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# On-the-Fly Performance Evaluation of Large-Scale Fiber Tracking

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## Abstract

*Large-scale fiber tracking in the images serial-sectioned from material samples is a critical step to analyze physical properties of continuous fiber reinforced composite materials. In serial-section imaging, increasing the sampling sparsity, i.e., the inter-slice intervals, can lead to significant speedups in data collection. However, increasing the sampling sparsity leads to difficulties in tracking large-scale crowded and similar-appearance fibers through the serial-section slices. One way to address this issue is to dynamically adjust the sampling rate by balancing the tracking accuracy with the data collection time. For this purpose, it is necessary to develop methods for estimating the tracking accuracy on the fly, i.e., immediately after tracking is updated on a new serial-section slice. Typical tracking accuracy metrics require ground truths, which are usually constructed by human annotations and unavailable on the fly. In this paper, we present a new approach to evaluate the performance of online large-scale fiber tracking* **without** *involving the ground truth. Specifically, we explore the local spatial consistency of the fibers between adjacent slices and define a new performance-evaluation metric based on this spatial consistency. A set of experiments on real composite-material images are conducted to illustrate the effectiveness and accuracy of the proposed performance-evaluation metric for large-scale fiber tracking.*

## Introduction

In materials science and research, an important problem is to quickly and accurately reconstruct and characterize the underlying microstructure of a material sample [6]. For fiber-reinforced composite materials, the microstructure feature of interest is the fibers, whose shapes, orientations, and distributions directly affect the mechanical properties [10, 13]. One typical approach to reconstruct the large-scale fibers is to serial section the 3D material sample, take high-resolution microscopic images for each slice, and finally detect/track all the fibers through the slices [14, 16]. However, dense sampling of serial-sectioning, i.e., with very small inter-slice intervals, is time consuming and prevents the quick processing of large-sized material sample. On the other hand, overly sparse sampling of serial-sectioning, i.e., with very large inter-slice intervals, introduces uncertainty and ambiguity in tracking fibers across slices. One effective approach to address this issue is to dynamically adjust the sampling rate, i.e, the inter-slice intervals, in serial-sectioning by balancing the tracking accuracy with the data collection time.

To achieve this goal, it is necessary to have a reliable evaluation of the tracking performance on the available slices with their inter-slice intervals before moving to serial-sectioning the next slice. This requires the use of an online tracking algorithm and the development of an on-the-fly tracking performance evaluation metric. By using an online tracking algorithm, such as Kalman filters, the fibers can be tracked based on the available slices and updated as soon as a new serial-sectioned slice is available. The on-the-fly performance evaluation continuously and quickly assesses the fiber-tracking performance as soon as a new slice is serial-sectioned and the online fiber tracking is updated using this new slice. The estimated tracking performance can then be used to adjust the inter-slice interval for the next slice.

In material science, materials are reinforced by embedded objects such as small particles, fibers, or boundaries between different crystals. In order to be effective, these objects must be fairly dense, leading to a common characteristic that the microscopic structure is composed of crowded or densely packed mixtures of embedded objects. The objects are mainly fibers in this paper. The fact that the fibers are crowded induces a spatial consistency for fiber neighbors in different slices, so we take advantage of that spatial consistency in estimating the performance of large-scale fiber tracking. In this paper, we focus on addressing the problem of on-the-fly performance evaluation such that the fiber tracking performance can be quickly estimated without any interruption after a new slice is serial sectioned and the online tracking is extended to this new slice. In particular, this requires to exclude the human interactions from the tracking performance evaluation. Unfortunately, existing multi-target tracking performance evaluations metrics, such as the widely used Multiple Object Tracking Accuracy (MOTA) [5], usually require the ground-truth tracking results. For fiber tracking, these evaluation metrics count the coincidence between the tracked fibers and ground-truth fibers to evaluate the tracking performance. The construction of the ground-truth fibers requires manual annotation of fibers on each slice and manual linking of the fibers between slices. Manually annotating ground truth for large-scale fibers (about 500 similar-appearance fibers in one slice) in an image sequence makes the whole system not automatic. The objective of this paper is to develop a new metric that can evaluate the performance of online large-scale fiber tracking without requiring the ground truth.

