REPERCUSSIONS OF USING SURFACE MODELS OF GREATER FIDELITY IN AREA-BASED MATCHING

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ABSTRACT

Area-based least squares matching is the most accurate technique for matching un-targetted surface points, but further refinement of the accuracy and reliability of the area-based technique is possible. This paper explores the benefits of enhancing the fidelity of the pixel co-ordinate transformation model, as a means of extending the window size, to improve accuracy and reliability. Surface models, based on first- and second-order surface gradients within the match patches have been developed. However, the models require numerous parameters, including co-ordinates of the corresponding point on the right image, relative orientation parameters of the cameras and surface gradients, and the computational load is heavier. Greater intricacy in the geometric models deserves to be explored only if the improved accuracy and reliability is not offset by the cost of increased complexity.

With the revised models higher precision was achieved. The number of iterations in the least squares solution was reduced, suggesting that the functional model had been improved. Computation times were only marginally improved, despite the reduced number of iterations. Larger window sizes can be used. Because the results were more precise, the complexity is justified, and modelling the surface mathematically, as an alternative to the conventional surface element models, is advantageous.

More complex models could produce further improvements to accuracy and reliability, but precisions can deteriorate if the model is too complex for the surface. It is suggested that the complexity of the model needs to vary with the complexity of the surface, and the model therefore needs to be adaptive.

1 DEFICIENCIES IN AREA-BASED POINT TRANSFER

Development of the so-called area-based least squares matching method may seem now to be complete. After all, it was first outlined around 15 years ago, (Förstner, 1982; Grün, 1985), and saw significant developments within a decade, e.g., by Rosenholm (1987). Attention has been given to the use of multiple images (e.g., Grün and Baltsavias, 1988), and multiple points (e.g., Li, 1991), and to the means of selecting initial match points (e.g., Hannah, 1989). Now the number of papers concerning development of area-based matching has recently dwindled. But it is argued that further refinement of the accuracy and reliability of area-based matching techniques, which, given sufficient image texture, is the most accurate technique for matching un-targetted surface points, is still possible and warranted. Although impressive developments in photogrammetric matching theory and practice have occurred over the past decade, and their effectiveness is indicated by the commercial availability of software for DTM generation of topographic areas from stereoscopic pairs of aerial photographs, the use of stereo-image matching software for automated DTM generation has not achieved absolute reliability in practice. See, e.g. Baltsavias *et al.,* 1996, for a report of matching success rates in a practical case. In close-range measurement, when the objects are typically more convoluted than the topography seen on aerial photographs, matching may be expected to be even less reliable. So, while the study of area-based matching has seen a decline in the number of photogrammetric research publications, opportunities clearly still exist to further refine the matching technique. Heipke, (1996, Section 1) argued that "*... matching ... still is one of the most challenging tasks in photogrammetric research and development*". And, according to Walker (1999), "*The automatic generation of DTMs* *by image matching is another accepted, stable part of digital photogrammetry. The difficulties of matching in certain types of terrain and with certain types of imagery is well known. The requirement for human editting is acknowledged ...*". Matters such as resolving ambiguous matches, pixel intensity interpolation procedures and the choice of the best match criterion, offer scope for further development to provide greater reliability, speed, versatility and accuracy. This paper focusses specifically on refinement of the fundamental mathematical model, which concerns the co-ordinate transformation between the pixels of image patches used for the point transfer.

