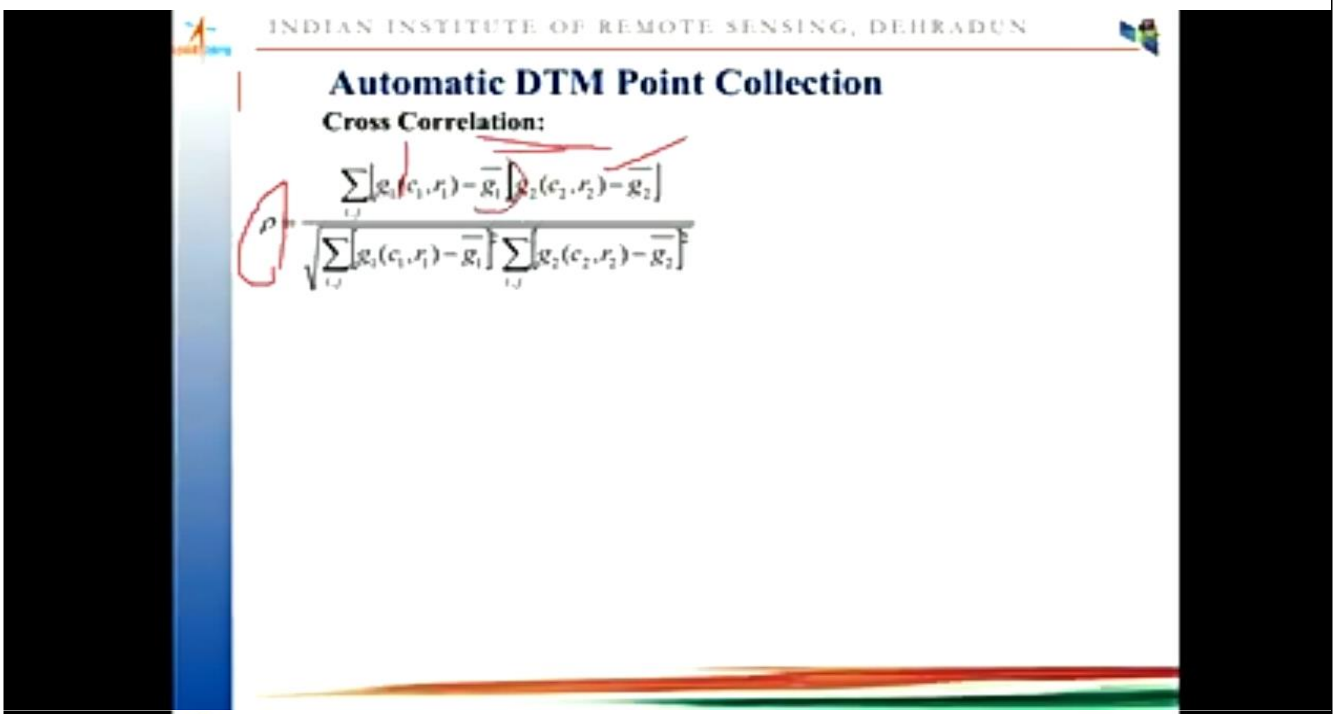
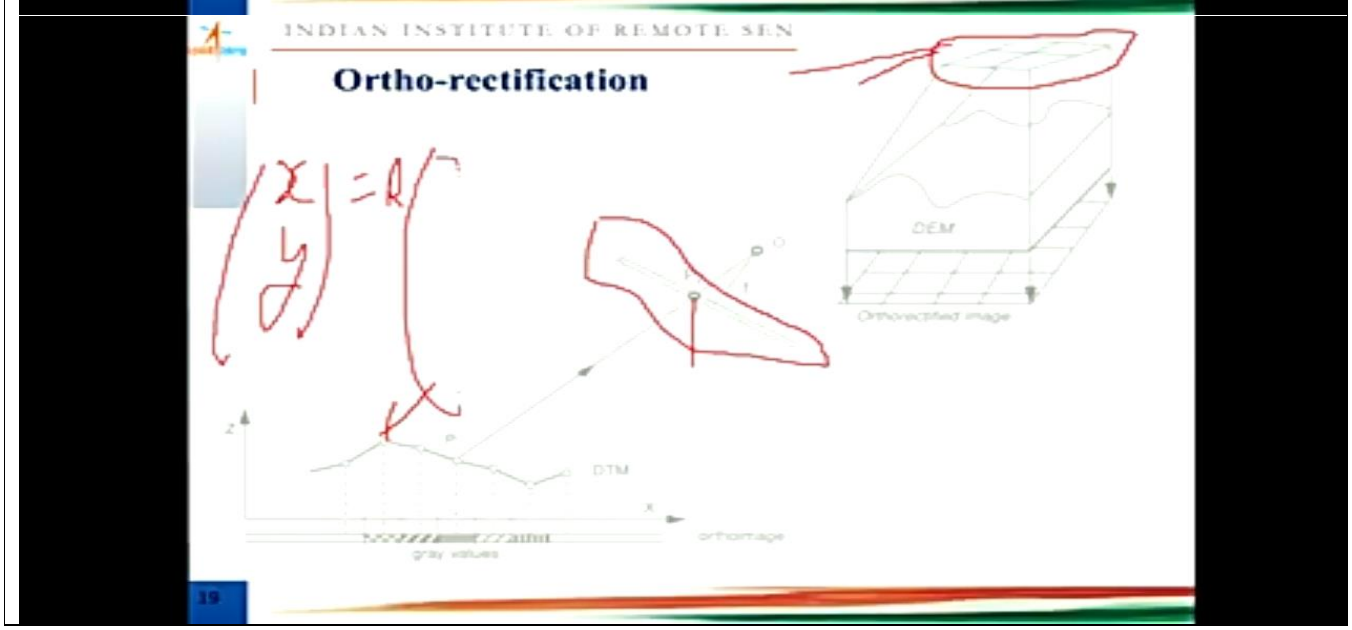
DAILY ASSESSMENT FORMAT

