Unsupervised Classification and Separation of Objects in 3D

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Abstract

Object segmentation for the purpose object and pattern recognition has been a long standing subject of interest in the field of machine vision. Despite the significant attention given to the development of segmentation and recognition methods, the critical challenge of separating merged objects did not share the spotlight. In the work presented in this manuscript, we propose a simple yet novel approach to overcome this hurdle, by developing a methodology for unsupervised classification and separation of objects in 3D. Lower dimensionality classifiers are joined to provide a powerful higher dimensionality classification. The robustness of this approach is illustrated through its implementation on two case studies of merged objects. Applications of this methodology can further extend from structural classification to general problems of clustering and classification in various fields.

Keywords: Unsupervised Classification, Computer Vision, Machine Vision, Objects Separation

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1. Introduction

As the Fourth Industrial Revolution rapidly takes form, the importance of digitization is indisputable, particularly in the fields of artificial intelligence and autonomous machines and systems [1]. A key requirement for any autonomous mechanism is the capability to gather and assimilate information regarding its surroundings, information to be incorporated in the decision making process. Face recognition systems [2], terrain analysis [3], autonomous vehicles and vehicles tracking [4, 5], and medical-imaging based diagnosis [6, 7, 8] are only several examples for such mechanisms. Equipping machines and systems with capabilities which are similar to the human vision and image perception, is paramount.

Identifying structural element in 2D and 3D imaging has become a common practice in many fields as imaging technology availability grow. In microstructural material modeling and analysis, computed tomographic (CT), micro-computed tomographic (μCT) imaging, and other imaging techniques are often used for structural reconstruction and analysis [9, 10, 11]. Moreover, these imaging techniques become a valuable tool for analyzing failure processes such as fracture, creep and other damage mechanisms [12, 13, 14].

Object and pattern recognition, and the preceding image segmentation, play a pivotal role in machine vision, as they are essential for any vision based operation. Spatial descriptors of generic objects, originated in information extracted from images, enable us to identify objects and associate their different instances to various classes. Prior to recognition, objects must first be segmented through the process of image segmentation, in which an image is partitioned to different regions of interest based on their characteristics (gray levels for example) [15]. A widely used segmentation methodology includes clustering based segmentation methods, in which regions or objects in images are segmented based on clusters of visual distinct features (such as color, pixel intensity or texture).

Many studies in the field of machine vision have focused on the challenges in object recognition and image segmentation, covering different aspects, both in 2D and 3D. A technique for analyzing complex multi-mode features, called feature space analysis, was introduced in [16]. In feature space analysis, densities of image subsets, estimated with the mean shift method, received parametric representations in the parameter space. Significant features in the image could then be identified based on the density distribution in the parameter space, which corresponded to the image features. Segmentation based on the mean shift method was extended in [7, 17] to the temporal dimension. Spatial-temporal filtering and segmentation of magnetic resonance images (MRI), resulted in segmentation and tracking of multiple sclerosis (MS) lesions.

Probability distribution based segmentation was explored in [18] for the purpose of segmenting skeletal fiber tracts. The spatial information for tracts segmentation was provided by combining diffusion maps and a probability density based metric. Measuring tract similarity, the aforementioned metric was obtained from the affinity between multivariate Gaussian probability densities, which represented fiber tract. A similar approach was taken in [6], where a different probabilistic measure for clustering fiber tracts into bundles was suggested. Expanding the work on 2D fiber tracts segmentation, a framework for 3D classification of fiber tracts based on curvature points was developed in [8].

The work presented in [19] yielded a simple clustering based segmentation method, which incorporated spatial position constraint of pixels. After the image was partitioned to blocks and their descriptors were extracted, the blocks were clustered using K-means algorithm. An automatic segmentation using Constrained Parametric Min-Cuts (CPMC) was developed in [20]. The segmentation process included two steps, first the target image was partitioned to sub-regions that were segmented and ordered according their alignment with the image contours. In the second step, the sub-regions were ranked based on the probability of similarity to real-world objects. The highest ranked ob-

ject hypotheses were then evaluated and compared against the original image. This method was further developed in [21] by combining it with Unsupervised Discriminant Clustering (UDC). Segment hypotheses with high percentage of object regions were clustered together with the purpose of obtaining shape segmentation with higher accuracy.

