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Relative accuracy of spin-image-based registration of partial capitate bones in 4DCT of the wrist

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Abstract

In image-based biomechanical analyses, registration transformations are the data of interest. In dynamic 4DCT imaging the capitate is often partially imaged. While alignment of incomplete objects poses a significant registration challenge, the established spin-image surface-matching algorithm can be utilized to align two surfaces representing disparate but overlapping portions of an object. For this reason the spin-image algorithm was chosen for the registration of partial bone geometry in 4DCT of the wrist. Registrations were performed on eleven 4DCT datasets using complete and partial capitate meshes generated by cropping complete meshes. Relative accuracy was assessed as the difference between partial- and complete-geometry registrations. Accurate registration of partial capitates geometry was achieved with 55% of the proximal capitate geometry on average, and in some cases as little as 35%. Requisite geometry depends on feature salience and imaging resolution, however the spin-image algorithm should be considered a valuable tool for biomechanists and image analysts.

1. INTRODUCTION

In medical image processing, registration refers to the transformation of multiple image sets into a single coordinate system and it is employed to increase the diagnostic usefulness of the images (Goshtasby 2005, Maintz and Viergever 1998). In image-based kinematic analyses, registration transformations *are* the data of interest (Banks and Hodge 1996, Miranda et al. 2013, Tashman and Anderst 2003), i.e. the transformations quantify the relative positions and orientations of imaged objects in serial image sets. When used with a dynamic imaging modality, registration allows for the quantification of joint movement between image volumes ('frames') under physiological loading. However, because of object

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size or position relative to a finite field-of-view or longitudinal coverage, it is often necessary to register partially-imaged objects. When an object cannot be completely imaged, the registration problem is exacerbated. In particular, the absence of some geometry from one or both image sets being co-registered means that only the geometry common to both image sets can be used to establish the relative pose (position and orientation) of a given object in the image sets. Further, discerning common geometry presents its own challenge. In this work, we propose to characterize the relative accuracy of registration-based pose estimation in four-dimensional computed tomography, where partial geometry poses a significant limitation.

Four-dimensional computed tomography (4DCT) is a medical imaging modality that acquires a temporal sequence of image volumes of anatomical structures in motion (Garcia-Elias et al. 2013, Leng et al. 2011, Shores et al. 2013). In this regard, it is comparable to cine CT (Rees et al. 1986, Song and Leahy 1991) or cine MRI (Asakawa et al. 2003, Sheehan et al. 1999); however these methods are either gated, requiring cyclic/repeatable motions (acquiring each image volume from a subsequent cycle of the motion), or they acquire a series of static image volumes that are later sequenced into a movie, merely simulating motion. A recently developed ‘active-MR’ protocol allows for continuous acquisition of wrist motion, but it only acquires a single planar slice through the joint (Boutin et al. 2013). As implemented in this study, 4DCT allows for the acquisition of freely moving joints without constraints on reproducibility of the motion; it captures the entire range of wrist motion in approximately 2 seconds with a temporal resolution of 75ms (Leng, Zhao, Qu, An, Berger and McCollough 2011). Because it can acquire less constrained in-vivo motion, 4DCT has the potential to aid in early diagnosis of orthopedic injuries where symptoms are present only during motion. However 4DCT has a limited capture volume, restricted along the z-axis by the size of the x-ray detector array(s) used and the size of the field of view, often resulting in partial imaging of some of the structures being imaged.

