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A feature point identification method for positron emission particle tracking with multiple tracers

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ABSTRACT

A novel detection algorithm for Positron Emission Particle Tracking (PEPT) with multiple tracers based on optical feature point identification (FPI) methods is presented. This new method, the FPI method, is compared to a previous multiple PEPT method via analyses of experimental and simulated data. The FPI method outperforms the older method in cases of large particle numbers and fine time resolution. Simulated data show the FPI method to be capable of identifying 100 particles at 0.5 mm average spatial error. Detection error is seen to vary with the inverse square root of the number of lines of response (LORs) used for detection and increases as particle separation decreases.

1. Introduction

Positron emission particle tracking (PEPT) uses positron emission tomography (PET) technology to track the motion of an activated particle in time [1]. Tracer particles are radiolabelled using a positron-emitting isotope such as ^{18}F, ^{11}C, or ^{22}Na. After emission, the positron annihilates with a nearby electron, producing coincident, back-to-back, 511 keV gamma rays. By detecting coincident gamma ray pairs, one can draw a series of lines of response (LORs) between detection pairs. Each LOR will then pass near the location of the tracer. By examining a series of collections of LORs, one can recreate the position of the tracer particle in time.

Since the invention of PEPT, it has been used to study a number of flow and other industrial systems [2–5]. The majority of the experiments detailed in the literature are single particle tracking experiments. Further experiments have been conducted with multiple particle tracking, but the majority of these have required *a priori* knowledge of the number of particles in the system and their initial locations [6–8]. It is desired to have a PEPT method that does not require such *a priori* knowledge and allows particles to enter and leave the field of view (FOV) of the system. Such a measurement technique could be used for Lagrangian flow measurements in which multiple tracer particles can pass through a test section as part of a recirculating flow loop. Wiggins et al. [8] developed such a method for multiple particle tracking, and this has been used to study both vortical flow in a transparent test section [9] and jet flow induced between baffle plates [10]. In this paper, a new method for multiple particle tracking is introduced and compared to the previous.

2. Particle tracking techniques

The most commonly used method for single particle PEPT analysis is the Birmingham method developed by Parker et al. [1]. In this method, one collects LORs over a given amount of time and finds the point in space that minimizes the sum of square distances to the lines. This point is taken to be the particle location. An adaptation of this has been created for tracking multiple particles in the case that the particles are of very different activity [6].

A second method developed by Bickell et al. [7] searches for a region of the FOV of the detector that has the highest density of LORs by segmenting the FOV into a three-dimensional grid, counting the number of LOR crossings at each grid point, finding the maximum grid element, and applying a Gaussian fit to the data at this point. This method is then expanded to a method capable of tracking multiple particles in the case that the number of particles and their initial positions are known. The methods for multiple particle tracking presented herein are derivatives of this "line density" method in that they all begin by dividing the full data into time slices and creating a grid of LOR density in each slice.

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2.1. G-means clustering approach

Wiggins et al. [8] developed an algorithm for multiple particle tracking that does not require *a priori* information of the number of particles in the system. In this way, it can be used to track particles entering and leaving the FOV of the detector system as is typical in recirculating flow experiments. In this method, LOR crossings are tallied across a superimposed grid, as in the line density method, and regions of high line density are detected via G-means clustering [11]. This method will henceforth be referred to as the G-means method for PEPT in this work. A brief review of this method follows.

For the LOR dataset, let $N^t(x,y,z)$ be the be the number of line crossings at grid point (x,y,z) during time frame t, and let N^t_{max} be the maximum value in the LOR grid at this time. Grid elements having LOR crossing values in the upper r^{th}-percentile of their given frame are selected for use in particle location. The value r is adjusted based on the amount of LOR noise in an experiment, as well as the distribution of activities of particles used in an experiment. At each frame, any point (x,y,z) having a number of line crossings greater than $r\times N^t_{max}$ is treated as a number of $N^t(x,y,z)-r\times N^t_{max}$ points in 3D space at location (x,y,z). G-means, a divisive clustering algorithm based on the well-established k-means algorithm, is then used to group all the points in a given frame. In this method, one begins with a k=1 clustering (i.e. universal centroid identification) of the set. This algorithm then subsequently splits and re-clusters any clusters that are not normally distributed along their main principal components. The process terminates when all clusters are Gaussian, as determined by a 1-D Anderson-Darling test [12]. The centroids of the detected clusters are then taken to be the particle locations, and the standard deviations of the centroids are taken to be the uncertainties.

Particle locations in each frame are then linked into trajectories based on a nearest-neighbors approach. A modified Kuhn-Munkres algorithm [13,14] is used to find the inter-frame linking which minimizes the sum of particle displacements. The primary input parameters to this linking method are v_{max}, a maximum velocity limiting the allowed between frame displacement for particle links, and R, a linking range indicating over how many frames a particle will look for a candidate match, similar to that found in [15]. For further discussion of both the identification and linking phases of this algorithm, see [8].

