Hyperspectral tree crown classification using the multiple instance adaptive cosine estimator

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PeerJ Preprints | https://doi.org/10.7287/peerj.preprints.27052v1 | CC BY 4.0 Open Access | rec: 26 Jul 2018, publ: 26 Jul 2018

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ABSTRACT

Tree species classification using hyperspectral imagery is a challenging task due to the high spectral similarity between species and large intra-species variability. This paper proposes a solution using the Multiple Instance Adaptive Cosine Estimator (MI-ACE) algorithm. MI-ACE estimates a discriminative target signature to differentiate between a pair of tree species while accounting for label uncertainty. Additionally, the performance of MI-ACE does not rely on parameter settings that require tuning resulting in a method that is easy to use in application. Results presented are using training and testing data provided by a data analysis competition aimed at encouraging the development of methods for extracting ecological information through remote sensing obtained through participation in the competition.

Keywords: tree crown, classification, hyperspectral, multiple instance

INTRODUCTION

Spectral signatures of tree crowns across species often have high spectral similarity as well as significant intra-species variability (Cochrane, 2000), making tree crown classification from hyperspectral imagery a challenging task. In this work, a discriminative multiple instance hyperspectral target characterization method, the Multiple Instance Adaptive Cosine Estimator (MI-ACE) algorithm (Zare et al., 2018b), is proposed for this problem.

In many remote sensing applications, precise pixel level training labels are expensive or infeasible to obtain (Blum and Mitchell, 1998). In the case of tree crown classification, pixel level ground truth labeling for tree crowns can be extremely challenging to collect. When looking at aerial hyperspectral imagery, given overlapping tree crowns and *mixed pixels* in which individual pixels contain responses from multiple neighboring tree species due to the image spatial resolution, manually labeling individual tree crowns is generally infeasible as the precise outline of each tree cannot be easily identified. Marconi et al. (2018) organized data science challenges for airborne remote sensing data. One of these challenges was to perform species classification of individual trees given airborne hyperspectral data. The challenge provided competitors (Anderson, 2018; Sumsion et al., 2018; Dalponte et al., 2018) with training and testing hyperspectral signatures extracted from individual tree crowns in the National Ecological Observatory Network (NEON) hyperspectral data collected at the Ordway-Swisher Biological Station in north-central Florida. These signatures were extracted from the imagery and labeled by the competition organizers by generating individual tree crown polygons using a tablet computer, GIS software, and an external GPS device in the field as described by Marconi et al. (2018). The team loaded the aerial hyperspectral imagery onto tablet computers in the field and simultaneously visually assessed the scene in person and the aerial imagery to mark and digitize the outlines of individual tree crowns. This was a time consuming process that required some subjectivity in assessing the field and the overhead view. The difficulty of this process and the subjectivity needed may result in some individual pixels in tree crown polygons being mislabeled. The MI-ACE algorithm presented in this paper is designed to be robust to this sort of imprecise labels without the need for any parameter tuning or any additional steps for outlier removal.

MI-ACE is a multiple instance learning (MIL) algorithm (Maron and Lozano-Pérez, 1998) where precise instance level labels are not necessary. Instead only a *bag* level label indicating the existence or abscence of a target in a bag (or set) of instances is needed. In MIL, a bag is labeled as a *positive bag*

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containing a target if at least one data point in the bag corresponds to target and a bag is labeled as a *negative bag* if none of the data in the bag correspond to the target. The MI-ACE algorithm estimates a discriminative target signature from data with this sort of bag-level labels. This target signature can then be used within the ACE detector to perform pixel-level target detection and classification (Kraut et al., 2001). Since MI-ACE needs only bag-level labels, the algorithm naturally addresses the tree crown classification problem outlined above. Each tree crown (and the associated set of hyperspectral signatures) are considered a bag and that bag is labeled as the corresponding target tree species. Since MI-ACE assumes multiple instance style labels, the algorithm does not assume that each pixel in every bag is representative of the associated tree species (but only assumes that there exists at least one representative signature in the tree crown) and, thus, addresses imprecision in labeling.

PROPOSED APPROACH

In this section, a brief review of MI-ACE is presented, then the proposed one-vs-one MI-ACE tree species classification approach is outlined.