## Related Works

In most of the previous work [15, 9, 1, 8, 14], performance evaluation for object tracking requires manually annotated ground-truth tracking. By comparing generated tracking results with the ground-truth tracking on each image through the whole image sequence, many metrics have been proposed to evaluate the tracking performance from different perspectives such as MOTA, Multiple Object Tracking Precision (MOTP), Mostly Tracked (MT), Most Lost (ML), Recall, False Positive (FP), False Negative (FN), ID Switch (IDSW) and so on [5, 8]. Among these evaluation metrics, MOTA is the most widely used one by comprehensively considering the errors of FP, FN and IDSW. Different from these metrics, in this paper we propose a new metric to evaluate the large-scale fiber tracking without using any ground-truth tracking.

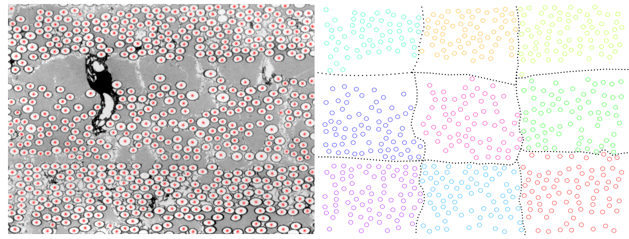
There have been some prior work [3, 2, 12] on performance measures for tracking without using ground-truth tracking. Inter-frame differences of color histogram and motion are used to evaluate the segmentation and tracking performance of a single object in [3, 2]. In [12], the difference of shape, appearance and motion of the tracked objects across consecutive frames are fitted into a naive Bayesian classifier to determine whether the tracking is good or bad. However, the existing evaluation methods without using ground truth cannot effectively evaluate large-scale fiber tracking studied in this paper. First, in fiber tracking, a large number of fibers share similar appearance (color, size, shape) and motion through the sequence, so the existing work based on appearance and motion consistency fails. Second, the existing work ignored the local spatial consistency of the fibers which has been shown as an important property in large-scale fiber tracking [14, 16]. In this paper, a new metric (without using ground truth) based on local spatial consistency of the fibers is proposed to evaluate the performance of online large-scale fiber tracking.

## Proposed Metric

As in many other multi-target tracking tasks, large-scale fibers in a composite material are usually formed into tows (bundles) that are then embedded in a matrix material [14, 16]. Tow construction may be unknown, so we alternately apply $K$-means algorithm to divide fibers into several clusters. We find that the fibers in one cluster usually show good proximity and parallelism. As a result, the tracked fibers within one cluster are expected to show good spatial consistency between adjacent slices. In this paper, we plan to quantify the fiber spatial consistency between slices and then use this to evaluate the fiber tracking performance, which does not involve any ground-truth tracking.

Given the on-the-fly tracking results on an image sequence of existing $N$ slices ($N > 1$), our goal is to evaluate the existing tracking results without using ground truth. Spatial location has been shown as an effective and reliable representation for similar-appearance objects as described in [7, 14, 16]. Therefore, to obtain the clusters, we first apply $K$-means algorithm to divide the trackers/fibers on the first slice into $K$ clusters using their spatial locations as features. Figure 1 shows an example of obtaining clusters by $K$-means algorithm on the first slice of the image sequence.

After knowing the clusters, local spatial consistency is evaluated for each cluster separately. Figure 2 shows an example of good and bad tracking for one sample tracker/fiber according to the local spatial consistency. For each tracker/fiber $i$ in one cluster, say $\theta$-th cluster, we can obtain its spatial $H$ nearest neighbors in slices $t-1$ and $t$ respectively. Please note that the neighbors are represented by their tracker identities. Let $\lambda_i^t$ be the number of common neighbors for the tracker/fiber $i$ in two adjacent slices



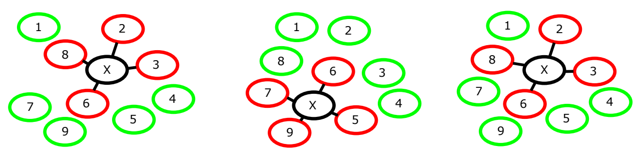
(a) (b)

