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An Automated Three-Dimensional Particle Tracking Technique for the Study of Modeled Arterial Flow Fields

An automated three-dimensional particle tracking technique has been developed to study particle motion in modeled flow fields. A high speed video recording system, Kodak Ektaapro 1000, with two cameras arranged relatively orthogonally is used for this technique. The particle tracking data are compared to theoretical Poiseuille flow and to laser Doppler data from a axisymmetric stenosis model. The particle tracking data are in good agreement with both theoretical and laser Doppler data, and at least 79 percent of the particle paths were determined successfully. Fluid dynamic properties derived by this technique are: 3-D particle paths, velocity, and particle residence time.

Introduction

Hemodynamic investigations, especially those related to the interaction of blood with the vessel wall, require not only a knowledge of the Eulerian flow field, including velocity profiles and wall shear stress behavior, but also information on the motion of blood-borne elements such as platelets, monocytes, and macromolecules which may have significance with respect to specific biological processes at focal locations along the vessel surface. Consequently, the customary Eulerian methods for fluid velocity measurement, in which measuring probes or sample volumes are fixed at specific positions while data are recorded, may provide incomplete and even inadequate information. A Lagrangian measurement approach of determining the motion of small particles in a flow field can provide necessary complementary information. While, in principle, Lagrangian motion may be constructed from Eulerian data, in practice this is often difficult; it requires essentially a complete Eulerian flow field description (such as from a computational solution of the Navier–Stokes equations) in order to effect the transformation. Knowledge of the time-varying, three-dimensional spatial coordinates of small, neutrally buoyant particles can yield not only velocity components within the field but also other particle-specific data such as the proximity of an individual particle to a surface and the history of those particles which arrive in the neighborhood of specific sites along a surface.

Lagrangian approaches to the study of biofluid dynamics have been carried out by Karino et al. (1979) and Talukder et al. (1983) who seeded in vitro flows with small particles and observed their motion through high speed cine-cameras. In order to determine three dimensional particle trajectories, orthogonal views of the flow model were taken simultaneously, in the work of Talukder et al., and sequentially in the case of Karino et al. Particle identification and tracking were performed manually however; an observer followed the frame-by-frame position of each particle, recorded its coordinates from enlarged projections of the field of view and computed the particle velocity from these time-varying coordinates.

Although several investigators have developed automated three dimensional particle tracking techniques for general fluid dynamic studies, limitations can be found in each tracking method. Racca and Dewey (1988) required a special configuration and alignment for their viewing device and tested their algorithm in 30 frames with 10 particles in an
unstable flow downstream of an orifice, Economikos et al. (1990) used colored particles to assist in particle identification, and although they stated that 3000 particles could be identified, the experimental results presented only data from tracking 16 particles through 16 frames. Kasagi and Nishino (1991) developed a three-camera system which, in one application, tracked 441 particle paths; but they did not include an algorithm to separate overlapped particles, so that the successful tracking rate was only 25 to 33 percent. Maas et al. (1993) developed a three to four camera system for 3-D particle tracking which could track up to approximately 1000 velocity vectors at 25 images per second. Additional cameras were used to help solve the problem of overlapping particle images.

Our laboratory is particularly interested in modeled biological flow fields in which, in addition to velocity profile information, knowledge of the trajectories of individual particles such as monocytes (Pritchard et al., 1992) may be important to the interpretation of experimental results. The particle tracking method developed in the present study to circumvent previous limitations is automated and three-dimensional with particle trajectories which last several hundred frames, and it allows a simple experimental setup since it does not require a precise alignment of the two cameras. Between 20 to 30 individual particles in each frame have been tracked through the incorporation of a routine to separate particles when the images of two particles are overlapped in a given view. Thus, this technique provides information about the Lagrangian description of a moderately large number of individual particle trajectories, which can be employed to compute three-dimensional velocity data and other variables of interest in a flow field.

Flow in the neighborhood of a stenosis has long been an important model in the study of hemodynamics and arterial disease. The stenosis model is somewhat simplified, but it does present a geometry which simulates the localized narrowing created by atherosclerotic plaque formation with the concomitant high velocity and wall shear stress region in the throat followed by flow separation, recirculation and low wall shear stress. Additionally, coarctations in the thoracic aorta have been employed in animal models in an effort to provide hemodynamic manipulations which can be employed to identify specific hemodynamics-artery wall interaction mechanisms. Thus, we elected to apply the 3-D particle tracking method to flow through a stenosis as a biologically relevant test of the potential of the technique to determine particle trajectories, velocity profiles and the residence time of particles near sites on the model surface. The latter are particularly interesting in the recirculation region because of possible relevance to atherogenesis.