It is noted that in this G-means method, results depend on the selection of the Anderson-Darling critical value, A_{crit}, used when determining of number of clusters present, especially in the case of multiple particle detection. The standard values of A_{crit}, derived by Stephens [16], are for continuous data and have been found unsuitable for the discrete data created from the LOR crossing grid. It has been found in testing that several values of A_{crit} must often be tried before the resulting number of clusters found by G-means matches the true number of particles. It is desired that a multiple particle detection method be devised that does not depend on a parameter which must be adjusted without full understanding for best results.

2.2. Feature point identification method

When considering the aforementioned grid of LOR crossings, one can view each element of the grid as a 3D counterpart to the pixel called a “voxel”, with the number of line crossings being analogous to a greyscale value. As such, traditional optical particle tracking methods may be adapted for use in PEPT. A new approach to multiple PEPT analysis is presented, based on the feature point identification techniques of Crocker and Grier [17] and Sbalzarini and Koumoutsakos [15]. For this reason, this method will be referred to as the feature point identification (FPI) method. This method is carried out in four stages: smoothing, position estimation, position refinement, and trajectory linking.

As with previous methods, this method begins by collecting LORs for a given amount of time and counting line crossings across a grid superimposed on the system's FOV. Continuing the previous notation, let $N^t(x,y,z)$ be the be the number of line crossings at position (x,y,z) during time frame t. The grid is first smoothed via a box-car average over a cubic region of width $2f$+1:

$$N^{t'}(x,\ y,\ z)=\frac{1}{(2f+1)^3}\sum_{i=x-f}^{x+f}\sum_{j=y-f}^{y+f}\sum_{k=z-f}^{z+f}N^t(i,\ j,\ k) \tag{1}$$

where f is taken to be a smoothing size. In most studies, f is set to 1 (minimal smoothing) or 0 (no smoothing). In the above operation, the outer f elements are neglected in each dimension. Crocker and Grier [17] and Sbalzarini and Koumoutsakos [15] convolve each frame with a Gaussian surface of rotation of half-width 1 pixel to reduce camera pixelation noise, and use convolution with a larger box-car kernel as a means to estimate background noise. An analog was attempted for this study; however, no significant benefit was seen, and this operation only added to computational costs. This more complex smoothing step will be omitted until the noise associated with the grid-based discretization of LORs is further understood.

Next, particle positions are estimated by finding local maxima in the smoothed grid, $N^{t'}$. Local maxima are taken to be grid elements having LOR crossing values in the upper rth-percentile of their given frame and having values greater than any of their neighbors within a cube of width $2w$+1. As in the G-means approach, the value r is adjusted based on the amount of LOR noise in an experiment, as well as the distribution of activities of particles used in an experiment.

The parameter w serves as an apparent particle radius where the virtual particle can be viewed as a cloud of high LOR density. However, w limits the between particle separation that can be resolved in a given frame to w times the side length of the grid elements used. Below this separation, only the particle that appears “brightest” in LOR crossing space, i.e. the one corresponding to the highest LOR crossing peak, will be detected, and any others will only serve to bias this measured position toward the centroid of the particles involved. Thus, in the case of two particles approaching closely, it is likely that the trajectory of the higher activity particle will be continued while there will be a break in the measured history of the other. As such, w can be adjusted in a given experiment according to expected particle density so that it is greater than the expected inter-particle separation. Furthermore, in searching for local maxima, the outer w elements are neglected in each dimension. This prevents bias along the edges of the scanner but restricts the useable FOV of the scanner based on the selection of w.

Ties in the local maxima search are handled on a “first come, first serve” basis. If two grid elements of identical smoothed LOR crossing value are identified as local maxima and are found in the same cubic region of side length $2w$+1, the first one detected by the algorithm will be accepted as a particle position estimate, and the second will be rejected. It is expected that any bias introduced here is reduced or eliminated during the particle position refinement stage of the algorithm. Furthermore, the frequency of such ties is reduced by the use of the aforementioned smoothing filter.

After particle positions are estimated, refinements are made according to a centroid calculation over a cubic region of side length $2w$+1 centered at each estimate. Given an estimate position of $\boldsymbol{x}=(x,\ y,\ z)^T$, a final position, $\boldsymbol{x'}=(x',\ y',\ z')^T$ is calculated by:

$$\begin{pmatrix}x'\\y'\\z'\end{pmatrix}=\frac{1}{K}\sum_{i=x-w}^{x+w}\sum_{j=y-w}^{y+w}\sum_{k=z-w}^{z+w}\begin{pmatrix}i\\j\\k\end{pmatrix}N^{t'}(i,\ j,\ k) \tag{2}$$

with normalization:

$$K=\sum_{i=x-w}^{x+w}\sum_{j=y-w}^{y+w}\sum_{k=z-w}^{z+w}N^{t'}(i,\ j,\ k). \tag{3}$$

Individual particle positions are linked into trajectories via the aforementioned nearest-neighbors method found in [8]. A four-frame