The issue of partial acquisition in 4DCT imaging has been previously described (Leng, Zhao, Qu, An, Berger and McCollough 2011), and although x-ray detector array size varies by scanner/manufacture, larger detector arrays (and greater longitudinal coverage) come at the expense of lower temporal resolutions and sampling rates (Shores, Demehri and Chhabra 2013, Vereecke et al. 2013). Insufficient temporal resolution results in motion artifacting and blurring (Leng et al. 2012), which can only be abated by restricting movements to slower, often un-physiological speeds. Leng et al. (2011) have demonstrated the potential utility of 4DCT for visualizing carpal bones during movement, however, depending on individual wrist size, distal row carpal bones may only be partially imaged when the wrist is in the neutral position; i.e. when the fingertips and palm are aligned with the axis of the forearm. The capitate is located in the distal carpal row and is of particular interest because it tracks well with the third metacarpal (Rainbow et al. 2013), and can provide a quantitative measure of overall wrist motion. Unfortunately, there is significant variation in the portion of the bone imaged throughout the wrist range of motion; the distal pole of the bone enters and leaves the imaged volume during the movement cycle. To remedy this difficulty in registration, we propose the use of Johnson and Hebert’s spin-image algorithm (Johnson 1997, Johnson and Hebert 1998, Johnson and Hebert 1999), as it is robust to clutter, occlusion, and partial geometry.

Spin-images are object-centered descriptors of an object's shape, which are used as a feature space for establishing corresponding points on the two surfaces to be registered. These correspondences are filtered and grouped using geometric consistency. From each group of correspondences, a rigid body transformation (aligning the two surfaces) is calculated. These transformations are then 'verified' by confirming that a sufficient number of points on each surface are well-aligned by calculating the distance between corresponding points on the overlapping portions of the two surfaces after transformation. Verified transformations—those exhibiting a large number of points where the distance between the aligned surfaces is small—are then refined to yield a more accurate alignment. A more detailed explanation of our implementation of the spin-image algorithm is provided in section 2.3.

The spin-image algorithm was chosen to register partial bone surfaces because of its robustness to occlusion and partial geometry, and its ability to align surfaces with few salient features (Johnson and Hebert 1998, 1999). The algorithm is insensitive to the completeness of the mesh of an object because it is correspondence-based; it specifically seeks out the common geometry between the surfaces being registered. Correspondence-based approaches also allow for closed-form solutions for alignment (Arun et al. 1987, Challis 1995, Eggert et al. 1997, Horn 1987), reducing the problem of local-minima present in optimization-based solutions. For these reasons, the absence of some portion of the capitate bone in 4DCT can be overcome using this algorithm.

The purpose of the present study was to assess the viability of the spin-image algorithm as a method to register partial capitate bone surfaces from 4DCT. Our goal was to assess the relative effect of missing geometry on spin-image based registration accuracy. Registrations were performed using the complete capitate geometry and distally cropped geometry, to mimic partial acquisition of the bone. Partial-geometry registrations were performed using 30% to 95% of the proximal capitate, in 5% increments. The approach simulates the worst-case scenario in which the least geometry would be available, i.e. when the wrist passes through the neutral position. These data are useful because omission of large, continuous portions of an object will influence the algorithm's ability to register the object, potentially preventing accurate registration. This is especially true for the capitate as its proximal pole is practically hemispherical and largely devoid of salient features, making determination of its orientation difficult in the absence of the distal features. When the remaining partial geometry is insufficient, in quantity or uniqueness, the algorithm will be unable to accurately estimate the alignment of the capitate. However, it was hypothesized that sufficient geometry *will* be present even when a considerable portion (at least half) of the distal capitate is missing. Further, it is hypothesized that omission of geometry will have only a marginal effect on registration accuracy, assuming that registration can be achieved. The work described herein is an expansion and refinement of a previous study of a single case with fewer partial registration cases and only a single set of scans (Breighner et al. 2013).

2. METHODS

In this section, the 4DCT datasets used in this study are described, followed by a the segmentation and meshing methods used to generate mesh data for the spin-image

registration algorithm. We then present an overview of the spin-image algorithm itself. Finally, we describe the measures of relative registration accuracy used for evaluating the algorithm.