Classification or recognition of objects or patterns are the most common applications to follow the segmentation process. Fiber dye classification method was presented in [4]. Fibers reflectance spectra dimensionality was reduced using Principal Component Analysis (PCA), and fiber dyes were identified based on nearest neighbor classification of their principal components. A scheme developed in [22] suggested a two steps process for unsupervised classification large dimensionality hyperspectral imaging. Fit parameters associated with image features were clustered based on their histograms, after sets of basis functions were generated based on the relevant fit parameters.

The problem of recognizing an object class based on a small number of unsegmented images was addressed in [23] using a learning model. Learning Objects Classes with Unsupervised Segmentation (LOCUS) was employed in learning the shape of a representative objects, by inferring object segmentation throughout the learning process. Recognizing objects in a point cloud was a subject of interest in several studies, such as [24] for example. A pipeline for computing a recognition threshold was proposed, by extracting key point feature of the point cloud and matching them with descriptors of segmented objects.

For the purpose of tracking objects in space in the context of robotic sensing, [25] applied object recognition to thermal imaging in, by mapping thermal data to a point cloud, and recognizing objects by their heat radiation. Objects tracking was also discussed in [5], where a framework for vehicle tracking was developed. In the proposed framework object detection and segmentation were followed by camera self calibration and vehicle modeling. The final stage of the framework employed adaptive segmentation in order to deal with problem of

objects merging, caused by poor segmentation due to color similarities between objects. Although image segmentation and object recognition are key challenges in machine vision, and despite the numerous studies and different methodologies dedicated to the subject [15, 26, 27], as pointed out in [28], the problem of separating merged or overlapping objects still poses a great challenge.

In the work described in this paper, we present a methodology for unsupervised separation and classification of merged objects in 3D. The foundation on which our methodology was built upon, is one of the central ideas in learning - Boosting. By incorporating several "weak classifiers" to form a "committee", boosting methods produce a robust classifier [29, 30]. Furthermore, the suggested methodology was expended to establish a framework applicable to the field of microstructural modeling. We focused in particular on fiber reinforced composite materials, and the described methods were implemented on a ceramic matrix composite arranged in an eight-harness weave architecture and a high-performance fiber reinforced concrete. The methodology described above takes a concrete form in the next section (Sec. 2), as the unsupervised separation and classification process is explained. The methods in section 2 are followed by their implementation on two cases of microstructural material reconstruction in section 3. Section 4, where the work and the results of this study are discussed, brings the manuscript to a close.

2. Methods

2.1. Image Processing

As a preliminary step to the separation and classification process, a few image processing measures were carried out in order to filter and smooth the raw 3D imaging data. It is worth mentioning that images were in a grayscale to begin with, or converted to that format. First histogram equalization method was used for image enhancement [26, 27], this was followed by applying threshold

to the image. Image threshold process was chosen based on the input quality and characteristics. Lastly, morphological opening was done for the purpose of smoothing the image.

2.2. Initial Volume Based Segmentation

The 3D processed image was further analyzed in order to find and label connected volumetric objects. First, the elements of the 3D array, representing the voxels in the 3D image, were scanned. If an unlabeled voxel was identified, the voxel and all connected voxels were assigned a new label using a flood-fill algorithm [31]. Voxels connectivity was detrained based on the 6 nearest neighbors to a certain voxel (for example, the nearest neighbors of $v_{i,j,k}$ were $v_{i-1,j,k}$, $v_{i+1,j,k}$, $v_{i,j-1,k}$, $v_{i,j+1,k}$, $v_{i,j,k-1}$ and $v_{i,j,k+1}$). This process was repeated until all voxels were labeled.

2.3. Plane Based Segmentation

A single connected object was in fact composed of several intersecting, overlapping or tangent objects - a bundle of fibers for example. In order to separate the connected objects, the following assumption was made: All points of a convex body in R^n will belong to the same sub-body in R^m, where $m < n$. In other words: all points of a 3D convex objects will belong to the same 2D convex object, in any cutting plane. It is important to point out that this approach was based on the boosting concept, in the sense that an improved classification (or connectivity) of voxels in a higher dimension was achieved by combining the output of "weak" classifiers in a lower dimension.

The 2D connectivity in the cross-sectional planes was determined using an efficient *run-length* implementation of the *local table method* [31, 15]. The process included 4 stages: (i) Encoding the image using *run-length encoding* - A list of pixel runs was generated. Each run recorded the location of the start pixel and the length of the run (the term *run* refers to a sequence of pixels in

1D). (ii) Preliminary labeling and label equivalency - Each run was assigned a preliminary label, adjacent runs were aggregated to an equivalent class label and their labels were recorded as well (adjacent runs were then determined as equivalent). (iii) Determining class equivalency - Different classes containing equivalent runs were merged into a single class. (iv) Relabeling - The merged classes were relabeled where each merged class contained all the equivalent runs. An illustrated example of the runs and classes appears in Fig. 1.