The benefit of improving the geometric model is that, because only pixels fitting the selected co-ordinate transformation should be used in the match, enhancement of the fidelity of the transformation model is a possible means of extending the window size. This in turn allows a greater number of pixels to be incorporated legitimately into the least squares solution, thereby increasing the number of redundancies, improving accuracy and reliability. Krupnik & Schenk, (1997, p161) argue for larger windows to improve reliability in matching for aerial triangulation, and the use of a larger number of image points is supported by Heipke (1996). Even though greater intelligence appears to be needed to improve work-station robustness in the task of matching of aerial photography, according to Heipke (1997), he draws attention to Ackermann's assertion that, *"It is the basic philosophy of low level automation to replace intelligence functions by redundancy,..."* (Ackermann, 1996). Redundancy can be achieved through multiple imagery, but this paper, instead, argues for redundancy through greater pixel numbers: it investigates the use of surface models based on first- and second-order surface gradients within the match patches. If the benefit of the model, in terms of improved accuracy and reliability, is not offset by the cost of increased complexity, it may suggest that yet further intricacy in the geometric models, and perhaps the radiometric models, deserves to be explored. Mustaffar (1996), Mitchell & Mustaffar (1997) and Mustaffar & Mitchell (1999) have previously reported the development and testing of the models described here, but this paper concentrates on the argument behind the changes, and the costs and benefits of the revised algorithm.

2 THE ROLE OF GEOMETRIC MODELS IN AREA-BASED MATCHING

The aim of area-based matching is presumed to be the determination of correspondence for a single "point of interest". The matching method uses a window of pixels around the point of interest to provide sufficient signal to alleviate the ill-posed nature of the matching, a problem which is highlighted by Heipke (1996, Section 2; 1997). However, all points in the window, not just one specific point of interest, are "matched", so point transfer is achieved for all points in the window, and not necessarily the centre of the window of comparison, as implied by Heipke (1996, section 3.1.1). ("Point transfer" is therefore not necessarily a good term. Transfer of any point can be calculated, given the transformation obtained from the match results).

Although the area-based matching theory has often been given before, (e.g., Förstner, 1982; Grün 1985, Rosenholm (1987), it is useful to repeat some aspects of it here to clarify some issues. Area-based matching is an image intensity correlation procedure, which compares the radiometric intensity at a number of selected positions on one image and the intensities at conjugate (sub-pixel) positions on another image. Area-based matching is regarded as low-level processing, as the signal is not interpreted. Accordingly, the name "area-based matching" is preferred here to "signal-based matching". The radiometric intensity at a number of selected positions on one image is compared with the intensity at conjugate (if necessary sub-pixel) positions on another image, with some allowance for noise, via the basic relationship of area-based matching:-

$$I_L(x_L, y_L) + n(x_L, y_L) = I_R(x_R, y_R) \qquad (1)$$

where

- I_L and I_R are the intensities of the corresponding left and right pixels (or at sub-pixel points);
- x_L, y_L are the image co-ordinates of the left pixel;
- x_R, y_R are the corresponding image co-ordinates on the right image; and
- $n(x_L,y_L)$ is the difference caused by noise, allocated to the point on the left image.

(The images are assumed here to be "left" and "right", denoted by sub-scripts L and R, not 1 and 2.)

Clearly, in this form, Eqn. (1) cannot be used in a least squares solution as it does not allow us to solve for x_R or y_R. But recognising that the initial estimates of x_R or y_R need to be improved by dx_R and dy_R, Eqn. (1) can be expanded to:

$$I_L(x_L, y_L) + n(x_L, y_L) = I_R(x_R, y_R) + \left(\frac{\partial I_R}{\partial x_R}\right)dx_R + \left(\frac{\partial I_R}{\partial y_R}\right)dy_R \tag{2}$$

The terms dI_R/dx_R and dI_R/dy_R are the gradients of the intensities in the x and y directions across the image, and are estimated numerically. Eqn. (2) is useable if all points in the window require the same positional corrections, (dx_R, dy_R). But a transformation based on shifts only is clearly too simplistic. Corresponding pixels are more generally related by a co-ordinate transformation model, whose parameters can be introduced into Eqn. (2), so that they are also determined in the least squares solution. The task of the **geometric model** in area-based matching of two images is to provide a co-ordinate transformation to enable the determination of which co-ordinates (x_R, y_R) for a pixel abstracted from the right image (say) corresponds to the pixel having co-ordinates (x_L, y_L) abstracted from the left image. If the co-ordinate transformation is given by:

$$x_R = f_{xR}(x_L, y_L, a_1, a_2, ...) \tag{3a}$$
$$y_R = f_{yR}(x_L, y_L, b_1, b_2, ...) \tag{3b}$$

where a_i and b_i are parameters of the transformation between x_L, y_L and x_R, y_R, then dx_R and dy_R can be replaced in Eqn. (2) by the corrections to the parameters, using:

$$dx_R = (\partial f_{xR}/\partial da_1)\ da_1 + ...$$
$$dy_R = (\partial f_{yR}/\partial db_1)\ db_1 + ...$$

giving:

$$I_L(x_L, y_L) + n(x_L, y_L) = I_R(x_R, y_R) + [(\frac{\partial fx_R}{\partial a_1})da_1 + ...]\frac{dI_R}{dx_R} + [(\frac{\partial fy_R}{\partial b_1})db_1 + ...]\frac{dI_R}{dy_R} \tag{4}$$

In practice, the transformation function is often simplified by creating a window or patch co-ordinate system, with the origin of the left window co-ordinates located at the point of interest on the left image and that of the right image at the initially estimated conjugate point.

A least squares solution is most frequently utilised to find the corrections, da_1, etc., and hence the transformation parameters. Solution of the relevant (linearised) equations for the transformation parameters by least squares is not considered further here. Back substitution of any (x_L,y_L) values then gives the corresponding (x_R,y_R). It may now be noted that the window does not have to be a rectangular. The points used need not even be contiguous! Moreover, the point of interest does not have to be the centre of the window, and the transformation applies to all points chosen. Indeed, the point of interest being transferred need not even be one of those used in the solution! However, it will be apparent that the fidelity of the transformation model adopted in area-based matching is crucial.

It is worth recognising that the introduction of the gradients dI/dx and dI/dy in the equation shows that the signal variation, i.e., the texture, is important, and perhaps even that low texture areas can be excluded from the solution.

3 SELECTION OF A TRANSFORMATION FUNCTION

The question now is: what is the pixel co-ordinate transformation to be used? A rigorous relationship between a pair of points on two images can be derived using two pairs of collinearity equations, in terms of object space co-ordinates as well as image co-ordinates. But each pair of pixels will introduce a new set of object point co-ordinates, so this model introduces a different set of transformation parameters for each point, which is unworkable, because it introduces too many parameters. Avoiding this problem by using the coplanarity equations is assumed to be too complicated. The problem of having a complex model and too many transformation parameters has been overcome in most area-based matching by using a single transformation relationship which holds for all pairs of conjugate pixels for each window. This approach may involve eliminating or ignoring the object co-ordinates and relating the image co-ordinates of conjugate pixels by a transformation whose parameters are the same for all pixel pairs. No information of the object is taken into account in the matching process. A bivariate polynomial can be used, (Grün, 1996, p220), but more typically, for a small but plane window, the projective transformation is approximated by a six-parameter affine transformation "*because the facet image is formed by a narrow bundle of rays*", (Grün, 1996, p221). Because matching uses only those pixels in those sub-areas of the images in which the affine relationship still holds, the windows must be kept "small".

For a more rigorous alternative for a plane surface, the perspective projection equations can be reduced to two transformation equations in eight parameters. These again are not directly related to the surface co-ordinates, but the approach does have the advantage of using parameters which have a physical meaning.

It should be noted that, for any of the models described above, information is normally available on the orientation and location parameters of the imaging devices, and this information can be utilised to constrain the various possible transformations between the conjugate points (which also helps to ameliorate the ill-posed nature of the problem). An "epipolar condition" recognises that, if the relative orientation is indeed known, then the relationship between y_R and x_R at the point corresponding to (x_L, y_L) is known, so that either x_R or y_R only need be found.