2.1 Scan Data

In this study, registration experiments were conducted on 11 pairs of image sets (from 9 wrists) as collected in vivo, under a larger IRB-approved study of wrist biomechanics. Each pair included a static (conventional) CT from the mid-forearm through the fingertips, with the wrist in the neutral position, and an 18-volume 4DCT motion sequence during either a complete flexion/extension or radial/ulnar deviation cycle. CT scans were performed using a Siemens SOMATOM Definition Flash dual-source CT scanner and a modified cardiac perfusion protocol (Leng, Zhao, Qu, An, Berger and McCollough 2011). Image reconstruction was done using the Siemens B70 edge-enhancing kernel. Voxel dimensions of the scans were 0.234mm in-plane and 0.4mm in the longitudinal direction, and subsequently converted to isotropic at the in-plane resolution (0.234mm). From the 18 dynamic volumes of the 4DCTs, one volume in which the entire capitate was visible was selected, to which the capitate from the conventional CT would be registered. A more detailed description of these imaging protocols is available in Leng et al. (2011).

2.2 Segmentation and Meshing

The capitate bone geometry was segmented from both the conventional static and selected 4DCT image volumes for each subject using global thresholding followed by a graph-based connected components method (Salembier and Serra 1995). Subsequently, the segmented capitates were meshed using marching cubes (Lorensen and Cline 1987) followed by an adaptive deformation approach (Lin and Robb 2000). Preprocessing was performed using Analyze 11.0 software (Mayo Clinic Biomedical Imaging Resource, Rochester, MN). Meshes were then reduced to their external hulls using a hidden-points-removal (HPR) algorithm (Katz et al. 2007). The HPR algorithm establishes the ‘visibility’ of points (mesh vertices) from a specified viewpoint. In our implementation of HPR, the viewpoint was initially placed a fixed distance (50mm) from the centroid of each mesh and run iteratively as the viewpoint was rotated around each mesh in 18° increments, aggregating the externally visible vertices. This was done to ensure that only the outer cortex of the bone would be meshed. Further, the HPR algorithm also reduced total spin-image algorithm computation time by directly reducing the number of vertices matched and eliminated points from interior surfaces that were dissimilar between the meshes being co-registered. Segmentation differences, partial-volume effects, and differing signal intensities due to motion caused the differences in these interior points during acquisition (Figure 1). For convenience, the complete capitate surface mesh from conventional CT will be referred to as the ‘source,’ and the surface from 4DCT will be called the ‘target.’

2.3 The spin-image surface matching algorithm

The spin-image algorithm consists of 5 main steps: generation, establishing candidate correspondences, correspondence filtering and grouping, transformation verification, and refinement. Mesh resolution, used in setting parameters and constants in the algorithm, is

defined as the median length of all mesh edges in the source mesh (approximately 0.63 mm in this study).

Spin-image generation for any vertex begins with the establishment of an oriented-point basis; a local coordinate system centered with an axis aligned with the vertex's unit normal vector. In this pseudo-cylindrical coordinate system, radial (α) and longitudinal (β) distances from the vertex are calculated (Figure 2). The 2D plotting of the projected coordinates (α , β) produces a spin map (Figure 3a). A spin-image (Figure 3b) is the 2D histogram of the spin map. Bilinear interpolation is used to distribute the contribution of points in the spin map to pixels in the spin-image. The intensity of each pixel denotes the sum of point contributions from the spin-map to the pixel.

Spin-images are governed by three parameters that specify image descriptiveness and size; image width (W), pixel or bin size (b_s), and support angle (A_s). The first two parameters, W and b_s , characterize the size and resolution of spin-images. Image width specifies width and height of the images in pixels, and pixel size denotes the size of the bins. Johnson and Hebert (1998) established that bin size should be set between 1–2x the mesh resolution. Parameters are uniform for the entire mesh and are generally the same for target and source meshes.

Bin size and image width determine the support distance, D_s (equation 1), which constrains the maximum allowable Euclidean distance separating included points from the oriented point for which the image is being generated.

$$D_s = W \times b_s \quad [1]$$

The support angle, A_s , excludes all points whose vertex normals point in a direction that is greater than A_s away from the oriented point's normal. From the literature, we have set the support angle to 60° (Johnson and Hebert 1998). Image width was 30 and bin size was set to 1x mesh resolution. These values allow spin-images to be matched between incomplete surfaces by restricting the included points to a subset of points representing surface geometry common to the two surfaces being aligned. Spin-images are generated for all vertices in the source mesh and a random subset of vertices in the target mesh.