The 2D connectivity in consecutive slices was used to determine 3D connectivity in a process conceptually similar to that of the *run-length* implementation. To this end, the equivalencies of merged classes in neighboring slices were evaluated. Equivalent classes were grouped into global classes (volumetric classes) and merged. The merged global classes were then relabeled and resulted in 3D connectivity based on 2D cross-sectional connectivity.

The classes equivalency in the different slices was determined in the manner described below, where *local labels* were the labels of the merged classes in 2D and *global labels* were the labels of the merged global classes in 3D. The process described here is also illustrated in Fig. 2. While advancing from one slice to another in a specific direction, the local and global labels of all pixels in the i-th slice were recorded in an equivalency table. Several scenarios of local and global labeling were possible:

1. A class with a local label but without a global label.
2. A class with a local label but only a subset of the class had a global label.
3. A class with a single local label and subset of that class with different global labels.
4. Several classes with different local labels but with common global labels.

Examining each local label in the i-th slice yielded three possible events:

1. Non of the pixels in the class had a global label - in this case all pixels were assigned the same new global label.

2. Some of the pixels in the class had the same global label - here the unlabeled pixels were assigned the global label of the other pixels in that class.
3. Some of (or all) the pixels in the class had different global labels - this event occurred when two objects (or more) from previous slices merged into a single object.

The unlabeled pixels were iteratively assigned global labels using a nearest neighbor based hierarchial algorithm hereafter referred to as the *conflict resolution algorithm* (for which further details are provided below).

After each voxel in the i-th slice was assigned a global label, the slice was checked for disconnected global labels. This was the fourth possible event, in which a single object from previous slices was split to two or more objects. In this case, new global labels were assigned to the disconnected areas with the same global label, and backward adjustment correction was performed in all related previous slices using the *conflict resolution algorithm*.

In order to determine the voxel labeling where the same global label appeared in different local classes or where different global labels appeared in the same local class, the *conflict resolution algorithm* was used. First, all pixels in question were assigned global label based on the K nearest neighbors, where the number of nearest neighbors was set to be $K = 8$. This number of neighbors was chosen after providing the best results for the cases considered herein. If unlabeled pixels where to be found, after the initial assignment, another iteration was performed with $K = k - 1$ nearest neighbors. The process continued until all pixels were labeled or until K was reduced to zero. In case unlabeled pixels remained, a problem flag was raised. This did not happen in the present studies.

Once all classes that had local labels were assigned global labels as well, the global labels were projected to the next slice, and the process advanced onwards

to the $(i+1)$-st slice. Otherwise, the voxels with local labels but without a global one in $(i+1)$ were examined and assigned global labels separately. The global labels were projected to the next slice based on the following principle: if a voxel with a global label in i, had a parallel non-empty voxel in $i+1$ with a local label, the voxel in $i+1$ was assigned with the same global label as its parallel voxel in i.

Figure 1: Connectivity and labeling implementation in 2D and its 3D linkage.

2.4. Linking Different Segmentations

The process described above, yielding a plane based 3D voxels connectivity, was executed again as necessary (according to the structural complexity), each time in different progress direction. A voxels global labels table was then constructed, in which each row corresponded to a certain voxel, and contained

Figure 2: Process illustration of the secondary classification procedure in merging over segmented fibers.

the voxel's global labels from the plane based segmentations in the different directions.

Unique rows in the global labels table, which represented unique combinations of global labels (from the different directions), were identified, and voxels were grouped to 3D super classes based on these unique combinations of global labels. Finally, new labels were assigned to all super classes and, which represented the separated and segmented volumetric objects. In some cases the process described above resulted in over segmentation, where continuous objects were represented by several different smaller objects. An example of over

segmentation is given in the following section. Additional ad hoc steps, which are described below, were taken in order address the distinct challenges that arose from the different characteristics of the case studies.