Experimental Apparatus

The tracking algorithm was applied first to a straight tube model for which the velocity profile in steady flow is known from the Poiseuille result, in order to assess the accuracy of the technique. Next, an axisymmetric stenosis model with a 50 percent area reduction formed by a smooth cosine curve was studied because of its relevance to particle motion in diseased arteries. Reynolds numbers 300 to 450 were used to test the tracking program. The models were constructed with Dow Corning Sylgard 184, a silicone elastomer with a high degree of transparency and an index of refraction of 1.41. Optical distortion is minimized since the refractive index is matched with that of the working fluid, which was 58 percent (by mass) glycerine in water.

The experiments were conducted on a steady flow system as shown schematically in Fig. 1. The upstream and downstream portions of the test model were connected to plastic tubes of the same diameter (25.4 mm), and the tube leading to the upstream end of the test model was sufficiently long (over three times the Langhaart theoretical entrance length for laminar flow) to ensure that fully developed flow entered the test section. The fluid was seeded with 400–500 μm Amberlite IRA-904 particles. The density of the particles is 1.05 to 1.15 gram/cm³, which, for most of the particles, is lower than that of the working fluid (1.14 gram/cm³). However, due to a high degree of porosity, the particles become denser (1.149 ± 0.009 gram/cm³) after they are submerged in the working fluid. The density was measured by sedimentation velocity with the assumption that Stokes flow existed in the neighborhood of individual particles. The sedimentation velocity estimated from the average of 14 particles is 0.0118 ± 0.0017 cm/s.

The viewing area was illuminated with two fiber optic illuminators. The particles have good light reflection capability. To prevent clustering of the particles, they were applied into the system in dry condition. Two high speed video cameras, Kodak EktaPro 1000, were arranged approximately orthogonally to take separate side view and top view pictures of the test model. A simple alignment between two views with less than two to three pixels difference in the vertical direction should be made. Pictures are recorded on a 1/2-in. magnetic tape with the rate of 30, 60, 125, 250, 500, or 1000 frames per second. There is no shutter control for the cameras, but a clear image can be obtained by increasing record speed, with a sacrifice in the length of time available for recording data. The advantage of video cameras over movie cameras is the ability to immediately replay information, which helps to ensure the quality of the recorded pictures as experimental conditions change. High speed cameras increase the temporal resolution, but provide reduced picture resolution. For the camera used in this work, each picture was composed of 239 by 192 pixels with 256 gray levels per pixel. The system has split-screen capability which allows the two different views to be displayed and recorded simultaneously, with a reduction in resolution of each view to 239 by 96. The observation volume for this study was 70 X 28 X 28 mm³, so that each pixel occupied an area of approximately 0.3 X 0.3 mm.

Particle Tracking Algorithm

Figure 2(a) shows two orthogonal views of particles as they moved through the 50 percent area reduction stenosis model, with the top and side views of the model positioned at the top and bottom segments of the figure, respectively. These views are two-dimensional projections of three-dimensional particle locations, and particles in each picture are imaged as small round bulbs without inherent distinguishing features such as shape and color. The algorithm developed in our laboratory (Tsao, 1992) to obtain three-dimensional trajecto-
Two-Dimensional Particle Tracking. Particle centroids obtained from the image enhancement and segmentation methods are tracked separately in each orthogonal view by a linear extrapolation technique. The maximum particle displacement between frames is limited, by appropriate choice of frame rate, to 1.5 times the average particle diameter (i.e., 675 μm or 2.3 pixels) to ensure linear particle displacement between frames. Three sequential frames are required to execute the extrapolation, which estimates the location of a particle in the third frame, \( x_3 + \Delta x_3 \), where \( x_3 \) is the particle position in the second frame, and \( \Delta x_3 \) is the displacement vector between the first and second frames. A small circular area around \( x_3 \) is then searched to find the particle. The application of this method is straightforward for particles which have already been tracked in previous frames so that \( \Delta x_3 \) is already known. For particles which appear in a picture image for the first time, however, the estimated location cannot be constructed immediately, and an iterative method is required, which uses the next two frames. A large area around the particle's location in the first frame is searched in the second frame. Any particle found in this area is a candidate, and usually more than one particle will be found in the next frame within this relatively large searching area. One of the candidate particles is then selected in the second frame, and the basic three-frame linear extrapolation scheme is used to estimate the particle location in the third frame. If the program cannot find a particle within a small circular area around the newly estimated particle location, another candidate inside the large area in the second frame will be selected and linear extrapolation will be performed again. If none of the particle pairs can be successfully extended to the third frame, the new particle is deleted. This is also the procedure used to initiate the particle tracking process automatically at the outset of the process.