Candidate correspondences are established between target and source vertices using a similarity measure, Q , that relates their respective spin-images, incorporating image correlation coefficient I and the number of overlapping bins (N) via a weighted loss function (eqn. 2, Appendix B of Johnson (1997)). Lambda (λ) is automatically set to one-half of the median number of overlapping pixels for all target-source point combinations for which spin-images have been generated.

$$Q = \text{atanh}^2(R) - \frac{\lambda}{N-3} \quad [2]$$

Extreme upper outliers of the similarity measure, where values exceed the median by 3 times the interquartile range, are plausible correspondences. An example of two highly similar spin-images is shown in figures 4a and 4c, from target and source vertices, respectively.

Plausible correspondences are then filtered, first by eliminating those with similarity measures less than one-half of the maximum of all correspondences for each target point. Geometric consistency, D_{gc} , is the difference in spin-map distances (α, β) between two correspondences in the source and target meshes, and is used to further filter correspondences (eqn. 3). In both equations 3 and 4, $(\alpha, \beta)_{X_{ij}}$ denotes a vector locating the vertex in correspondence j with respect to the vertex in correspondence i in spin-map coordinates, where X specifies whether this vector is between the points in the source ($X = S$) or target ($X = T$). An upper threshold of 0.25 is used to filter D_{gc} ; that is, a set of two correspondences is said to be geometrically consistent if the distance between the two source points and the distance between their plausibly-corresponding target points differ by less than one-quarter of the average of the two distances in spin-map space. An individual correspondence is deemed geometrically consistent if, when paired with other correspondences, is geometrically consistent with at least $\frac{1}{4}$ of the correspondences remaining after the culling of correspondences using the similarity measure. Consistent correspondences are then grouped with other correspondences with which they are geometrically consistent using a grouping criterion, W_{gc} (eqn. 4), combining geometric consistency with weighting that favors correspondences that are far apart.

$$D_{gc}(C_i, C_j) = \frac{\|(\alpha, \beta)_{S_{ij}} - (\alpha, \beta)_{T_{ij}}\|}{\left(\|(\alpha, \beta)_{S_{ij}}\| + \|(\alpha, \beta)_{T_{ij}}\| \right) / 2} \quad [3]$$

$$W_{gc}(C_i, C_j) = \frac{D_{gc}(C_i, C_j)}{1 - \left[\exp \left(\|(\alpha, \beta)_{S_{ij}}\| + \|(\alpha, \beta)_{T_{ij}}\| \right) / 2\gamma \right]} \quad [4]$$

Combining geometric consistency and the Euclidean spacing between correspondences, the grouping criterion encourages accurate registration (by ensuring valid correspondences) and robustness to noise (because of broader separation of correspondences) (Chua and Jarvis 1996) as cited in (Johnson and Hebert 1998). Gamma (γ) is a constant, set to 4x mesh resolution. An upper bound of 0.25 is placed on the grouping criterion. Note that as geometric consistency and the grouping criterion are both asymmetric, i.e. $D_{gc}(C_i, C_j) \neq D_{gc}(C_j, C_i)$, the greater of the two values is always used. Starting with a seed correspondence (any geometrically consistent correspondence), other correspondences which satisfy the upper bound on W_{gc} are grouped with the seed until no more can be added. This is repeated for all geometrically consistent correspondences.