More rigorous models are discussed by some writers. Grün (1985, p180) raises the prospect of models incorporating the spatial structure of the object; see also, e.g., Grün (1996) or Heipke (1997), but reports of the practical implementation of such models and their evaluation are rare. Models based on multiple patches are of interest because they represent attempts to develop and incorporate models of the surface, but they are ignored from here on as they adopt a finite-element surface representation rather than a mathematical function for the surface. Similarly, the extension of the theory sketched above to global matching, involving surface geometry and radiometry models covering the complete areas of interest on the image must also be mentioned, as they incorporate a mathematical surface model, but their complexity suggests that they be treated as a separate category to those covered here.

A radiometric model is normally also used to relate image intensities, and for this study, a simple two-parameter radiometric model was incorporated in the model, but that aspect of the model is not relevant to the pixel co-ordinate transformation under discussion, and radiometric considerations are ignored from this point.

4 TRANSFORMATIONS BASED ON PLANE AND CURVED SURFACE MODELS

The problem of having too many transformation parameters has been overcome here by adopting a surface model across the window. The theory of the surface models has been developed previously by Mustaffar (1996), Mitchell & Mustaffar (1997) and Mustaffar & Mitchell (1999) and only the crucial elements are reproduced here. The known co-ordinates, (x_L,y_L), of the point of interest on the left image are related to the unknown object space co-ordinates (X_O,Y_O,Z_O) through the collinearity equations. If the neighbouring points within the left window are at position increments $(\Delta x_L,\Delta y_L)$ from the transfer point in x and y directions respectively, and if the differences between the transfer point co-ordinates (X_O,Y_O,Z_O) and the positional incremented ground point are given by ΔX, ΔY and ΔZ, then $\Delta x_L,\Delta y_L$ effectively establish a local co-ordinate system for the window, and, through the collinearity equations:

$$x_L+\Delta x_L = f_{x_L}(X_O+\Delta X, Y_O+\Delta Y, Z_O+\Delta Z) \tag{5}$$

and similarly for y_L , x_R, and y_R . These are effectively a variant of equations given by Grün (1996, Eqn. 8.3.10). The four equations can be combined to create the co-ordinate transformation, which involves the gradient parameters of the corresponding surface patches. That is, the basic equation can be linearised to:

$$\begin{aligned} I_L(x_L+\Delta x_L, y_L+\Delta y_L)+n(x_L+\Delta x_L, y_L+\Delta y_L) &= I_R(x_R+\Delta x_R, y_R+\Delta y_R) \\ &+\left(\frac{\partial I_R}{\partial x_R}\right)dx_R+\left(\frac{\partial I_R}{\partial y_R}\right)dy_R+\left(\frac{\partial I_R}{\partial x_R}\right)d\Delta x_R+\left(\frac{\partial I_R}{\partial y_R}\right)d\Delta y_R \end{aligned} \tag{6}$$

which is a variation on Eqn. (2). The unknown terms are dx_R and dy_R, (corrections to the initial estimates of the co-ordinates of the point of interest), and $d\Delta x_R$ and $d\Delta y_R$ (corrections to the positions of other points in the window).

Suppose that matching is to be done for a surface which is plane within the image window. The model specifies that a change of elevation (ΔZ) at any point on the surface is related to the positional increments in X and Y directions:

$$\Delta Z = \frac{\partial Z}{\partial X}\Delta X + \frac{\partial Z}{\partial Y}\Delta Y \tag{7}$$

where ($\partial Z/\partial X$) and ($\partial Z/\partial Y$) are the gradients of Z in X and Y directions respectively. They define the model surface and are evaluated in the solution. Mustaffar (1996), Mitchell & Mustaffar (1997) and Mustaffar & Mitchell (1999) show that:

$$\begin{aligned}\Delta x_R = &\left(\frac{\partial x_R}{\partial X}\cdot\frac{\partial X}{\partial x_L} + \frac{\partial x_R}{\partial Y}\cdot\frac{\partial Y}{\partial x_L}\right)\Delta x_L + \left(\frac{\partial x_R}{\partial X}\cdot\frac{\partial X}{\partial y_L} + \frac{\partial x_R}{\partial Y}\cdot\frac{\partial Y}{\partial y_L}\right)\Delta y_L \\ &+ \left(\frac{\partial x_R}{\partial Z}\cdot\frac{\partial X}{\partial x_L}\Delta x_L + \frac{\partial x_R}{\partial Z}\cdot\frac{\partial X}{\partial y_L}\Delta y_L\right)G_X + \left(\frac{\partial x_R}{\partial Z}\cdot\frac{\partial Y}{\partial x_L}\Delta x_L + \frac{\partial x_R}{\partial Z}\cdot\frac{\partial Y}{\partial y_L}\Delta y_L\right)G_Y\end{aligned} \tag{8}$$

where parameters G_X and G_Y define the plane surface model, and are unknowns which can be found in the solution.
This equation determines the position at which I_R is evaluated in Eqn. (6). Further, in Eqn. (6), the small correction $d\Delta x_R$ may be written in terms of corrections to G_X and G_Y, i.e., in terms of dG_X and dG_Y.

$$d\Delta x_R = \frac{\partial \Delta x_R}{\partial G_X} dG_X + \frac{\partial \Delta x_R}{\partial G_Y} dG_Y \tag{9}$$

The corrections $d\Delta x_R$ and $d\Delta y_R$ can be written in terms of corrections to the surface gradients. The partial derivatives ($\partial\Delta x_R/\partial G_X$) and ($\partial\Delta x_R/\partial G_Y$) are obtained directly from Eqn. (9):

$$\frac{\partial \Delta x_R}{\partial G_X} = \frac{\partial x_R}{\partial Z}\cdot\frac{\partial X}{\partial x_L}\Delta x_L + \frac{\partial x_R}{\partial Z}\cdot\frac{\partial X}{\partial y_L}\Delta y_L \tag{10a}$$

$$\frac{\partial \Delta x_R}{\partial G_Y} = \frac{\partial x_R}{\partial Z}\cdot\frac{\partial Y}{\partial x_L}\Delta x_L + \frac{\partial x_R}{\partial Z}\cdot\frac{\partial Y}{\partial y_L}\Delta y_L \tag{10b}$$

Similarly, relationships for Δy_R and $d\Delta y_R$ are obtained. When matching is to be done for curved surfaces elements, the planar surface model must be replaced with an appropriate higher order surface model so that the fidelity of the transformation between the windows remains high. A second order surface has been introduced by Mitchell & Mustaffar (1997) and Mustaffar & Mitchell (1999) by extending Eqn. (7):

$$\Delta Z = \frac{\partial Z}{\partial X}\Delta X + \frac{\partial Z}{\partial Y}\Delta Y + \frac{1}{2}\cdot\frac{\partial^2 Z}{\partial X^2}\Delta X^2 + \frac{1}{2}\cdot\frac{\partial^2 Z}{\partial Y^2}\Delta Y^2 + \frac{\partial^2 Z}{\partial X \partial Y}\Delta X \Delta Y \tag{11}$$

The equivalent of eqn. (8) is:

$$
\begin{aligned}
\Delta x_R = {} & \frac{\partial x_R}{\partial X}\left(\frac{\partial X}{\partial x_L}\Delta x_L + \frac{\partial X}{\partial y_L}\Delta y_L\right) + \frac{\partial x_R}{\partial Y}\left(\frac{\partial Y}{\partial x_L}\Delta x_L + \frac{\partial Y}{\partial y_L}\Delta y_L\right) \\
& + \frac{\partial x_R}{\partial Z}\left\{G_X\left(\frac{\partial X}{\partial x_L}\Delta x_L + \frac{\partial X}{\partial y_L}\Delta y_L\right) + G_Y\left(\frac{\partial Y}{\partial x_L}\Delta x_L + \frac{\partial Y}{\partial y_L}\Delta y_L\right)\right. \\
& + \frac{1}{2}G_{XX}\left(\frac{\partial X}{\partial x_L}\Delta x_L + \frac{\partial X}{\partial y_L}\Delta y_L\right)^2 + G_{XY}\left(\frac{\partial X}{\partial x_L}\Delta x_L + \frac{\partial X}{\partial y_L}\Delta x_L\right)\left(\frac{\partial Y}{\partial x_L}\Delta x_L + \frac{\partial Y}{\partial y_L}\Delta x_L\right) \\
& \left. + \frac{1}{2}G_{YY}\left(\frac{\partial Y}{\partial x_L}\Delta x_L + \frac{\partial Y}{\partial y_L}\Delta y_L\right)^2 \right\}
\end{aligned}
\tag{12}
$$