The size of the searching area is critical because it determines the success of this tracking method. There are two kinds of searching areas, a relatively large area for new particles and a small area for successive tracking. The large area is employed to initiate a searching process, and it is calculated as the maximum expected flow velocity under study divided by the time between frames. If the area is too large, tracking time is unnecessarily increased. The selection of the small area is more complicated in that it depends on flow acceleration, pixel noise, lens distortion, particle size, overlapped condition, and recording rate. For example, the maximum particle acceleration in the current stenosis case is 350 cm/s² with a 500 s⁻¹ frame rate. Thus, the theoretical displacement between frames caused by acceleration \( \frac{1}{2} at^2 = 0.5 \times 350/(500^2 \times 500) = 0.0007 \) cm (0.03 pixel), where \( a \) is the acceleration and \( t \) is the time between frames. Therefore, in the current study, the particle acceleration does not cause a large change in displacement. If 0.5 pixel is assumed to be the maximum displacement change between frames, the maximum acceleration that can be tracked by the current method is 3500 cm/s². For the nonoverlapped particles, the other factors which have to be considered are pixel noise and lens distortion. The value of these factors will be discussed in the section on particle reconstruction. The small search volume is estimated by the above factors. For the current study, the total displacement between frames was kept below 2.3 pixels through appropriate selection of frame rate, and the displacement associated with acceleration is less than half of that associated with velocity, so a 1.5 pixel search radius is sufficient. For the overlapped particles, the radii of the particles and the orientation of the overlap condition are added to the calculation of search volume. In the current study, a value of 6 pixels is used for the search radius.
Separation of Overlapped Particles. When two or more particles in one frame track to the same particle image in the next frame, these particles are considered to overlap. In this discussion the object image to which these particles track is called the composite image. If only two particles overlap, the centroids of the two individual particles are estimated from the composite image based upon their orientation with respect to each other. Since the new centroids of the overlapped particles are not exact, the use of these centroids, calculated by the composite image alone, to estimate the particle positions in the next frame may lead to position errors. Thus, second estimates of the particle centroids in the next frame are calculated as the average of each particle’s previous six displacements. The final coordinates are taken as the average of the estimated centroids calculated from the composite image and those calculated from the previous six displacements. For an overlap of three or more particles, the program estimates new particle centroids based on the previous displacement of each particle and limits their centroids to be located inside the overlapped particle’s boundary.

For the first three frames, tracking data are not available. Overlapped particles are then identified by particle size. If a particle size is larger than the average particle size plus three standard deviations, this particle is considered an overlapped particle, and the composite image is used to estimate new centroids, as described in the previous paragraph. Further details on the treatment of particle overlap are given in Tsao (1992).

Particle Matching. The previous method generates several particle paths in two orthogonal views, so the next step is to match two particle paths in two different views to determine the three-dimensional location. If the axial locations and average axial particle velocities in ten successive frames are similar, the program considers these two particle paths to be projections of the same path. (Due to the low resolution of the picture and different lighting conditions in different views, the axial velocity of a particle in different views may not appear to be the same.) If several paths have similar particle axial locations and average velocities in ten frames, the axial location of each particle is the primary factor for matching.

Matching is performed only on particle paths which have a trajectory of at least ten frames. Once a pair of particle paths is considered to be the same path in different views, then a unique path number is assigned to both these two-dimensional paths. When these advance to the next frame, each corresponding path number is passed to new locations also. The axial coordinates of these matching pairs are checked continuously in all subsequent frames to verify the match. For those paths matched only by axial locations, the unique path number is not automatically passed to the next frame because the program has to do the matching procedure in each frame until there is a pronounced difference in axial location or average velocity. If the program finds a conflict with path assignment, an error flag is assigned to the old particle path, and a new path number, based on the new matching is begun.