Johnson's original algorithm calculated transformations for each group of correspondences, first as quaternions (after Horn (1987)) and converted to transformation matrices. Our implementation uses a comparable method that calculates these transformations directly, eliminating the intermediate use of quaternions (Arun, Huang and Blostein 1987, Challis 1995, Eggert, Lorusso and Fischer 1997). Verification of plausible transformations follows, beginning with correspondence spreading—the recursive addition of vertices connected to established correspondence points on the target mesh and their nearest neighbors on the source mesh when the 6-dimensional distance (encoding vertex location and normal) between the two is below a fixed threshold of twice the mesh resolution. If the number of resulting correspondences (from both initial matching and spreading) is greater than 25–33% (Johnson and Hebert 1999) of the number of vertices in the source mesh, the match is 'verified.' Verified matches are refined using a more conventional alignment approach, iterative closest points (Besl and McKay 1992). To objectively obtain a repeatable registration, our implementation used the number of correspondences after verification (initial spin-image plus spread correspondences) as a criterion for the best match. Refinement is performed on this 'best' transformation; the ICP transformation is combined with the spin-image matching transformation to yield an overall registration transformation.

2.4 Relative Accuracy Measures

Processed meshes of the complete target and source capitates were registered using the spin-image algorithm. The effect of partial geometry on registration was assessed as the relative accuracy of registrations obtained using partial target surface geometries when compared to registration using the entire target surface. Partial geometries used were proximal portions (30–95%) of the complete 4DCT mesh. 'Proximal' is herein defined as the negative z direction (along the CT bore axis), when the wrist is in the neutral position. The complete target was aligned with the complete source using the inverse of the complete-geometry registration transformation; it was then reduced to the proximal submesh, and returned to its initial position and orientation. This simulated the situation in which longitudinal coverage of 4DCT was most restrictive with respect to available capitate geometry; in practice, the smallest amount of capitate geometry is captured in 4DCT when the wrist is passing through the neutral position. Figure 6 shows a complete target capitate surface, and 30% and 40% proximal regions used for partial registration.

Relative registration accuracy was determined as the difference between partial-geometry registrations and the complete-geometry registration. The translational errors are simply the remaining translations. Angular errors were obtained by Cardan angle decomposition of the remaining rotation, using a sequence beginning with the primary axis of motion and ending with the bore axis.

3. RESULTS

The spin-image algorithm was capable of achieving adequate registration with substantial geometry missing. Registration was achieved in 8 out of 11 of the 30% partial geometry registration cases. Failure to register (FTR) was defined as either a failure of the algorithm to identify a sufficient number of geometrically consistent and 'groupable' correspondences (at

least 3 are required) or when angular error magnitude exceeded 10 degrees after refinement. The 10-degree condition was chosen as it indicates that the spin-image match was insufficient to serve as an initial alignment for ICP-based refinement. Two of the FTR cases occurred under the former, and one under the latter condition. All registrations were successful for the remaining cases.

Figure 7 shows that while registration accuracy is relatively poor for 30% partial registrations, it improves appreciably between the 30 and 40% partial-mesh registrations. Sub-degree errors about any single axis are achieved with 40% partial geometry. Angular error magnitudes on the order of a single degree were, on average, achieved with approximately 55% of the original target mesh. Barring the FTR cases, sub-millimeter translational accuracy was seen universally. In figure 6, the mean values reported are determined from the absolute value of errors.

4. DISCUSSION AND CONCLUSION

Determining bone and joint kinematics (rotations and displacements) from dynamically acquired medical image sets requires accurate registration. However, all imaging modalities have some limit to the volume of space that they can image. In order to overcome this limitation, it is necessary to employ registration techniques that are robust to partial acquisition of the structures of interest, in our case carpal bones. Above, we have described our implementation of Johnson and Hebert's spin-image algorithm for surface matching as it can be implemented to register partial capitate bones. In particular, we assessed the accuracy of the algorithm to register partial bones with significant amounts of distal geometry missing. The omission of distal capitate geometry, arguably, presents the worst-case for registration—as compared to the omission of other geometry—as the proximal pole of the capitate possesses few discernable features (figure 6, above). Spin-images are capable of capturing the subtleties of surface topology, enabling registration in light of considerable absent geometry.