***Figure 1.*** *An example of obtaining clusters: (a) the first slice of one sample image sequence, (b) obtained clusters by $K$-means algorithm shown in different colors. 9 clusters are displayed in this example.*

$t-1$ and $t$, and then the on-the-fly metric for this tracker/fiber $i$ on slice $t$ is computed as follows:

$$M_i^t = \frac{\lambda_i^t}{H}, \tag{1}$$

where larger $M_i^t$ indicates that more stable neighbors are preserved in two adjacent slices $t-1$ and $t$ for this tracker/fiber $i$. Let $m$ be the number of trackers/fibers in $\theta$-th cluster. The on-the-fly metric for $\theta$-th cluster on the slice $t$, denoted as $MT_\theta^t$, could be calculated as the mean of $\{M_i^t\}_{i=1}^m$. Because there are multiple clusters, we average $\{MT_\theta^t\}_{\theta=1}^K$ and get the on-the-fly metric for all clusters on the slice $t$ as $\phi^t$. After obtaining the on-the-fly metric for all clusters on each slice, the final on-the-fly metric for the whole tracking results on existing $N$ slices, denoted as On The Fly Metric (OTFM), can be easily computed as the mean of $\{\phi^t\}_{t=2}^N$. Large OTFM metric means good and stable spatial consistency for the whole tracking results on existing $N$ slices. OTFM metric takes values in [0,1] and it does not need the ground-truth tracking.



(a) (b) (c)

***Figure 2.*** *An example of good and bad tracking for one sample tracker/fiber denoted as X. $H = 4$ nearest neighbors for X are displayed with their tracker/fiber identities in two adjacent slices: (a) slice $t-1$; (b) bad tracking with few common neighbors on slice $t$ ($\lambda_X^t = 1$); (c) good tracking with many common neighbors on slice $t$ ($\lambda_X^t = 4$). $H$ nearest eighbors for X are shown in red with links to X. Green colors indicate trackers/fibers that are not $H$ nearest eighbors for X.*

## Experiment

To verify the effectiveness of the proposed OTFM metric for tracking performance evaluation, we use OTFM to rank the performance of several multi-target tracking algorithms on three sequences of material image slices for fibers without involving ground truth. We then take the ground-truth tracking and use traditional MOTA metric to rank the same set of multi-target tracking algorithms. We examine whether the performance ranking of these algorithms using the proposed OTFM metric is consistent to the performance ranking of these algorithms using MOTA metric and use this consistency to justify the effectiveness of the proposed metric. In addition, the monotonicity of tracking-performance curves with increasing sparsity by OTFM and MOTA are compared.

### *Dataset and Settings*

The material images used in our experiment were collected at the Air Force Research Laboratories (AFRL) using the RoboMet.3D automated serial sectioning instrument, which is a publicized dataset in [16]. The tested material is S200, which is an amorphous SiC/SiC matrix reinforced by continuous Nicalon fibers. Using the RoboMet.3D instrument, the test material sample is cross sectioned and one microscopic image is taken for each cross-sectioned slice. The test microscopic image sequence consisting of 100 slices, with an inter-slice distance of $1\mu m$ and the resolution of each slice is $1292\times968$. Figure 3 shows the way to collect the data as described above. This test image sequence contains hundreds of crowded fibers. Three sets of data with manually annotated ground truth for large-scale fiber tracking, denoted as Data 1, Data 2 and Data 3, are collected in the publicized dataset [16]. In this publicized dataset, to test the tracking performance under sparsely sampled image sequences, the original image sequence is down sampled. In particular, $C$ slices are skipped before taking the next slice in the original sequence, until the end of original sequence is reached, to construct such sparsely sampled image sequences. The parameter $C$ is named as *sparsity*: the larger the parameter $C$, the lower the inter-slice continuity of the constructed image sequence. The sparsity $C$ is in the range of [0,19]. Large-scale fiber tracking is performed in the image sequences under different sparsity cases.