Particle Reconstruction. The Direct Linear Transformation (DLT) method (Abdel-Aziz and Karara, 1971) is used to calculate the three-dimensional coordinates of each particle. This method relates the two-dimensional picture image of a camera to three-dimensional space coordinates by the following equations:

\[
x = \frac{L_5 X + L_6 Y + L_7 Z + L_8}{L_9 X + L_{10} Y + L_{11} Z + 1}
\]

(1)

\[
y = \frac{L_5 X + L_6 Y + L_7 Z + L_8}{L_9 X + L_{10} Y + L_{11} Z + 1}
\]

(2)

where \(x\) and \(y\) are two-dimensional image coordinates of a point, \(X\), \(Y\), and \(Z\) are three-dimensional space coordinates of that point, and \(L_i\) through \(L_{11}\) are calibration coefficients associated with the camera internal and external parameters. This equation includes corrections for the linear components of lens distortion and also includes correction for the distortion caused by refractive index differences (Majumdar et al., 1985).

The DLT method requires two views of a calibration model to establish the calibration coefficients. This model was constructed of the same material as the test model, and it has 277 particles embedded inside each with known three-dimensional coordinates. The outside dimensions of both models are the same, so that with the calibration model located at the same position as the test model, the coordinates of the particles inside the calibration model can be used to simulate the particle locations inside the fluid test model. Although 277 particles are embedded inside this model, only those particles imaged by both cameras are used by the DLT method. Among these, at least six particles are employed to calculate the eleven DLT calibration coefficients, and the others are used to calculate error. The root mean square (rms) error of this method in identifying particle coordinates is approximately 0.67 pixel widths. The sources of this error include lens distortion, light diffraction, and pixel noise.

The displacement error from lens distortion and light diffraction decrease as particle displacement between frames decreases. This is because the nearby locations have similar lens distortion and light diffraction. This error can be estimated by moving the calibration model at a known displacement and then computing the error between calibration particle’s displacement and the known displacement. At the maximum displacement between frames for the current experiment (2.3 pixels), the lens distortion and light diffraction is estimated to be 0.29 pixel widths. The rms error due to pixel noise in the flow experiment is estimated to be 0.23 pixel widths. Simulation results with an ideal particle agree with this experimental estimate (Jones et al., 1994).

Velocity Calculation. The final step of this particle tracking algorithm is the velocity calculation. After the images have been processed by the above methods, a frame by frame sequence of three-dimensional coordinates for the centroid of each tracked particle is available, where the time interval between each set of coordinates is the reciprocal of the frame rate. Based on these coordinates, a Lagrangian velocity can be calculated, in principle, by simply dividing the centroid displacement between each time frame by the time interval of those frames. However, when the particle displacement approaches the spatial resolution of the centroid estimates, this method can lead to large errors in frame by frame velocity. Thus, in practice a smoothing function or low pass filter is needed. In our procedure a least-squares third degree polynomial curve is fit through the spatial coordinates of a particle over several consecutive particle locations and a time derivative at the midpoint is taken as the velocity estimate of the particle at that point. The selection of the number of consecutive frames is based on the characteristics of the flow—if particle velocity does not change significantly throughout the flow field, then a large number can be used; while if the change in particle velocity is large, then a smaller number should be used. As with any application where position and velocity must be estimated simultaneously, an uncertainty principle applies. In the present study, at least 50 frames were used for the straight tube case and a fixed number of consecutive frames, 20, was used for the stenosis case to perform the smoothing operation.
Results

The results include three-dimensional particle paths, three velocity components, and the percentage of successfully tracked particles, defined as the number of particles tracked successfully divided by the total number of particles in one set of sequential frames. Additionally, the concept of particle residence time (Tsao et al., 1992) was explored by tracking near-wall particle motion in the 50 percent stenosis model.