MI-ACE target characterization

MI-ACE (Zare et al., 2018b) is a discriminative target characterization method that based on ACE detector and multiple instance concept learning. In multiple instance learning, sets of data points (termed bags) are labeled as either positive or negative. Specifically, let $\mathbf{X} = [\mathbf{x}_1, \cdots, \mathbf{x}_N] \in \mathbb{R}^{d\times N}$ be training data where d is the dimensionality of an instance, $\mathbf{x}_i$, and N is the total number of training instances. The data is grouped into K bags, $\mathbf{B} = \{\mathbf{B}_1, \ldots, \mathbf{B}_K\}$, with associated binary bag-level labels, $L = \{L_1, \ldots, L_K\}$ where $L_j \in \{0,1\}$ and $\mathbf{x}_{ji} \in \mathbf{B}_j$ denotes the i^{th} instance in bag $\mathbf{B}_j$. Positive bags (i.e., $\mathbf{B}_j$ with $L_j = 1$, denoted as $\mathbf{B}_j^+$) contain at least one instance composed of some target:

$$\text{if } L_j = 1, \exists \mathbf{x}_{ji} \in \mathbf{B}_j^+ \text{ s.t. } \mathbf{x}_{ji} \sim \mathcal{N}\left(\alpha_{it}\mathbf{s} + \mu_b, \sigma_1^2 \Sigma_b\right), \alpha_{it} \neq 0 \tag{1}$$

where Σ_b is the background covariance, μ_b is the mean of the background, s is the known target signature which is scaled by a target abundance, a, and $\sigma_1^2 = \frac{1}{d}\left(\mathbf{x} - a\mathbf{s}\right)^T \Sigma_b^{-1}\left(\mathbf{x} - a\mathbf{s}\right)$. However, the number of instances in a positive bag with a target component is unknown. If $\mathbf{B}_j$ is a negative bag (i.e., $L_j = 0$, denoted as $\mathbf{B}_j^-$), then this indicates that $\mathbf{B}_j^-$ does not contain any target:

$$\text{if } L_j = 0, \mathbf{x}_{ji} \sim \mathcal{N}\left(\mu_b, \sigma_1^2 \Sigma_b\right) \forall \mathbf{x}_{ji} \in \mathbf{B}_j^- \tag{2}$$

Given this problem formulation, the goal of MI-ACE is to estimate the target signature, $\mathbf{s}$, that maximizes the corresponding adaptive cosine estimator (ACE) detection statistic for the target instances in each positive bag and minimize the detection statistic over all negative instances. This is accomplished by maximizing the following objective:

$$\arg\max_{\mathbf{s}} \frac{1}{N^+} \sum_{j:L_j=1} D_{ACE}(\mathbf{x}_j^*, \mathbf{s}) - \frac{1}{N^-} \sum_{j:L_j=0} \frac{1}{N_j^-} \sum_{\mathbf{x}_i \in B_j^-} D_{ACE}(\mathbf{x}_i, \mathbf{s}) \tag{3}$$

where N^+ and N^- are the number of positive and negative bags, respectively, N_j^- is the number of instances in the j^{th} negative bag, and $\mathbf{x}_j^*$ is the selected instance from the positive bag B_j^+ that is mostly likely a target instance in the bag. The selected instance is identified as the point with the maximum detection statistic given a target signature, $\mathbf{s}$:

$$\mathbf{x}_j^* = \arg\max_{\mathbf{x}_i \in B_j^+} D_{ACE}(\mathbf{x}_i, \mathbf{s}) \tag{4}$$

Since the first term of the objective function relies only on the selected instance from each positive bag, the method is robust to outliers and incorrectly labeled samples. The D_{ACE} is the ACE detection statistic,

$$D_{ACE}(\mathbf{x}, \mathbf{s}) = \left(\frac{\hat{\mathbf{s}}}{\|\hat{\mathbf{s}}\|}\right)^T \left(\frac{\hat{\mathbf{x}}}{\|\hat{\mathbf{x}}\|}\right) = \hat{\hat{\mathbf{s}}}^T \hat{\hat{\mathbf{x}}} \tag{5}$$

where $\hat{\mathbf{x}} = \mathbf{D}^{-\frac{1}{2}}\mathbf{U}^T(\mathbf{x} - \mu_b)$ and $\hat{\mathbf{s}} = \mathbf{D}^{-\frac{1}{2}}\mathbf{U}^T\mathbf{s}$, $\mathbf{U}$ and $\mathbf{D}$ are the eigenvectors and eigenvalues of the background covariance matrix, respectively.