Registration performance was assessed in the absence of distal geometry (up to 70% omitted) when compared to registrations obtained using the complete capitate. Registration errors generally declined, monotonically with more available geometry. The magnitudes of errors reported here are small, however, it is important to note that these errors are relative to the registration achieved using the entire capitate, and not relative to a true benchmark. The refinement method is based on ICP (Besl and Mckay 1992), thus it is reasonable to assume that the worst-case absolute errors using the spin-image algorithm will be less than or equal to those errors previously reported for the ICP approach to registering bones (Beek et al. 2010), as ICP refinement is done *after* correspondence-based surface matching is used. Further, ICP-based refinement uses only geometry found to be common between source and target surfaces, reducing or eliminating extraneous geometry from both. Based on existing studies of carpal bone size (Crisco et al. 2005), and the available capture volume of 4DCT, the registration approach should be applicable to nearly all wrists and provide registration accuracies comparable to when the entire bone is available for registration. In applications to other anatomic structures, the amount of geometry necessary for the algorithm to accurately register bone surfaces will vary with the salience and scale of features in the available

geometry in relation to the imaging and meshing resolutions used. More feature-rich surfaces and higher imaging resolutions will require less geometry to achieve accurate registration, whereas flat/smooth surfaces and lower imaging resolutions will require more geometry.

Johnson and Hebert (1997) demonstrated the potential medical application of the spin-image descriptor and algorithm from its inception. Additionally, a method using similar surface descriptors has been used to register tooth surfaces (Xiao et al. 2005). More recently, Reda et al. (2012) have used the algorithm, in conjunction with intensity-based methods, for co-registering pre- and intra-operative regions of the skull for navigation during cochlear implant surgery. These prior works utilizing spin-images and similar descriptors illuminate the broad applicability of the algorithm, however their purpose has primarily been alignment of singular datasets and/or object recognition. Our work represents the first use of spin-images to compute registrations from dynamic imaging. In the past, this type of analysis may have been hindered by computational limitations and/or data size; however, modern workstations and even hardware is more than capable of computing the registrations motions in “real-world” useful time. For example, Reda’s (2012) implementation utilizes much larger spin-images (4x) than Johnson had originally proposed ($W = 10$ to 20), requiring more memory and increasing the number of computations required to compare the images, but still runs in under a minute. Our implementation is comparable in run time and uses similarly sized spin-images.

Broader use of the spin-image algorithm can enable additional tasks in surgical navigation such as registering optical range data (3D laser or structured light scans) to pre-operative CT or MRI scans. Additionally, the robustness of the algorithm to partial geometry could be useful in 3D puzzle solving for reconstructing comminuted fractures (Thomas et al. 2011). In conclusion, the spin-image algorithm has been shown to tolerate substantial, continuous regions of omitted/missing geometry and should be considered a valuable tool for image analysts and biomechanists for registration and image-based motion capture.

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References

1. Arun KS, Huang TS, Blostein SD. Least-Squares Fitting of 2 3-D Point Sets. *Ieee T Pattern Anal.* 1987 Sep.9:699–700.
2. Asakawa DS, Pappas GP, Blemker SS, Drace JE, Delp SL. Cine phase-contrast magnetic resonance imaging as a tool for quantification of skeletal muscle motion. *Seminars in musculoskeletal radiology.* 2003 Dec.7:287–295. [PubMed: 14735427]
3. Banks SA, Hodge WA. Accurate measurement of three-dimensional knee replacement kinematics using single-plane fluoroscopy. *IEEE transactions on bio-medical engineering.* 1996 Jun.43:638–649. [PubMed: 8987268]
4. Beek M, Small CF, Ellis RE, Sellens RW, Pichora DR. Bone alignment using the iterative closest point algorithm. *Journal of applied biomechanics.* 2010 Nov.26:526–530. [PubMed: 21245515]