Date:	3^{rd} July2020	**Name:**	Soundarya NA
Course:	IIRS Outreach Program on Satellite Photogeommetry	**USN:**	4AL16EC077
Topic:	IIRS Outreach Program on Satellite Photogeommetry	**Semester & Section:**	8^{th} - B

FORENOON SESSION DETAILS
Image of session





Report:

Filtering of ground points is a key step for most applications of airborne LiDAR point clouds. Although many filtering algorithms have been proposed in recent years, most of them suffer from parameter setting or thresholds fine-tuning. This is most often time-consuming and reduces the degree of automation of the applied algorithm. To overcome such problems, this paper proposes a threshold-free filtering algorithm based on expectation–maximization (EM). The filter is developed based on the assumption that point clouds are seen as a mixture of Gaussian models. Thus, the separation of ground points and non-ground points from point clouds is partitioning of the point clouds by a mixed Gaussian model that is used for screening ground points. EM is applied to realize the separation, which calculates the maximum likelihood estimates of the mixture parameters. Using the estimated parameters, the likelihoods of each point belonging to ground or non-ground are computed. Noticeably, point clouds are labeled as the component with a larger likelihood. The proposed method has been tested using the standard filtering datasets provided by the ISPRS. Experimental results showed that the proposed method performed the best in comparison with the classic progressive triangulated irregular network densification (PTD) and segment-based PTD methods in terms of omission error. The average omission error of the proposed method was 52.81% and 16.78% lower than the classic PTD method and the segment-based PTD method, respectively. Moreover, the proposed method was able to reduce its average total error by 31.95% compared to the classic PTD method.

In morphology-based approaches, some morphology operations, namely, dilation, erosion, opening and closing are involved. To realize this kind of method, the key issue is to choose an appropriate window size. A large window size will flatten the terrain details, while a small window size has no effects on filtering large building roofs. To overcome this problem, proposed a progressive morphological filtering method by gradually changing the window size and threshold. Nonetheless, there are two main problems with this algorithm. First, this method assumes the slope of the entire terrain as a constant, which is obviously unreasonable in undulation environments. Second, this method cannot effectively protect the terrain details. To solve these problems, many modified variants of this traditional work have been proposed. Recently, Hui et al. improved the progressive morphological filter by combining it with a multi-level interpolation filtering method. Promising results were achieved in complicated terrain environments.

According to the central limit theorem, naturally measured LiDAR data will lead to a normal distribution [39,40]. Conversely, due to the complex terrain environments, point clouds can be assumed as a mixture of Gaussian models. Therefore, the separation of ground points and non-ground points from point clouds can be seen as a separation of a mixed Gaussian model. EM is an approach for fitting probability distributions and calculates the maximum likelihood estimates of parameters to probabilistic models being fit to the data. When we do not know which component (ground or non-ground) the point belongs to, EM can be used to calculate maximum likelihood estimates of the mixture parameters. Using the estimated parameters, the likelihood of each point belonging to ground or non-ground can be computed. It is obvious that the point is labeled as the class corresponding to the maximum likelihood.

Although most of the proposed methods in the literature yield good filtering performance, they still require complicated parameter tuning when encountering various types of terrain, such as urban areas, mountainous areas, forested areas, etc. Parameter-tuning is generally time consuming and always incurs heavy manual editing costs. Thus, these algorithms are not easy for inexperienced users to realize filtering. To overcome this problem, this paper proposes a parameter-free filtering algorithm based on expectation–maximization (EM). The proposed algorithm is developed based on the assumption that point clouds are seen as a mixture of Gaussian models. The separation of ground points and non-ground points from point clouds partitions the point clouds by a mixed Gaussian model that is used for screening ground points. EM is applied for realizing the separation. The proposed method is tested using the datasets provided by the International Society for Photogrammetry and Remote Sensing (ISPRS). Experimental results show that the proposed EM method achieves good performance under variant terrain features without any human manipulation. Thus, the proposed method will be user-friendly, thereby providing a good foundation for the automatic algorithm development of post-processing applications for airborne LiDAR.

Because point clouds are generally irregularly distributed, it is inefficient to locate one point's neighbors. In this paper, the neighbors of one point refer to the nearest points of one point in the x and y directions. The brute force nearest neighbor search has computational complexity O(n), which is linear to the number of points n. To speed up the search, this paper organizes point clouds using a k-dimensional (kd) tree. The kd-tree algorithm splits the data in half at each level of the tree on the dimension for which the data exhibit the greatest variance. The recursive binary splitting can reduce the average complexity to O(log n). Each non-leaf node (referring to each LiDAR point in the subspace) can be seen as a segmentation hyper plane, which is perpendicular to the coordinate axis and divides the space into two parts. The main steps of the kd-tree construction are as follows:

1. Determine the split domain. Calculate the variance of the LiDAR data in the x and y dimensions. Choose the dimension corresponding to the larger variance as the split domain. For instance, we choose the x dimension as the split domain.
2. Find the segmentation hyper plane. Sort the LiDAR data in the x direction and find the midpoint as the segmentation node. The hyper plane is the one through the segmentation node and perpendicular to the x-axis.
3. Determine the left subspace and right subspace. According to the hyper plane, the points with x coordinates less than the segmentation node belong to the left subspace, while the points with x coordinates greater than the segmentation node belong to the right subspace.