where $(\partial Z / \partial X), (\partial Z / \partial Y), (\partial^2 Z / \partial X^2), (\partial^2 Z / \partial Y^2)$ and $(\partial^2 Z / \partial X \partial Y)$ are replaced by G_X, G_Y, G_{XX}, G_{YY}, and G_{XY} respectively, the five unknown surface model parameters, and the equivalent of Eqn. (9) is:

$$
\begin{aligned}
d\Delta x_R = {} & \frac{\partial \Delta x_R}{\partial G_X} dG_X + \frac{\partial \Delta x_R}{\partial G_Y} dG_Y + \frac{\partial \Delta x_R}{\partial G_{XX}} dG_{XX} \\
& + \frac{\partial \Delta x_R}{\partial G_{YY}} dG_{YY} + \frac{\partial \Delta x_R}{\partial G_{XY}} dG_{XY}
\end{aligned}
$$

The partial derivatives $(\partial \Delta x_R / \partial G_X)$ and $(\partial \Delta x_R / \partial G_Y)$ are as given by Eqns. (12a) and (12b) respectively, while the partial derivatives $(\partial \Delta x_R / \partial G_{XX})$, $(\partial \Delta x_R / \partial G_{YY})$ and $(\partial \Delta x_R / \partial G_{XY})$ are given by the equivalent of Eqn. (10)

$$
\frac{\partial \Delta x_R}{\partial G_{XX}} = \frac{1}{2} \cdot \frac{\partial x_R}{\partial Z}\left(\frac{\partial X}{\partial x_L}\Delta x_L + \frac{\partial X}{\partial y_L}\Delta y_L\right)^2 \tag{13a}
$$

$$
\frac{\partial \Delta x_R}{\partial G_{YY}} = \frac{1}{2} \cdot \frac{\partial x_R}{\partial Z}\left(\frac{\partial Y}{\partial x_L}\Delta x_L + \frac{\partial Y}{\partial y_L}\Delta y_L\right)^2 \tag{13b}
$$

$$
\frac{\partial \Delta x_R}{\partial G_{XY}} = \frac{\partial x_R}{\partial Z}\left(\frac{\partial X}{\partial x_L}\Delta x_L + \frac{\partial X}{\partial y_L}\Delta y_L\right)\left(\frac{\partial Y}{\partial x_L}\Delta x_L + \frac{\partial Y}{\partial y_L}\Delta y_L\right) \tag{13c}
$$

Disadvantages of the surface models approach, in comparison with the conventional area based matching based on the affine transformation, are:

a) The integration of a surface model and the collinearity conditions into the basic area-based matching functional model has made the proposed method more complex than the conventional method. As a result the computational load is heavier.
b) The revised method requires co-ordinates of the point in the left window, provisional co-ordinates of the corresponding point on the right image, relative orientation parameters of the cameras/sensors and provisional values of the surface's gradients while the conventional affine method requires only provisional co-ordinates of the point in the right window and provisional affine transformation parameters, usually simply zero or unity.
c) The use of the surface gradients usually means that *a priori* knowledge of the surface is required to derive their estimates, which can however be estimated by a series of initial affine-transformation-based matches.
d) Since the proposed method is based on the relative orientations of the images, any inaccuracies in the orientation parameters might affect the fidelity of the transformation between the images.