5. Besl PJ, McKay ND. A Method for Registration of 3-D Shapes. *Ieee T Pattern Anal.* 1992 Feb. 14:239–256.
6. Boutin RD, Buonocore MH, Immerman I, Ashwell Z, Sonico GJ, Szabo RM, Chaudhari AJ. Real-time magnetic resonance imaging (MRI) during active wrist motion--initial observations. *PloS one.* 2013; 8:e84004. Epub 2014/01/07. [PubMed: 24391865]
7. Breighner R, Holmes DR, Leng S, An K-N, McCollough C, Zhao K. 3D-3D registration of partial capitate bones using spin-images. 2013
8. Challis JH. A Procedure for Determining Rigid-Body Transformation Parameters. *J Biomech.* 1995 Jun.28:733–737. [PubMed: 7601872]
9. Chua CS, Jarvis R. 3D free-form surface registration and object recognition. *Int J Comput Vision.* 1996 Jan.17:77–99.
10. Crisco JJ, Coburn JC, Moore DC, Upal MA. Carpal bone size and scaling in men versus in women. *The Journal of hand surgery.* 2005 Jan.30:35–42. [PubMed: 15680553]
11. Eggert DW, Lorusso A, Fischer RB. Estimating 3-D rigid body transformations: A comparison of four major algorithms. *Mach Vision Appl.* 1997; 9:272–290.
12. Garcia-Elias M, Alomar Serrallach X, Monill Serra J. Dart-throwing motion in patients with scapholunate instability: a dynamic four-dimensional computed tomography study. *The Journal of hand surgery, European volume.* 2013 Apr 8.
13. Goshtasby, A. 2-D and 3-D image registration for medical, remote sensing, and industrial applications. Hoboken, NJ: J. Wiley & Sons; 2005.
14. Horn BKP. Closed-Form Solution of Absolute Orientation Using Unit Quaternions. *J Opt Soc Am A.* 1987 Apr.4:629–642.
15. Johnson, AE. Spin-Images: A Representation for 3-D Surface Matching Carnegie Mellon University. 1997.
16. Johnson AE, Hebert M. Surface matching for object recognition in complex three-dimensional scenes. *Image Vision Comput.* 1998 Jul.16:635–651.
17. Johnson AE, Hebert M. Using spin images for efficient object recognition in cluttered 3D scenes. *Ieee T Pattern Anal.* 1999 May.21:433–449.
18. Katz S, Tal A, Basri R. Direct visibility of point sets. *Acm T Graphic.* 2007 Jul.26
19. Leng S, Gomez-Cardona D, Zhao K, Babb A, McCollough B, McCollough CH, Breighner R. Influence of Temporal Resolution on Image Quality in 4DCT Assessment of Wrist Joint Instability. *Radiological Society of North America: Scientific Assembly and Annual Meeting.* 2012
20. Leng S, Zhao K, Qu M, An KN, Berger R, McCollough CH. Dynamic CT technique for assessment of wrist joint instabilities. *Med Phys.* 2011 Jul.38(Suppl 1):S50. Epub 2012/01/26. [PubMed: 21978117]
21. Lin WT, Robb RA. Patient specific physics-based model for interactive visualization of cardiac dynamics. *Stud Health Technol Inform.* 2000; 70:182–188. Epub 2000/09/08. [PubMed: 10977536]
22. Lorensen WE, Cline HE. Marching Cubes: A high resolution 3D surface construction algorithm. *Computer Graphics.* 1987; 21:163–169.
23. Maintz JB, Viergever MA. A survey of medical image registration. *Med Image Anal.* 1998 Mar. 2:1–36. [PubMed: 10638851]
24. Miranda DL, Rainbow MJ, Crisco JJ, Fleming BC. Kinematic differences between optical motion capture and biplanar videoradiography during a jump-cut maneuver. *J Biomech.* 2013 Feb 1.46:567–573. [PubMed: 23084785]
25. Rainbow MJ, Kamal RN, Leventhal E, Akelman E, Moore DC, Wolfe SW, Crisco JJ. In Vivo Kinematics of the Scaphoid, Lunate, Capitate, and Third Metacarpal in Extreme Wrist Flexion and Extension. *J Hand Surg-Am.* 2013 Feb.38A:278–288. [PubMed: 23266007]
26. Reda FA, Noble JH, Labadie RF, Dawant BM. Automatic Pre- to Intra-Operative CT Registration for Image-Guided Cochlear Implant Surgery. *Ieee T Bio-Med Eng.* 2012 Nov.59:3070–3077.