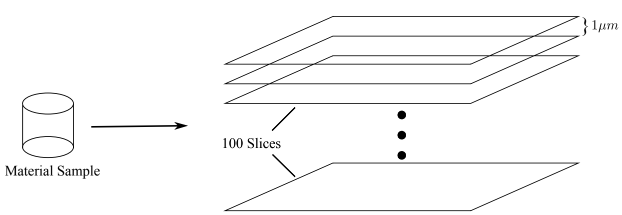



*Figure 3. Data collection. Three 100-slice image sequences, denoted as Data 1, Data 2 and Data 3, are collected in the publicized dataset [16]. Using RoboMet.3D, it takes about 15 minutes to grind for one slice.*

Based on the test image sequences under different sparsity cases, four Kalman-filter based online tracking algorithms [16] are used to track the large-scale fibers in the image sequence: 1) Kalman filter using nearest neighboring algorithm for association, 2) Kalman filter using Hungarian algorithm for association, 3) Kalman filter using a global thin-plate spline for association, and 4) Kaman filter using groupwise thin-plate splines for association. These four algorithms are denoted as Kalman-NN, Kalman-Hung, Kalman-Global and Kalman-Groupwise, respectively. For each sparsity case, we evaluate the corresponding tracking results by MOTA metric with ground truth and OTFM metric without ground truth independently and check their evaluation consistency.

There are two parameters to set in the OTFM metric. The number of clusters $K$ for $K$-means clustering is set to 9 in our experiment. The number of spatial nearest neighbors $H$ in Eq. (1) is set to 8 in our experiment.

### *Experimental Results*

MOTA and OTFM evaluations for the tracking performance of the four tracking methods (Kalman-NN, Kalman-Hung, Kalman-Global and Kalman-Groupwise) are illustrated in Fig. 4. We can find that OTFM without using ground truth could get quite similar evaluation results as MOTA which uses ground truth. As shown in Fig. 4, the monotonicity of each tracking method's performance curve by OTFM is highly consistent with that by MOTA as sparsity increases and the performance-ranking order of different tracking methods by OTFM is also quite consistent with that by MOTA.

The correlation coefficients of the evaluation results by MOTA and OTFM for different tracking methods are shown in Table 1. The mean correlation coefficient in Table 1 is 0.95. The high correlation coefficient demonstrates that the evaluation results by MOTA and OTFM are highly consistent for each tracking methods. In other words, the tracking performances by MOTA and OTFM show highly similar monotonicity as sparsity increases.

**Table 1. Correlation coefficients of evaluation results by MOTA and OTFM for different tracking methods.**

| Methods | Data 1 | Data 2 | Data 3 |
|---|---|---|---|
| Kalman-NN | 0.99 | 0.99 | 0.99 |
| Kalman-Hung | 0.99 | 0.99 | 0.99 |
| Kalman-Global | 0.95 | 0.88 | 0.77 |
| Kalman-Groupwise | 0.94 | 0.96 | 0.94 |

In addition, we also conduct experiments to compare the performance ranking by MOTA and OTFM. Under each sparsity case, the performance-ranking order of the four tracking methods by MOTA and OTFM should be consistent. There are some commonly used rank measures to compare ordering [4]. Under one sparsity case, let the sorted performance-ranking order of the four tracking methods by MOTA and OTFM to be $Rank_{MOTA}$ and $Rank_{OTFM}$ respectively. To compare $Rank_{MOTA}$ and $Rank_{OTFM}$, the area under the ROC curve (AUC) and accuracy (acc) are computed. Given $n$ tracking methods, we treat the tracking methods whose ranked position is greater than $\frac{n}{2}$ in $Rank_{MOTA}$ as *real positive* tracking methods and the rest as *real negative*. Suppose the ranked position of the *real positive* tracking methods in $Rank_{OTFM}$ are $P_1, P_2, ..., P_a$, where $a = \left\lceil \frac{n}{2} \right\rceil$. AUC is computed as $\frac{\sum_{i=1}^{a}(P_i - i)}{a^2}$. Similar to AUC, in $Rank_{OTFM}$, we classify tracking methods whose ranked position above half as positive and the rest as negative. Compared to *real positive* and *real negative* tracking methods, acc is computed as $\frac{tp+tn}{n}$ where $tp$ and $tn$ are the number of correctly classified positive and negative tracking methods by the above classification using $Rank_{OTFM}$. AUC and acc are in the range of [0,1]. Details about computing AUC and acc of ranking-order measures can be found in [4]. Then, the AUC and acc results are averaged over different sparsity cases. Large AUC and acc results indicate consistent ranking order of $Rank_{MOTA}$ and