As outlined by Zare et al. (2018b), the MI-ACE algorithm optimizes (3) using an alternating optimization strategy. After optimization, an estimate for a discriminative target signature (that is used to distinguish between two classes and perform pixel level classification using the D_{ACE} detector) is obtained. The MI-ACE code is available and published on our GitHub site (Zare et al., 2018a).

Proposed one-vs-one MI-ACE

The original MI-ACE algorithm was designed for target detection. Target detection can also be viewed as a two-class classification problem with one class being target and the other class being non-target or background (often with heavily imbalanced class sizes). In this work, we extend MI-ACE using a one-vs-one scheme for application to multi-class classification problems. The basic idea for the proposed approach is to train a set of MI-ACE classifiers. Two MI-ACE classifiers are trained for every pair of two classes in the multi-class classification problem. Two classifiers are trained so that each class can be considered as the target class once in this pair. An MI-ACE classifier consists of a trained discriminative target signature (estimated using the MI-ACE approach outlined in the previous section), a background mean and covariance computed using the training samples from the non-target class, and a threshold value used to assign a target or non-target label to individual data points given their ACE detection confidence computed using the estimated target signature, background mean and background covariance values.

During testing, each trained MI-ACE classifier is applied to an input test point. Since each classifier yields a classification result, the final classification for a testing bag is obtained by aggregating all of the individual results. Specifically, a test bag is assigned the class label associated with the class that had the largest number of votes associated with each class. The votes are tallied by, first, averaging the confidence values estimated from each of the individual classifiers applied to each test point in the bag and, then, thresholding these average confidence values to obtain a binary target vs. non-target label the test bag. Then, the class label with the largest number of votes from the binary classification results is assigned as the final class label. Pseudocode for the proposed method is shown below. In the pseudocode, let $\mathbf{X}$ and $\mathbf{Y}$ be the set of all training and testing bags, respectively, with $\mathbf{X}_L$ being the set of all bags assigned label L, $\mathbf{Y}_m$ being the m^{th} testing bag, and $\mathbf{Y}_{m,n}$ being the n^{th} data point in the m^{th} testing bag. Let $\mathbf{L}$ and $\mathbf{R}$ be the corresponding bag level labels for the training and testing bags, respectively. C denotes the number of classes. M denotes the number of testing bags. The variables $\mathbf{s}_{i,j}$ and $\tau_{i,j}$ represent the estimated target signature and classification threshold for target class i and background class j, respectively, and $z_{m,i,j}$ denotes the confidence value estimated by ACE detector given the estimated $\mathbf{s}_{i,j}$ and $\tau_{i,j}$ values for the m^{th} test bag. The threshold value is set by determining the threshold that minimizes classification error on the training data. This approach does not have any parameters to tune as all parameters are estimated from the training data.

EXPERIMENTAL RESULTS

The proposed method was applied to and entered into the tree crown classification challenge organized and described by Marconi et al. (2018).

Data description

The training data released by Marconi et al. (2018) contains the hyperspectral signatures from 305 tree crowns collected over the Ordway-Swisher Biological Station (OSBS) by the National Ecological Observatory Network (NEON). The data from NEON included the following data products: 1) Woody plant vegetation structure (NEON.DP1.10098); 2) Spectrometer orthorectified surface directional reflectance - flightline (NEON.DP1.30008); 3) Ecosystem structure (NEON.DP3.30015); and High-resolution orthorectified camera imagery (NEON.DP1.30010). Figure 1 shows a region in OSBS containing various tree species. However, for this tree crown classification challenge, only individual spectral signatures for each tree crown are stored and provided. Thus, no spatial information is given nor can any image processing approach be applied. The signatures provided contain 426 spectral bands ranging from 383 nm to 2512 nm. Water absorption wavelengths, of which reflectance are set to be 1.5 as shown in Figure 2, correspond to 1345 nm to 1430 nm, 1800 nm to 1956 nm and 2482 nm to 2512 nm. Each training tree crown is paired with a genus class label and a species class label. The genus consisted of 5 classes which are *Acer* (AC), *Liquidambar* (LI), *Pinus* (PI), *Quercus* (QU) and OTHERS (OT). OTHERS represent the tree crowns that cannot be classified to any one of the four known genera. Each genus has a different number of associated species. AC and LI contains only one species, which are *Acer rubrum* (ACRU) and