27. Rees MR, MacMillan RM, Fender B, Clark DL. Cine-CT technique for evaluation of left ventricular function during supine exercise. *AJR American journal of roentgenology*. 1986 Nov. 147:916–918. [PubMed: 3490163]
28. Salembier P, Serra J. Flat Zones Filtering, Connected Operators, and Filters by Reconstruction. *Ieee T Image Process*. 1995 Aug.4:1153–1160.
29. Sheehan FT, Zajac FE, Drace JE. In vivo tracking of the human patella using cine phase contrast magnetic resonance imaging. *J Biomech Eng*. 1999 Dec.121:650–656. [PubMed: 10633267]
30. Shores JT, Demehri S, Chhabra A. Kinematic “4 Dimensional” CT Imaging in the Assessment of Wrist Biomechanics Before and After Surgical Repair. *Eplasty*. 2013; 13:e9. [PubMed: 23573338]
31. Song SM, Leahy RM. Computation of 3-D velocity fields from 3-D cine CT images of a human heart. *IEEE transactions on medical imaging*. 1991; 10:295–306. [PubMed: 18222831]
32. Tashman S, Anderst W. In-Vivo Measurement of Dynamic Motion Using High Speed Biplane Radiography and CT: Application to Canine ACL Deficiency. *J Biomech Eng*. 2003 Apr 09.125:8. Epub 245.
33. Thomas TP, Anderson DD, Willis AR, Liu PC, Frank MC, Marsh JL, Brown TD. A computational/experimental platform for investigating three-dimensional puzzle solving of comminuted articular fractures. *Comput Method Biomec*. 2011; 14:263–270.
34. Vereecke EE, Kerkhof F, Brugman E, Stockmans F. Dynamic CT Scanning of Motion at the Basal Thumb Joint. *Proceedings of the Proceedings of the 1st International Thumb Osteoarthritis Workshop*. 2013
35. Xiao G, Ong SH, Foong KWC. Efficient partial-surface registration for 3D objects. *Comput Vis Image Und*. 2005 May.98:271–294.

Figure 1. Partially transparent model capitulum showing the entire mesh including interior elements (6526 points, 13232 faces, left) and the HPR reduced mesh showing the remaining exterior surfaces (4422 points, 8776 faces, right).

Figure 2.

Spin-map coordinates from oriented point O . n denotes the vertex normal of point O . The location, O , and the direction, n , form the oriented point basis of point O . As each spin-image is based upon its respective vertex normal, spin-images are rotationally invariant features.

Figure 3.

A spin-map (a) and respective spin-image (b). The parameters used for generating the spin-image allow for the encoding of the entire capitae geometry with respect to the oriented point (located at the origin of the spin map). In general, spin-images are constrained to a smaller subset of the object geometry.

Figure 4.

Example spin-images ($W = 15$, $b_s = 1$). (a) is from a target surface vertex and (b-d) are from source vertices. (c) is the spin-image most similar to (a), whereas (b) contains significant extraneous information, and (d) contains almost few overlapping pixels with target spin-image.

Figure 5.

Spin-images as a feature space. Spin-images describe global geometry from the perspective of a particular vertex. The variation of spin-images from relatively featureless regions enables greater discrimination when establishing correspondences between surfaces.

Figure 6. Complete (100%) capitulum surface and 30% and 40% sub-surfaces. Note the loss of features between 40% and 30%.

Figure 7.

Mean absolute rotation and translation errors under partial-mesh registration. e_x , e_y , e_z denote single axis errors (along or about x, y, z), and $\|e_t\|$ denotes the magnitude of the error. FTR cases excluded.