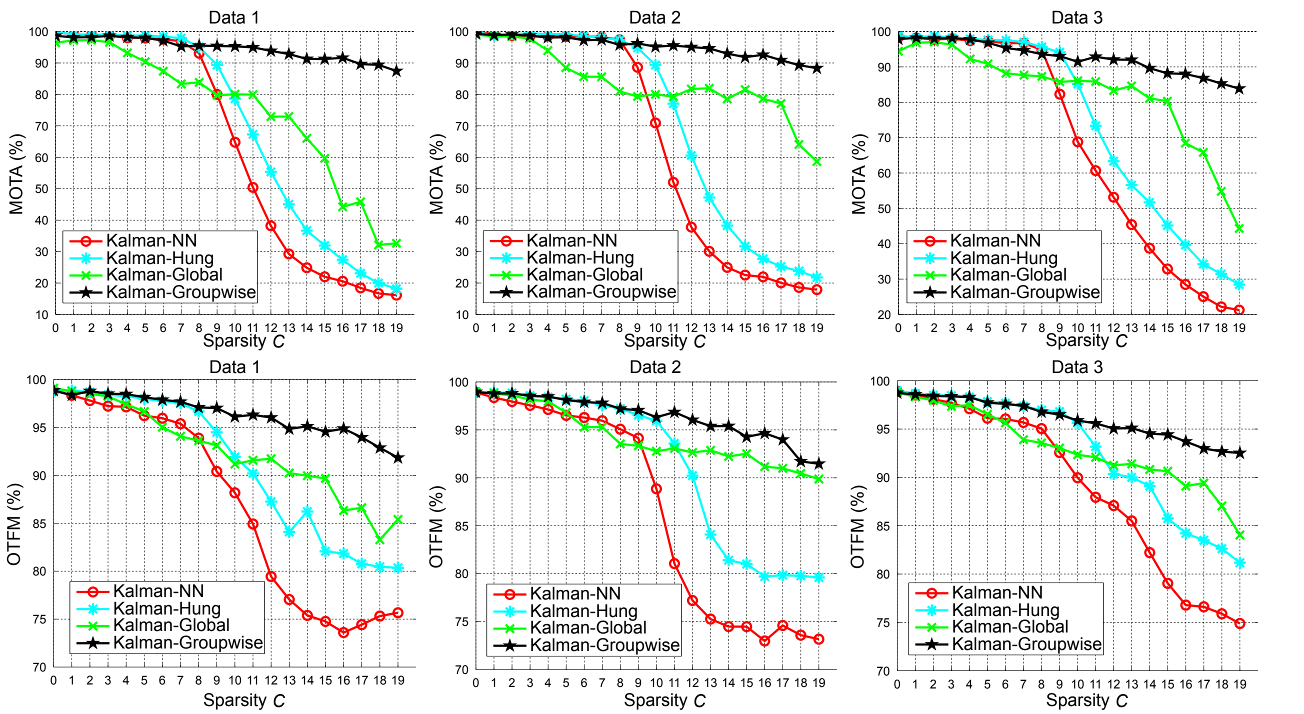



***Figure 4.*** *Tracking Performance by MOTA using ground truth and OTFM without involving ground truth under different sparsity cases on Data 1, Data 2 and Data 3. Top row: MOTA results using ground truth; Bottom row: OTFM results without involving ground truth.*

$Rank_{OTFM}$. The resulting AUC and acc results are shown in Table 2. Over the three sets of data, the mean AUC is 0.92 and the mean acc is 0.89, which means the performance ranking of the four tracking methods by MOTA and OTFM are quite consistent.