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Procedure 1 One-vs-one MI-ACE classification

Train two MI-ACE classifiers for each pair of class labels:
Input: $\mathbf{X}, \mathbf{Y}, \mathbf{L}$
for Every pair of classes $c_1 = 1 : C$ and $c_2 = 1 : C$ where $c_2 \neq c_1$ **do**
  Train MI-ACE: $(\mathbf{s}_{c_1,c_2}, \tau_{c_1,c_2}, \mu_{c_2}, \Sigma_{c_2}) = \text{MI-ACE}(X_{L=c1}, X_{L=c2})$
  Train MI-ACE: $(\mathbf{s}_{c_2,c_1}, \tau_{c_2,c_1}, \mu_{c_1}, \Sigma_{c_1}) = \text{MI-ACE}(X_{L=c2}, X_{L=c1})$
end for
Test using a one-vs-one voting scheme:
for Every test bag $m = 1 : M$ **do**
  for Every pair of classes $c_1 = 1 : C$ and $c_2 = 1 : C$ where $c_2 \neq c_1$ **do**
    for Every data point, $n = 1 : N_m$ in bag m **do**
      Apply the c_1 vs. c_2 classifier: $z_{m,n,c_1,c_2} = \text{ACE}(\mathbf{Y}_{m,n}, \mathbf{s}_{c_1,c_2})$
    end for
    Average the confidence scores over all points in the bag: $z_{m,c_1,c_2} = \frac{1}{N}\sum_{n=1}^{N_m} z_{m,n,c_1,c_2}$
    if $z_{m,c_1,c_2} > \tau_{c_1,c_2}$ **then**
      R_{m,c_1,c_2} gets one vote for class c_1
    else
      R_{m,c_1,c_2} gets one vote for class c_2
    end if
  end for
  R_m is assigned to the class with the largest number of votes.
end for
Output: $\mathbf{R}$

Liquidambar styraciflua (LIST), respectively. PI and QU contains more than 3 species individually, which are *Pinus elliottii* (PIEL), *Pinus palustris* (PIPA), *Pinus taeda* (PITA) and OTHERS (for PI), *Quercus geminata* (QUGE), *Quercus laevis* (QULA), *Quercus nigra* (QUNI) and OTHERS (for QU). The number of tree polygons for each species are shown in Table 1. In the current implementation of this work, OTHERS in both the genus and species level are not used for training as the proposed approach did not have a mechanism to identify points that did not belong to any of the labeled training classes.

Species	ACRU	LIST	PIEL	PIPA	PITA	QUGE	QULA	QUNI	OTHERS
Number	6	4	5	197	14	12	54	5	8

Table 1. The number of training tree crowns for each species

The testing data was also NEON tree crown hyperspectral data in the same format. There were 126 testing tree crowns. The test labels were not provided by the competition organizers.

Data preprocessing and MI-ACE training

Prior to application of the MI-ACE algorithm, the water bands of the spectral signatures are removed. Then, since in our current implementation data points labeled as OTHERS genus or species are not addressed, the signatures that were labeled as OTHERS are removed from the training set.

After removal of the water bands and the OTHERS data points, the target signatures and classification threshold values are trained using the proposed one-vs-one MI-ACE approach. Training was conducted at two levels, the genus and the species levels. During the training phase, each training tree crown was considered a bag for MI-ACE, thus the training label (genus or species level) was the bag label. A one-vs-one MI-ACE was used in which a set of MI-ACE target signatures representing the difference between every two genera or species were estimated. For instance, a target signature was trained to distinguish between the genus PI and the genus QU where tree crown labeled as PI was labeled target (or '1') and QU was labeled as non-target (or '0'). For this competition only one MI-ACE classifier was trained for each pair of classes (as opposed to two for each pair) because results were similar between the two approaches. Similarly, a set of target signatures were estimated between every two species (if there were at least two species) that belonged to the same genus. For example, a target signature was estimated