Particle Paths. For the straight tube case, a camera frame rate of 250 frames/s was used at Reynolds number 350. The average particle image size was 11 pixels, and the maximum number of particles per frame was 31. The 3-D particle tracking technique determined at least 90 percent of the particle paths, and the number of frames of a successfully tracked particle path ranged from 100 to 500 frames. Approximately 50 percent of the particles traveled through the entire field of view. For the 50 percent stenosis, Reynolds numbers (Re) 300 and 450 were examined at frame rate of 500 frames/s. These values are representative of mean Reynolds numbers in major arteries, such as the human carotid and abdominal aorta. Examples of the particle paths within the stenosis model at Re = 450 are shown in Fig. 3 by solid lines which represent two-dimensional projections of paths formed by particle motion in the flow field (the dotted lines show the stenosis boundary for reference). The data in Fig. 3 display a core flow region, where particles flow directly from upstream to downstream in the test section, and a recirculation region where particles travel back and forth within a separation zone downstream of the throat. The result of these two experiments showed that the automatic 3-D particle tracking program determined at least 79 percent of the particle paths in this 50 percent stenosis model. The maximum number of particles tracked simultaneously was 26, and particle trajectory ranged from 100 to 500 frames. In most cases for which particle paths could not be determined, tracking was disrupted when three or more particles overlapped in several frames.

Particle Velocity. Results from particle tracking were compared to the velocity profiles calculated from the Poiseuille equation and to those laser Doppler anemometry (LDA) measurements, a well-established method which measures an average flow velocity within a spatially-fixed sample volume. Although based upon the transit of scattering particles through the sample volume, the LDA provides Eulerian data in contrast to the particle tracking method which gives Lagrangian results for the velocity of individual particles. If the particles are sufficiently small and neutrally buoyant, their velocity is a good approximation to that of fluid elements, and hence velocity field information can be derived. Since the velocity profiles for steady flow through both the straight tube model and the 50 percent area reduction stenosis model are theoretically axisymmetric, they can be reduced to a single smooth curve of velocity as a function of radial position. This curve should be the same as the axial velocity profile through the midplane of the model, as obtained from an LDA measurement. The particle coordinates from the tracking data were therefore converted from Cartesian to cylindrical coordinates, and the data were compared to those from one side of the centerline velocity profile obtained from the LDA method. To quantify the comparison, a multiple linear regression analysis was used to fit a polynomial curve to the LDA data points, and this curve was then used to estimate LDA velocity at each radial location for which particle tracking data were available. The standard deviation between the particle tracking data and the curve fit of the velocity from LDA data was then calculated, and comparisons were made for both the straight tube model and the 50 percent area reduction model.

A DISA 55L MARK II LDA system was used to measure axial velocity within the two models. In these experiments, cornstarch particles were used to scatter the laser light. To verify that the straight tube flow was fully developed, LDA measurements were taken along the diameter of the straight tube at a Reynolds number of 350. The standard deviation between the particle tracking data and the velocity estimated from a curve fit of LDA data was 3.12 percent of the average cross-sectional velocity. For the stenosis model, LDA measurements of the velocity profile were taken at upstream, throat, and recirculation region locations. Good agreement was found between particle tracking data and between particle tracking data and LDA data.

Figure 4 presents the straight tube velocity profiles, and the agreement between the theoretical quadratic polynomial velocity curve and that derived from particle motion is good. Figure 5 presents comparisons for the stenosis model at the
location $x = 13$ cm which is in the recirculation region. Again, the agreement is good, and the slightly negative velocities in the zone of separated flow can be observed in both sets of data. The standard deviations between LDA and particle tracking velocity measurements in the stenosis model were 8.18, 11.23, 4.54, and 4.21 percent of the average cross-sectional velocity ($V_{avg}$) upstream of the constriction for the upstream, throat, recirculation, and downstream regions, respectively.

Because the tracking system as set up for the present study could image particles within a large volume of the test section, it was possible to acquire particle velocities at numerous spatial locations in the field. Thus, with acquisition of a sufficient quantity of particles a great deal of velocity information can be derived, as illustrated in Fig. 6 which shows a graph of the axial velocity component of all particles which passed through the plane located at $x = 13$ cm. This result, a smoothed curve computed by application of the Kriging method to the 134 particle velocities, shows the separation region around the periphery of the model. In practice, a larger number of particles with a more disperse spatial distribution would improve the resolution of the velocity results.