**Table 2. AUC and acc measurement by comparing $Rank_{MOTA}$ and $Rank_{OTFM}$.**

| Ranking Order Measure | Data 1 | Data 2 | Data 3 |
|---|---|---|---|
| AUC | 0.89 | 0.93 | 0.94 |
| acc | 0.90 | 0.90 | 0.88 |

Also, we randomly sample the evaluation results by MOTA with ground truth and compare them with the corresponding evaluation results by OTFM without ground truth, and repeat this comparison for 1000 iterations. In each iteration, we random choose 2 to 4 tracking methods and then random select 1 to 20 sparsity cases, which constructs a random sampled set, say $\mathbf{S}$. For the set $\mathbf{S}$ in one iteration, we concatenate the evaluation results of $\mathbf{S}$ by MOTA with ground truth and by OTFM without ground truth respectively. Let the sorted performance-ranking order of $\mathbf{S}$ by MOTA and OTFM to be $Rank^{\mathbf{S}}_{MOTA}$ and $Rank^{\mathbf{S}}_{OTFM}$ respectively (similar as before). For each iteration, we compute AUC and acc between $Rank^{\mathbf{S}}_{MOTA}$ and $Rank^{\mathbf{S}}_{OTFM}$. The histograms of AUC and acc distributions on the 1000 iterations are displayed in Fig. 5, from which we can see that most of AUC and acc results are pretty close to 1 with small variances. Table 3 shows mean and standard deviation for AUC and acc histograms displayed in Fig. 5. The distribution illustrates that the performance-ranking order by MOTA and OTFM are highly consistent.

In summary, Table 1, Table 2, Table 3, Fig. 4 and Fig. 5 together show that the proposed OTFM metric without using ground truth could achieve effective and consistent performance evaluation for online large-scale fiber tracking as the MOTA metric using ground truth.

### *Discussion*

As we described above, the range of OTFM metric is always in [0,1]. With different number of spatial nearest neighbors $H$ in Eq. (1), OTFM metric considers the local spatial consistency in different number of neighbors. Figure 6 shows the effects of different $H$ to OTFM computation. The performance curves with different $H$ are highly similar, indicating that OTFM computation is not sensitive to the parameter $H$.

For the computational efficiency, we record the running time of computing OTFM metric over an image sequence containing 663 fibers on a PC with 2.6GHz CPU and 4GB memory. It takes just 0.24 seconds to perform $K$-means clustering ($K = 9$) on the first slice and on average 1.86 seconds to calculate OTFM metric ($H = 8$) on one slice. Therefore, the computation for OTFM metric is very efficient, making it suitable for on-the-fly evaluation of large-scale fiber tracking.

## Conclusions

In this paper, we propose a new on-the-fly metric called OTFM for evaluating the performance of on-the-fly large-scale fiber tracking. Without requiring the ground-truth tracking, the proposed evaluation metric can evaluate the performance of online large-scale fiber tracking accurately and efficiently. The pro-