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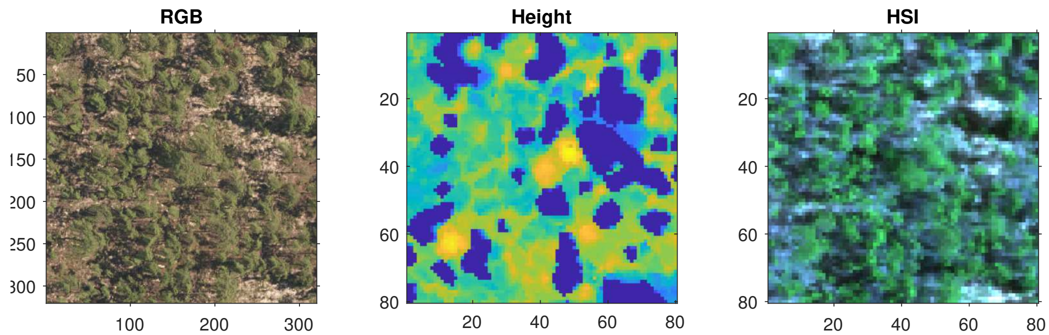
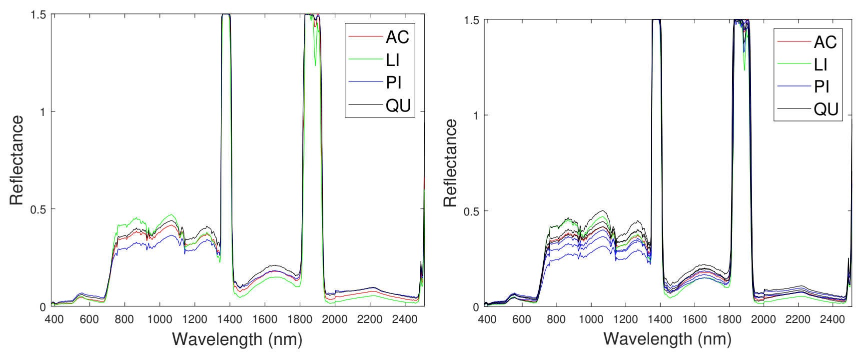


Figure 1. An example RGB, LiDAR, and (the RGB image generated from the corresponding) Hyperspectral image of a region in OSBS



(a) average genus spectra

(b) average species spectra

Figure 2. Average spectral signature of (a) all genera and (b) all species, colored by genera.

using training data to distinguish between species PIEL and PITA where the tree crowns labeled as PIEL were labeled as target (or '1') and PITA was labeled as non-target (or '0').

Testing using ACE detector and voting

Testing was also conducted in two stages where a test tree crown was first classified at the genus level and, then, further classified at the species level. An ACE detector was used to estimate the confidence value indicating how similar a test signature is to a trained target signature. Classification of test tree crowns consisted of the following steps. First, the confidence values of each instance signature inside the a test tree crown were computed using each of the six genus-level trained MI-ACE classifiers. Second, the confidence value for each testing crown was estimated by taking the average value over all of the instance-level confidence values. These average confidence values were then thresholded using the trained threshold values to obtain a binary classification result. The classification thresholds were determined during training to minimize the number of misclassified tree crowns in the training data. The final classification of a tree crown is the class label with the highest number of corresponding binary classifications. After the genus level classification, a test tree crown can be classified at species level using the same approach among the species associated with the genus to which the tree crown assigned.

Results

Genus level classification

Classification result when testing on training samples are shown via confusion matrix in Table 2. The overall classification accuracy on the training dataset is 97.31%. The pixel confidence distributions and the aggregated crown confidence distributions for each classifier are shown in Figure 3 (a) and (b), respectively. In Figure 3, each row represents one of the six classifiers and each column denotes each ground truth genus type. The associated threshold value for each classifier is plot as a vertical blue line in

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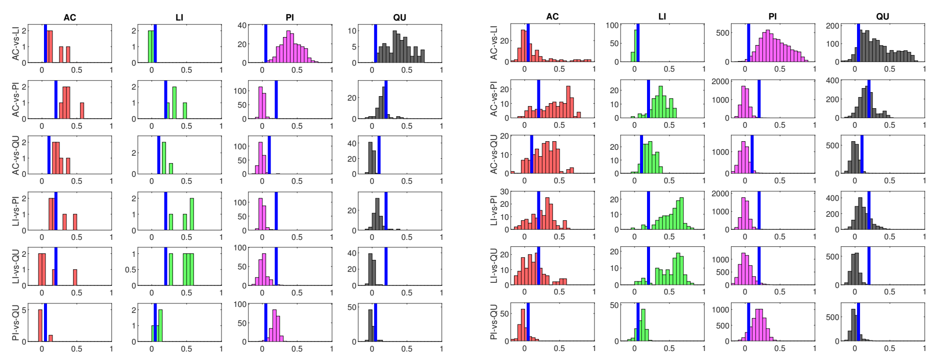
each subfigure. For instance, the top left subfigure in Figure 3 (a) shows the averaged ACE confidence value distribution of AC tree crowns detected using AC-vs-LI classifier and the same subfigure in Figure 3 (b) shows the corresponding pixel confidence value distributions. A good result for the AC-vs-LI classifier will have all AC confidence values to right of the threshold value and all LI confidence values (shown in the second plot in the first row) to the left of the threshold value. As can be seen, the AC-vs-LI classifier accurately distinguishes between these two classes on the aggregated crown-level scale. However, when considering the same plots in Figure 3 (b) for the pixel level confidences, we can see that there are many AC pixels to the left of the threshold causing significant overlap with the LI pixels confidences. This indicates that the aggregation procedure helps to improve results.