There may seem to no apparent advantage over the 8 parameter projective transformation. However, the parameters here are geometrically meaningful, and it is also possible to assess whether the surface slopes are realistic values for the object, and sensible initial values can be allocated to the parameters.

5 TESTING

The revised algorithm was compared with and the affine-based solution using images of a flat plate, a cylinder of known diameter, and the sole of a mannequin's foot. Photogrammetric details are given by Mustaffar (1996), Mitchell & Mustaffar (1997) and Mustaffar & Mitchell (1999). Sixty-six suitable pairs of points were selected for matching from the images of the plate, 95 pairs were found for the cylinder, and 301 from the images of the foot. The same pairs of points were used for all comparisons between models. In the experiments, the sizes of the windows were varied considerably, from 9 x 9 to 101 x 101 pixels.

Internal precision, as indicated by the size of the semi-major axis of the error ellipses for the positional increment parameters computed in the least squares adjustment, and the number of iterations required in the solution, were used as the primary basis for comparisons, on the assumption that they are indicators of the model fidelity, which is the matter of interest in this study. The number of iterations in the least squares solution reveal that the revised models more faithfully represent reality. Despite the reduced number of iterations, computation times were only marginally improved, presumably because of the greater computational complexity. The extensive results can best be summarised by Table 1. Accuracy is not reported here because absolute accuracy can be influenced by other sources of error, so an improvement in accuracy is not necessarily a meaningful indicator of point transfer accuracy alone.

Table 1: Summary of results obtained with planar and curvilinear surface models, compared with solution based on affine transformation as geometric model.

Object	Planar Surface Model	Curvilinear Surface Model
Plate	• Precision was much better than conventional matching method, by a factor of two or more, except for window sizes below 10 x 10 pixels. • Fewer iterations (around 50%) were needed than for conventional method. • Computation times were reduced by about 20% for all window sizes.	• Precision was better than the conventional method, but not as good as for the planar model on the same object. • Fewer iterations (around 50%) were needed than for conventional method. • Computation times were reduced by about 10%.
Cylinder	• Precision was generally better by at least a factor of two. • Fewer iterations (around 50%) were needed than for conventional method. • Computation times were reduced.	• Precision slightly better than planar model • Fewer iterations (around 50%) were needed than for conventional method. • Computation times similar to conventional model, (slower than planar model).
Foot	• Precision from the planar model was generally better by a factor of about two. • Fewer iterations (around 80% improvement) were needed than for conventional method. • Computation times were reduced.	• Precision from the planar model was generally better by a factor of about two. • Fewer iterations (around 80% improvement) were needed than for conventional method. • Computation times were increased.

6 CONCLUSIONS

While it is recognised that the results apply to the images as used, with their particular texture characteristics and their particular orientation values, some trends ae apparent. The integration of the collinearity conditions and surface shapes into the conventional area-based algorithm creates an enhanced model in area-based matching. Consequently, the functional model is much more complex than the conventional method. For both the plate and the cylinder, the internal precision of both the planar model and curvature model methods is much higher than matching based on the affine transformation. Computation times were mostly marginally improved but the number of iterations in the least squares solution were invariably reduced, which suggests that the widely-used conventional functional model has been improved to fit the observations more closely. Although precision is improved over the affine-based solution for any window size, even larger window sizes can be used. However, selection of the optimum window size is difficult. Modelling the errors introduced by the transformation model at different window sizes is complicated. The problem of finding the maximum window size for different surface curvatures also deserves to be investigated.

Because the results were more precise, the complexity is justifiable. Modelling the surface mathematically, as an alternative to surface element models, is advantageous. Moreover, it seems useful to further refine the model. More complex models may produce further improvements to accuracy and reliability, and opportunities to develop area-based matching remain. The complexity of the model needs to vary with the complexity of the surface, and it is suggested that the model therefore needs to be adaptive.

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