3. Implementation

3.1. Eight Harness Weave

An eight-harness weave (8HW) of a ceramic matrix composite (CMC) was considered herein to illustrate the implementation of the approach described above. A geometric model of the material, a model which was generated as part of the work presented in [11], is shown in Fig. 3. The relatively simple geometry of the problem, required a plane based volume segmentation in only one direction. Two directional segmentations are presented herein in order to highlight the similarities and differences between them. Due to the contacts and intersections of the warp and waft tows, the initial volume segmentation, which was determined based on six nearest neighbors connectivity, yielded a single volumetric object, merging the tows.

(a) (b)

Figure 3: Longitudinal (orange) and transverse (blue) tows (a); and separated tows (b).

The initial volume based segmentation was followed by determining the 2D

connectivity of the cross-sectional planes. Illustrated in Fig. 4 are the resulting connectivities in the y direction (Fig. 4a) and the x direction (Fig. 4b).

Figure 4: Eight harness weave plane based segmentation in the transverse direction (a) and the longitudinal direction (b), resulting in bundle separation and classification (c).

Linking the different cross-sectional connectivities in the y direction using the methods described above, led to the determination that the tow labeled as $\boldsymbol{\alpha}$ in Fig. 4c included the areas labeled as A2, A5, A9, A11, A13, A15, A19 and A21, as well as subareas in the areas labeled as A6 and A17 in Fig. 4a. Similarly, the tow labeled as $\boldsymbol{\beta}$ in Fig. 4c included the areas labeled as B2, B5, B9, B11, B12, B14, B18 and B21, as well as subareas in the areas labeled as B6 and B17 in Fig. 4b.

The subareas in the merged ares A6, A17, B6 and B17 (Fig. 4) were established based on neighboring slices according to the previously discussed methods. Another approach for detecting subareas in this case would involve exploring the overlaps between cross-sectional connectivities in several directions. For ex-

ample, the union between A17 and B1, B4, B6, B4, B64, B8, B10, B12, B14, B17, B20 and B22 would result in detecting the tow labeled as γ in Fig. 4c.

3.2. Fiber Reinforced Concrete

Attention was then focused on a sample of fiber reinforced concrete, in which straight and hooked fibers were embedded in a cement matrix (see Fig. 5). The material sample on which the classification and separation process was implemented on in this work, was first studied in [32, 32] in the context of energy dissipation mechanisms. Due to the high degree of contact and overlapping between the fibers, isolating individual fibers proved to be most challenging.

Figure 5: 3D reconstruction of the fiber reinforced concrete sample with (a) and without (b) the cement matrix, along with a representative sample of the reinforcement fibers (c). Figures courtesy of Ms. Lauren S. Flanders and Prof. Eric N. Landis [32].

The original sample, measured $1513 \times 1513 \times 2843$ pixels (see Fig. 6a), was partitioned to manageable sub-volumes. Herein one of the sub-volumes, measured $250 \times 250 \times 500$ pixels (see Fig. 6b), was considered in the implementation of the proposed segmentation approach. Initial volume segmentation of the original sample, using six nearest neighbors connectivity, yielded 131486

connected objects of any volume. However, less than 7000 objects remained, after excluding smaller objects with volumes ranging from 500 to 1500 voxels.

(a) (b)

Figure 6: 3D reconstruction of the original sample (a) and the analyzed sub-volume (b).

A representative sample of six objects, shown in Fig. 7, illustrates the problematic nature of fibers interactions. Cross intersection and tangential contact of fibers, as well as merging of separate fibers and splitting of fibers, led to an intricate geometric space for analysis and segmentation.

Figure 7: A representative sample six objects, demonstrating the variability of bundles of merged fibers.

The first steps of the segmentation process in this case, were similar to those employed in the segmentation of the eight harness weave model. Since the initial volume analysis identified more than one object, the plane based segmentation stage which followed was executed separately for each of the registered objects. In order to deal with the geometric complexity, the plane based segmentation was performed in three different directions: x, y and z.

Implementing the plane based segmentation on object #3 in Fig. 7, led to three subdivisions of the connected fibers in the object of interest. Each voxel was assigned three labels based on the distinctive partitioning in the x, y and z directions. Different number of subsegments, as well their morphology, the x, y and z directional segmentations resulted in 38, 8 and 7 partitioned volumetric segments respectively (shown in Fig. 8a, 8b and 8c).

Figure 8: The resulting plane based segmentation of object number 3 in the x (a), y (b) and z (c) directions.

Once the analysis was completed in all three directions, the directional segmentations were combined by identifying unique sequences of the directional labels. Each of the 60 unique sequences attained for object #3, was assigned a

new global label.Bearing in mind that object #3 consisted of only three fibers, the process yielded an over segmented output, which required further processing, specifically designed for this geometry. Considering the resulting over segmentation, merging and joining segments motivated the configuration of any additional handling.