Particle Residence Time. Particle residence time (PRT) can be defined as the duration of time which an individual particle spends within a small control volume adjacent to a specific site at the fluid-surface interface. Ideally, particle residence time should be defined at a “point 11 along the model wall, but a point implies zero volume, and it is necessary to prescribe a finite volume in the neighborhood of the point in order to define a “time” during which a particle remains within the volume. For the present research, a small control volume of cylindrical shape in space with one face adjacent to the model wall was prescribed; the height of this control volume is $h_c$ and the radius is $r_c$, so that the volume is $V_p = \pi r_c^2 h_c$. Assume at some particular time this volume contains $N$ particles. The particle residence time for steady flow can be defined by the relation:

$$PRT = \lim_{N \to \infty} \frac{1}{N} \sum_{i=1}^{N} T_i$$

where $T_i$ is the time required for the $i$th particle to travel a distance equal to the radius of the cylindrical control volume.

To calculate the particle residence time for the 50 percent area reduction stenosis model, a standard size control volume of dimensions 1 mm in height and 3 mm in diameter was defined. Spaced 5 mm apart in the axial direction, these were located at the top and bottom edges of each view and distributed from the upstream end to the downstream end of the stenosis as shown at the bottom section of Fig. 7. The PRT in each control volume was calculated according to the above relation, and Fig. 7 shows the results. The peaks in PRT are associated with flow separation and reattachment: and as can be interpreted from the particle paths shown in Fig. 3, a sharp increase in PRT is expected as one moves from the throat into the initial sections just past flow separation.

While the data in Fig. 7 show the tendency for long PRT near separation and reattachment around the periphery, the curves at the four circumferential locations clearly have differences among themselves. The data taken at the top of the model show the lowest values for PRT, those at the two sides of the models show intermediate values, and the PRT results from the bottom of the model show the longest residence times. The differences occur because the particles are not precisely neutrally buoyant—theyir density is slightly greater than that of the fluid, as discussed earlier. Thus, the particles in the recirculation region at the top of the model have an average distance from the wall which is somewhat greater than that for those at the bottom surface, with the result that the upper surface particles have a larger magnitude for velocity, on average. Additionally, several of the particles near the bottom surface may have actually come in contact with the wall, thus retarding their axial motion and resulting in a longer PRT. These buoyancy effects become stronger as the fluid velocity decreases and approaches the particle settling velocity. For the recirculation region, the ratio of settling velocity to the velocity of a particle averaged over the magnitude of its velocity in one circulation was approximately 0.03. The degree to which buoyancy prevents particle from following the fluid motion is of potential importance to the fluid dynamics of blood borne elements such as monocytes and platelets.

Discussion

The objective of this research is to develop a quantitative flow visualization method which uses a Lagrangian approach to determine three dimensional particle trajectory and velocity and which can consequently be used to relate the particle behavior in arterial models to the initiation and progression of arterial disease. Although several hemodynamic variables have been implicated as possible factors responsible for the localization of plaques, the underlying mechanisms by which the formation and progression of atherosclerotic plaques are
determined are not yet understood. Giddens et al. (1990) hypothesized that both force-related and mass transport-related mechanisms arising from the hemodynamic environment are involved in plaque localization. The force-related mechanism assumes that intimal thickening is a natural response of arteries to local hemodynamic forces, especially low wall shear stress and/or oscillating shear stress. While intimal thickening is not atherosclerosis per se, the spatially localized process of intimal thickening in low shear regions may favor the development of atherosclerosis. This can occur in the presence of a mass-transport-related mechanism which assumes that both the availability of atherogenic particles to specific sites of the artery wall and their biological activity affect transport into the artery wall. A relatively long PRT implies that circulating blood elements will linger in certain regions and thus increase their local exposure time to the adjacent artery wall, increasing the possibility of interaction between these blood elements and the artery wall. Therefore, PRT has been proposed as a factor which is relevant to a mass-transport-related mechanism (Zarins et al., 1990) for atherogenesis.

The particle tracking scheme presented here has several advantages. It is a method for describing particle motion, and this is an important factor in the study of hemodynamics. The technique is fully three-dimensional in that it describes three spatial coordinates of a particle as a function of time, thus providing three components of particle trajectory and velocity. With the current optical arrangement a large field of view is observed, leading to collection of information over large segments of the flow field without the use of traversing systems. This simplifies the experimental measurement apparatus and reduces data collection time by comparison with the LDA, for example. Furthermore, if the particles are sufficiently small and close to the fluid density, the particle velocity is a good measure of fluid velocity, so that the velocity field can be reconstructed in a fully 3-D rendering. It is of great importance, of course, that the procedure for quantifying particle motion is labor intensive for the computer, but not for the investigator. Although the current study applies to axisymmetric vessels, with proper optical and lighting arrangement, it could be applied to models of complex 3-D flow geometries, such as the carotid and coronary bifurcation.

