 pixels radius, below).

The motion estimator (registration procedure) adopted in this research determines the x- and y-shifts and rotations between any two images, but what is really required is the relative positions of a sequence of images. By calculating the shifts with respect to a single reference image, only one realization of the relative positions is obtained. By repeating the procedure for another reference image, a second estimate for the relative positions is made.

Continuing to repeat this process for all images in the sequence, a better estimate of the relative shifts, image to image, can be found. The statistical measure used to determine the ‘best’ possible value for all possible combinations of the motion vectors between a set of shifted low-resolution images is the vector median.

If the vector mean was taken instead of the median, then the final motion vector would be an entirely new vector, and not one of the vectors originally estimated. In addition, the mean is less robust than the median if outliers are present (Spiegel et al., 1999).

4 IMAGE RECONSTRUCTION

Once all the low-resolution images have been warped and registered to a sub-pixel level, they are projected or mapped on a uniformly spaced high-resolution grid (see Figure 4). A weighted arithmetic mean associates each known pixel of the low-resolution images to the high-resolution pixels.

For example, in Figure 4 the low-resolution pixel C1 can be related to the pixels of the high-resolution grid by way of Equation 4. In Figure 4 the Xi (i=1…25) represent the high-resolution pixels whereas the Cj, (j=1…6) are the low-resolution pixel.

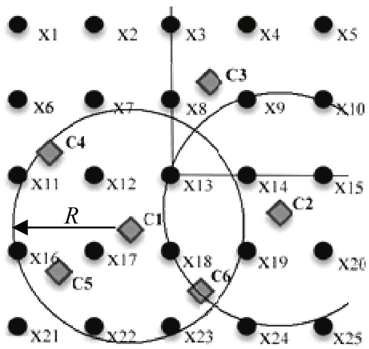


Figure 4: An idealized image enhancement set-up.

After C1 is related to the high-resolution coordinate system, the process moves on to the next low-resolution data pixel (i.e. C2) where another equation is constructed. This sequence of equations may be thought of as “observation equations” where the unknowns are the values of the high-resolution pixels (Xi). These linear equations can be solved by traditional least squares techniques (for example, Fryer et al., 2001).

$$C1 = \frac{w_{12}x_{12}+w_{13}x_{13}+w_{16}x_{16}+w_{17}x_{17}+\ldots+w_{23}x_{23}}{w_{12}+w_{13}+w_{16}+w_{17}\ldots+w_{23}} \quad (4)$$

The weights (w) are defined by the inverse of the distance that separates the low-resolution pixel from the unknown high-resolution pixels that fall within a circle of constant radius (R). This circle is centred on each low-resolution pixel as shown in Figure 4.

The dimension of the radius R depends on the magnification factor required. As a general rule, if the magnification factor is chosen to be equal to 2 then the minimum radius for the circle required to search all the high-resolution pixels is $2\sqrt{2}$. On the other hand, if the chosen magnification factor is n then the minimum search radius is taken as $n\sqrt{n}$, etc.

The example in Figure 4 relates to a magnification factor of 3 where the final high-resolution composite will have 3 times more pixel values in each coordinate direction than any of the low-resolution images. To comply with sampling theory, R must ensure that an overlapping occurs between the circles, as it is important that each of the unknown high-resolution pixels appear at least twice in different observation equations.

Note that there will be an equation for each low-resolution pixel, being the number of equations at least equal or greater than the number of desired high-resolution pixels in the final enhanced composite. Hence, when (say) five suitably overlapping images each of modest size 500x500 are considered, it becomes apparent that 500x500x5 = 1.25 million observation equations could be formed. If a magnification factor of 2 is chosen, then the resultant resolution enhanced image will exceed in size 1000 x 1000 thus requiring the solution of 1 million linear simultaneous equations.

Although more computationally expensive, as compared to direct interpolation methods, the process minimizes the error variance and sets the mean of the prediction errors to zero so that there are no over- or under-estimates. An important feature of this “reverse mapping” process is that it also gives an estimation of the error at each computed point, thus providing a measure of confidence for the accuracy and precision of each high-resolution pixel of the enhanced composite.

5 THE TEST IMAGES

To explore the performance of the image enhancement algorithm using images requiring warping, a sequence of dynamic low-resolution images of a lighthouse was taken with a digital camera in video mode. They were taken under similar lighting conditions, but each with slightly different scale, views and aspect.

These high-resolution images were then warped and subsequently matched to determine the sub-pixel shifts existing amongst them. The shifts were then used to map the low-resolution as described in the previous section and used to form the observation equations required to construct a high-resolution composite of the same scene.

A section of 640x480 pixels depicting the lighthouse was cropped from an image of a large poster taken at a resolution of 2560X1920 using a digital camera in still mode for a JPEG compression ratio of approximately 6 (as illustrated in Figure 5). This image section was considered as the true image in the following test.