Breaking away from the general directional segmentation process in order to focus on fiber reinforced like materials in general, and high performance concrete studied herein in particular, provided the necessary justification for making several simplifications and assumptions pertaining the geometry in question. Hence, the following assumptions were made regarding the objects that were to be identified:

1. Fibers had a cylindrical like geometry that was simplified as straight lines.
2. Fibers had a low width-to-length ratio ($w/l < R_{max}$), reflecting a difference of approximately one order of magnitude ($R_{max} = 0.2$).
3. Fibers had a maximal acceptable width w_{max}, where w_{max} was set as $w_{max} = 15[voxels]$.

The first stage of merging over segmented objects to fibers included two parts, which are illustrated in Fig 9. In the first part, after small objects and objects with w/l higher than the set threshold were excluded, the geometric characterizations of the remaining objects were determined. Geometric characteristics included object's center, object's axis (start and end points of the axis) and object's direction vector. In order to determine the latter two (object's axis and direction), Principal Components Analysis (PCA) [33] was employed in conjunction with Orthogonal Regression through the object's voxels [31], resulting in a line in space (the object's axis).

Serving as an input for the second part of the first stage, the geometric characteristics were used to identify parallel objects. Pairwise angles between unlabeled and labeled objects were calculated and pairs of objects with $\alpha <$

α_{max} were categorized as parallel (α_{max} was set as $\alpha_{max} = 7.5°$). Pairs of parallel labeled and unlabeled objects, for which the shortest distance between their edge points (axis start and end points) was less than d_{max}, were merged (d_{max} was set as $d_{max} = 15[voxels]$, similar to w_{max}).

A secondary classification procedure was executed in the second stage of the merging process (see Fig 10). The second stage, similarly to the first one, consisted of two parts. Some of the measures taken in the first stage were repeated, modified or accompanied by new ones. A bounding box was obtained for each unlabeled object, and its edges and shortest-longest edges ratio were examined. Objects with at least one edge longer than w_{max} or objects with $w_{sort}/w_{long} > R_{max}$ were ignored in the first part. Each unlabeled object was paired with each labeled object and all the pairing combinations were examined as followed:

1. Three angles between the unlabeled object and the labeled objects were calculated: (i) Angle between the axes (or direction vectors) of the two objects. (ii)Angle between the axis of the labeled object and the vector connecting the centers of the two objects. (iii) Angle between the axis of the unlabeled object and the vector connecting the centers of the two objects.
2. For each object in a pair (denoted as object A), three distances were measured with respect to the axis of its paired object (denoted as object B): start point (object A) - axis (object B), center point (object A) - axis (object B) and end point (object A) - axis (object B). Unlabeled objects of pairs in which all angles were smaller than α_{max} and all distances were shorter than d_{max}, were merged with their paired labeled object.

This concluded the first part of the second stage of the merging process.

In the second part of the second stage (the final portion of the merging process), each unlabeled voxel was considered separately. All labeled objects,

for which the voxel in question was inside their bounding box, were identified, and the distances between the voxel and their axes were calculated. The voxel was then assigned the label of the object with the nearest axis. Illustrating for object #3, the input and output of the aforementioned process are presented in Fig. 11. Inputting the result of applying plane based segmentation on object #3 (Fig. 11a), produced the desired fiber segmentation of object #3 (Fig. 11b).

Figure 9: Process illustration of the first stage in merging over segmented fibers.

Figure 10: Process illustration of the secondary classification procedure in merging over segmented fibers.

4. Discussion

In this paper we proposed a novel unsupervised classification based approach, for the separation of intersecting objects in 3D imaging. Based on the boosting idea from the field of statistical learning, we combined results from 2D classifications for the purpose of generating 3D classification. Conductivities between voxels in 3D were extracted by linking common pixels conductivities in 2D. The elemental classification yielded an over segmented result, and there by required additional processing that was designed based on the distinct geometric characteristics of the analyzed structure. Implemented on two different case studies, the proposed approach produced exceptionally accurate classification of object by means of separating merged and intersecting objects. Although

Figure 11: The over segmented object 3 prior to the merging procedure (a), and the final fiber segmentation after the merging process (b).

the suggested approach can be adopted mostly for objects with convex or convex like geometry, its significance lays in its potential to function as a starting point for many applications in the fields of machine vision, classification and clustering.

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