In the present study, the particles were mixed with the fluid in an upstream reservoir to achieve dispersion with the result that their locations in the test section were not easily predicted, so that there were data-rich and data-scarce regions. The recirculation region is an example of the latter, of course, since the separating streamline forming the separation region inhibits particles from entering this zone. In our studies the model had to be pre-seeded before the flow was started in order to "capture" particles in the recirculation region. The problems associated with seeding will be exacerbated when the method is applied to pulsatile flow, since a particle path is no longer a flow streamline.

Particle overlap precludes effective tracking when the particle concentration is not dilute. For heavy seeding, other methods of flow field analysis—such as tracking on structures comprising multiple particles—would be needed. Particles with different diameters could also be used to alleviate the heavy seeding problem, and these can be tracked by the present method, although the diameter difference may be less pronounced by differing light reflection from different locations or views. Particle size can be reduced to increase the number of successfully tracked particles in each frame. However, the particle diameter should not be less than one or two pixels or there is inadequate contrast between a particle and noise. This corresponds to 60 μm for the present lens and field of view. As with any measurement system there are trade-offs, and better spatial resolution comes at the price of poorer velocity resolution and a smaller field of view.

In the straight tube model we found that we could track up to approximately 30 particles per frame with a 90 percent success rate. This corresponds to a 1.5 percent pixel occupancy by the particles. While we have not tried to increase the pixel occupancy to determine a value at which the successful tracking rate is decreased below 90 percent, we expect that increases in pixel occupancy must ultimately reduce tracking efficiency due to an increase of overlapped particles. From simulation results (Tsao et al., 1994), the successful tracking rate is decreased to 85 percent for a maximum particle number of 40 per frame. Although use of three or four cameras can reduce the tracking difficulty due to overlapped particles, it complicates equipment installation and increases the necessary computation. The maximum velocity that can be tracked will be 70 cm/s based on the current camera system and tracking requirements. However, if the screen is split into three sub screens of each view, with the reduction of resolution to 1/3 of current value, the maximum velocity which can be tracked will be 210 cm/s. The maximum acceleration that can be tracked currently is 3500 cm/s², as stated in the Two-Dimensional Particle Tracking section. Therefore, this technique should be applicable to more complicated flows than have been presented in this paper.

The experiments reported here were not intended to model a specific blood cell, but rather were designed to develop the basic particle tracking method. To model a particle cell, such as a monocyte, requires a careful match of the size, shape and specific gravity with those of the relevant in vivo situation. In addition, the settling time of the cell, the time required for a cell to follow blood flow, and, in the low shear region, the dependence of viscosity on shear rate should be considered. The non-dimensional parameters include Reynolds number, the ratio of a blood cell's settling velocity to the average blood flow velocity, and a time ratio \( \tau_1/\tau_r \), where \( \tau_r \) is the characteristic time required for the particle to respond to a step change in fluid motion and \( \tau_1 \) is a time representative of the flow, such as diameter divided by average velocity. This would be especially important in determining particle residence time in a low shear region.

Despite limitations, however, the direct results of this automated 3-D particle tracking technique are the simultaneous calculation of particle trajectory and three velocity components for each seeding particle in a flow field. This information allows determination of the instantaneous spatially-dependent characteristics of a flow field, which are essential to the study of unsteady flow. The calculation of particle residence time enhances the utility of this technique. Furthermore, the automatic method reduces the difficulties and inconsistencies of human interpretation. Although 3-D particle tracking techniques have been developed by several researchers, the important difference in this research is that this method has been shown to track particle trajectories successfully for 100 to 500 frames with a moderate number of particles in each view. This allows a variety of fluid dynamic parameters, such as particle paths and particle residence time, to be deduced more readily than does LDA. Furthermore, it can be used to study the transport of components, such as red blood cells and monocytes, which do not necessarily follow the fluid motion. It is anticipated that this technique will become an extremely valuable complement to laser Doppler anemometry.

Acknowledgments

The authors gratefully acknowledge support of this work provided by the National Institutes of Health, under grant...
no. NHLBI P50 HL 15062 and grant no. RO1 HL41267-04, and a grant from the Whitaker Foundation.

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Transactions of the ASME