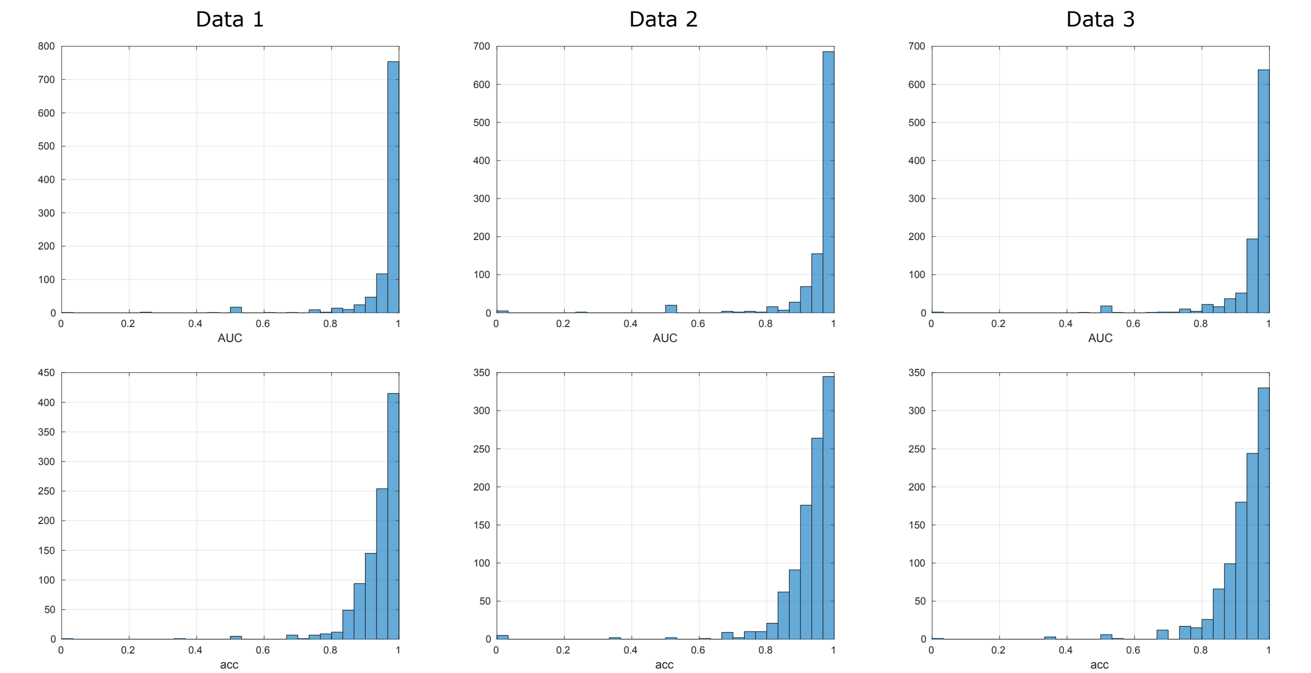



*Figure 5. AUC and acc histograms by comparing randomly sampled $Rank^{S}_{MOTA}$ and $Rank^{S}_{OTFM}$ on Data 1, Data 2 and Data 3. Each of the histograms holds 30 bins and 1000 values in total.*

**Table 3. Mean and standard deviation of AUC and acc histograms displayed in Fig. 5. In each cell, mean and standard deviation are displayed.**

| Histogram | Data 1 | Data 2 | Data 3 |
|---|---|---|---|
| AUC histogram | $0.96 \pm 0.09$ | $0.95 \pm 0.11$ | $0.95 \pm 0.09$ |
| acc histogram | $0.94 \pm 0.08$ | $0.93 \pm 0.10$ | $0.93 \pm 0.09$ |

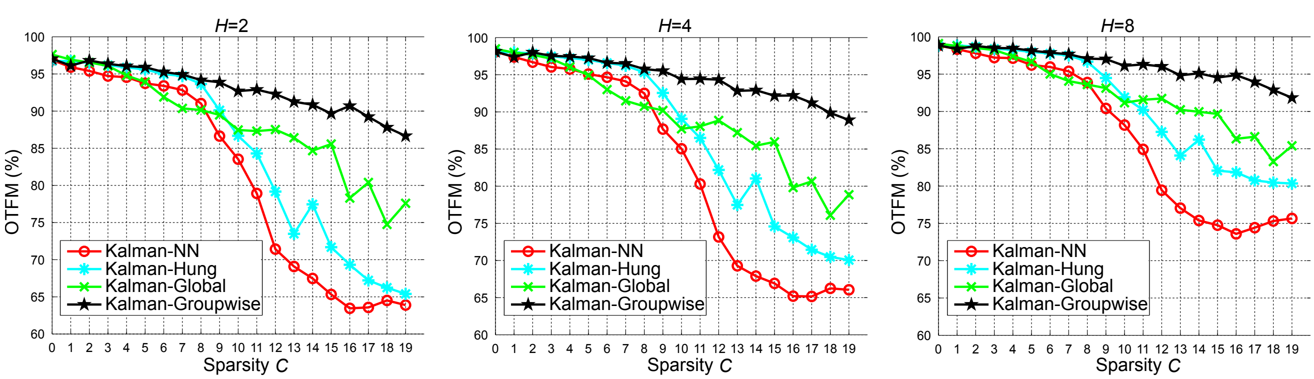



*Figure 6. OTFM evaluation results with different number of spatial nearest neighbors $H$. OTFM evaluation results when $H$=2, 4, 8 on Data 1 are shown from left to right. We find that OTFM computation is not sensitive to the parameter $H$.*

posed metric can be used to guide the adjustment of inter-slice intervals in serial-sectioning a material sample and therefore speed up data collection and processing. In the future, we plan to extend this work to evaluate crowded human tracking [11] without using ground-truth annotation.

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