Predict / True	AC	LI	PI	QU
AC	6	0	0	0
LI	0	4	0	0
PI	0	0	212	4
QU	0	0	4	67

Table 2. The classification confusion matrix on all training data (except for OHTERS) in genus level



(a) Crown-level averaged confidence distribution (b) Pixel-level confidence distribution

Figure 3. Confidence distributions of crown (left figure) and pixel (right figure) levels in training set. Rows from top to down are AC-vs-LI, AC-vs-PI, AC-vs-QU, LI-vs-PI, LI-vs-QU and PI-vs-QU classifiers, respectively. Columns from left to right are tree crowns genus types of AC, LI, PI, QU, respectively.

Since there were six classifiers trained and four classes in this data set, there are only a small set of possible voting cases. These cases are: a. (3,1,1,1) votes for each class; b. (3,2,1,0) votes for each class; c. (2,2,1,1) votes for each class and d. (2,2,2,0) votes for each class. For cases a. and b., there is a single class with the largest amount of votes, thus, labeling of the crown is straightforward. However, for voting cases c. and d., there are ties among 2 or 3 candidate classes. In our current implementation, we randomly assign the label of one of the tied classes. We found that cases c. and d. are rare in our training and testing results. In the testing on training data results, votes for all of the tree crowns fell into either case a. or b. When applying the trained approach to the testing dataset provided by the competition, there is only one tree crown in which there was a tie (and resulted in voting case is d). For this tree crown, we found that it has 2 votes for AC, 2 votes for LI and 2 votes for PI. Our implementation in test randomly assigned this tree crown to the AC class. Since the ground truth labels of testing data are not released by organizer, the true genus class of this testing tree crown is unknown. However, we found that in our classification results on testing data, there are three tree crowns that were predicted to be in class AC by our method. Two of these crowns were correctly classified into class AC and the other false positive tree crown actually belonged to the OTHER class (see Table 7). Thus, it is likely that this tree crown may be the tree crown with the tied result.

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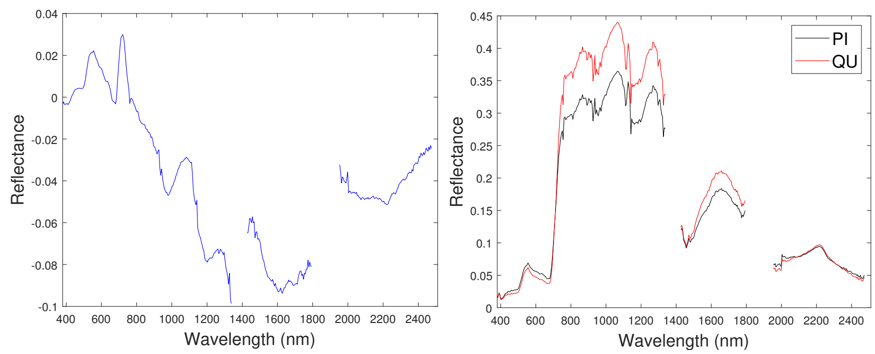
Cross validation studies on the training data were also conducted. There are a limited number of training tree crowns for the AC and LI classes (only 6 AC and 4 LI tree crowns). Due to this reason, cross validation experiments were not conducted for AC or LI. In the training phase, the PI training (pixel-level) samples and QU (pixel-level) training samples are considered target and background, respectively. The learned target signature is shown in Figure 4 (a), which characterizes the spectral difference between PI and QU shown in Figure 4 (b). In the testing phase, each pixel signature of PI and QU are compared with estimated target signature using the ACE detector resulting in a confidence value shown in Figure 5. Since most confidence values of PI pixels are larger than QU pixels, a threshold value (of 0.05) can be selected such that the misclassified error is minimized.