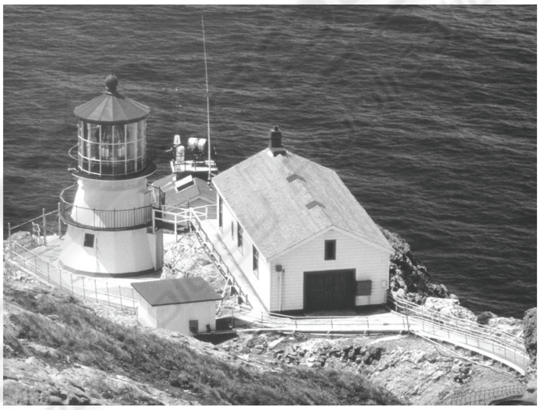


Figure 5: The original true image of the lighthouse (640x480).

The objective was to investigate how well a resolution-enhanced image could be recovered from 40 MPEG compressed image sections of the same scene extracted from the same camera in video mode. The video sequence was taken at a resolution of 640x480 and by moving the camera so as to sample the object of interest from slightly different angles and distances.

The 40 low-resolution images were cropped to be approximately of dimensions 160x120 pixels so as to depict the same scene. Figure 6 shows one of these low-resolution images.

For statistical purposes care was taken to obtain one of these low-resolution images (reference image) from exactly the same distance and perspective view as the true image. This was attained by fixing the camera to a tripod.

Since there were 40 low-resolution images, 39 different sub-pixel shifts in x and y could be defined for each image with respect to each of the others. All the low-resolution images were manually warped

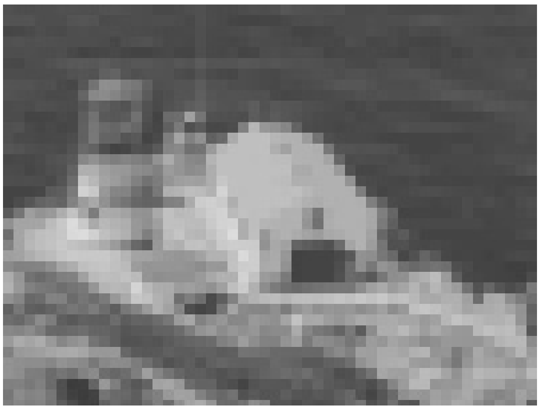


Figure 6: One example of the 40 low-resolution images (160x120).

Figure 7: The high-resolution composite (640x480) as constructed using 40 low-resolution distorted images (160x120).

as described in section 4 and aligned with the reference image. This tedious operation involved an average of 40 control points per image mostly distributed with the building areas of the image.

An enhanced image was then computed for a magnification factor of 4, and using the shifts as determined by the vector median of all possible combinations. Figure 7 shows the final enhanced composite.

The root mean square (r.m.s.) of the difference between the reconstructed composite shown in Figure 7 and the full resolution image or true image in Figure 5 was computed as ±5.22 grey-scale values with a correlation coefficient of 0.99968.

6 NUMBER OF IMAGES

The required number of low-resolution images generally depends on the distribution of the shifts, as well as on the signal-to-noise ratio, and the amount of noise present. For instance, to minimise the influence of noise it is important that the distribution of the shifts between the low-resolution images be as complete as possible.

The reconstruction of a higher resolution image with the minimum number of low-resolution images is possible, but it should not be expected to always achieve a high accuracy, especially for higher magnification factors (>5). High magnification factors require large numbers of low resolution images, meaning that these low resolution images must be relatively close to one another, that is, relatively small offsets.

The accuracy of detecting those offsets will clearly affect the accuracy of the final composite image as the uncertainty in an offset's determination may be of the same magnitude as the offset itself (Scarmana G. and Fryer J., 2006).

7 CONCLUSIONS

A procedure for reconstructing a high-resolution image from a sequence of low-resolution, distorted and compressed image sequences has been described.

The method makes use of an image warping technique to align or register the low-resolution and distorted images to a common reference framework. The results for a sequence of 40 video images of a static image that were manually warped in order to be compatible for the enhancement algorithm, showed an r.m.s. comparison with a higher resolution "true" image of +/- 5.22 grey scale values.

Refinements to the proposed methodology are presently being explored in an effort to further enhance the spatial and brightness resolution and thereby expand the range of applications that may benefit from using the proposed technique for image enhancement of small dynamic objects. Small is defined such that the total number of pixels on the border of the objects is significant, as compared to the amount of pixels within the object.

This is typical of objects of interest which appear small if compared to the field of view of the images and the relatively large distance between the image sensor and the scene (i.e., faces in security cameras).

The author is also currently investigating the possibility of adapting this enhancement process to a more generalised scheme whereby both sensor and object are dynamic and the illumination is non-uniform. A considerable amount of manual input was required to select control points for the warping procedure, and although there is an argument for manual input, investigations into automating the warping process with the automatic detection of specific landmarks on the images is under consideration.

The image enhancement algorithm described in this paper expands the possibilities for using either low-cost digital still cameras, video camcorders or even the new generation of videophones to obtain suitable imagery for numerous applications in security, forensic measurement, architecture, archaeology and other non-traditional areas of digital image processing.

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