(a) Estimated target signature (b) average PI and QU spectra

Figure 4. Comparison between estimated target signature and average class signatures. As can be seen, the target signature tends to be positive in the wavelengths where the target class has a larger response than the background class and negative where the target class has a smaller response. Thus, the target signature gives insight into discriminative features for the detection problem.

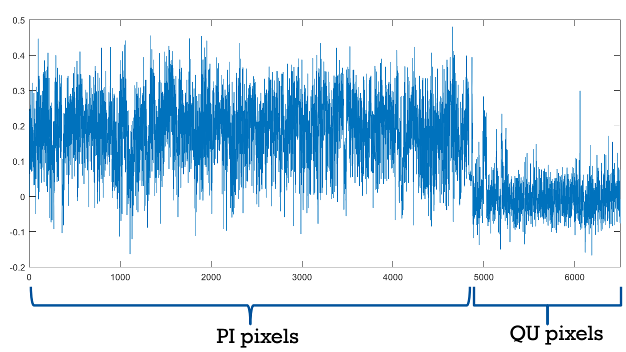


Figure 5. ACE detection statistic on PI & QU pixels

Two-fold cross validation was applied to the PI and QU samples. The PI and QU classes were randomly split into two datasets (50% of PI and QU tree crowns are selected as d_1 and the rest as d_2) We train on d_1 and validate on d_2, followed by training on d_2 and validating on d_1. After training the PI-vs-QU target signature and corresponding threshold, the histogram of the average confidence values on the validation set is shown in Figure 6. In this figure, the PI and QU tree crowns are colored by their ground truth classes, i.e., red for PI and blue for QU. The threshold value estimated from training can be directly applied to the validation set for classification of the validation training crowns.

The cross validation experiment was repeated ten times and the mean confusion matrix is shown in Table 3. The average classification accuracy on the PI and QU given two-fold cross validation dataset was 95.8%, which is similar to the test-on-train accuracy indicating robust results.

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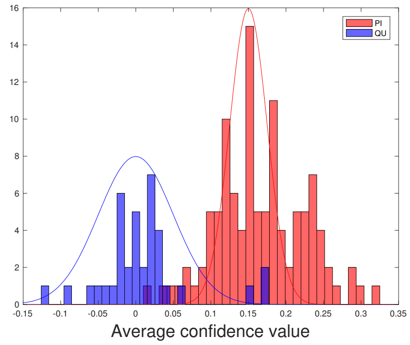

Figure 6. Histogram of average confidence values on validation set

Predict / True	PI	QU
PI	105.8	2.2
QU	3.8	31.2

Table 3. The mean classification confusion matrix on all PI and QU training data via cross validation

Species level classification

After the genus level classification, the tree crowns were further classified into species. If a tree is classified as AC or LI, it is classified also as ACRU or LIST automatically. If a tree is classified as PI or QU, the one-vs-one MI-ACE method is used to classify it into one of the corresponding species. The confusion matrices for species level classification (testing on training data) are shown in Table. 4. The classification (rank-1) accuracy is 95.62% on the training dataset in species level with a cross entropy value of 0.2649.

Predict / True	ACRU	LIST	PIEL	PIPA	PITA	QUGE	QULA	QUNI
ACRU	**6**	0	0	0	0	0	0	0
LIST	0	**4**	0	0	0	0	0	0
PIEL	0	0	**5**	0	0	0	0	0
PIPA	0	0	3	**188**	2	2	2	0
PITA	0	0	0	0	**14**	0	0	0
QUGE	0	0	0	2	0	**10**	0	0
QULA	0	0	0	2	0	0	**53**	0
QUNI	0	0	1	0	0	0	0	**4**

Table 4. The classification confusion matrix on all training data (except for OHTERS) in species level

The confusion matrices for species level classification for testing data are shown in Figure 7 as provided by the competition organizers. The classification (rank-1) accuracy is 86.40% and cross entropy is 0.9395 on the testing dataset. However, this accuracy includes data points labeled as OTHERS in the testing dataset which, using our approach, were all misclassified to one of the four genus types since we did not implement a mechanism to distinguish outliers in this approach. If the OTHERS tree crowns (3 tree crowns) are excluded, the classification accuracy would come to 88.52% and cross entropy would be 0.7918 on the testing dataset.

The species level classification results are further evaluated using several metrics on the testing data by the organizer, including per-class accuracy, specificity, precision, recall and F1 score. For comparison, we also evaluated the classification performance using the same metrics on the training data. The accuracy and specificity score, F1 score, precision, recall for both training and testing dataset are shown in Figure 8, 9, 10 and 11, respectively. As can be seen, accuracy and specificity results between training and testing

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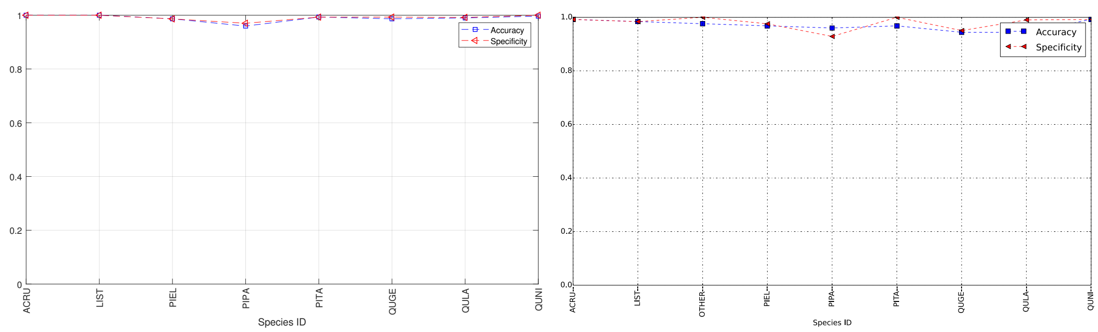
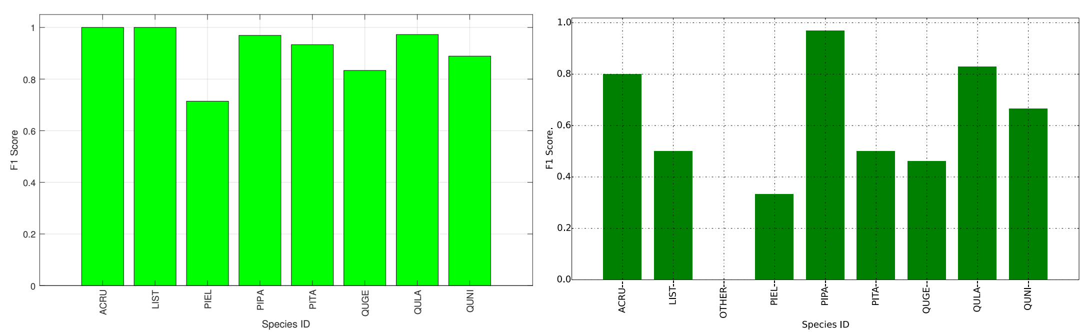
Species ID	ACRU	LIST	OTHER	PIEL	PIPA	PITA	QUGE	QULA	QUNI
ACRU	**2.00**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
LIST	0.00	**1.00**	0.00	0.00	0.00	0.00	0.00	0.00	0.00
OTHER	1.00	1.00	**0.00**	1.00	0.00	0.00	0.00	0.00	0.00
PIEL	0.00	0.00	0.00	**1.00**	0.00	0.00	1.00	0.00	0.00
PIPA	0.00	0.00	0.00	1.00	**81.00**	0.00	1.00	0.00	0.00
PITA	0.00	0.00	0.00	1.00	2.00	**2.00**	0.00	1.00	0.00
QUGE	0.00	1.00	0.00	0.00	0.00	0.00	**3.00**	0.00	0.00
QULA	0.00	0.00	0.00	0.00	1.00	0.00	4.00	**17.00**	1.00
QUNI	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**1.00**

Figure 7. The classification confusion matrix on all testing data (except for OHTERS) in species level (provided by competition)



(a) training data (b) testing data

Figure 8. Accuracy and Specificity Scores (Per-Class) for training data (a) and testing data (b - provided by competition)



(a) training data (b) testing data

Figure 9. F1 Scores (Per-Class) for training data (a) and testing data (b - provided by competition)

222 data are similar whereas the F1, precision and recall curves highlight that challenging classes in the testing data were PIEL, PITA and QUGE.

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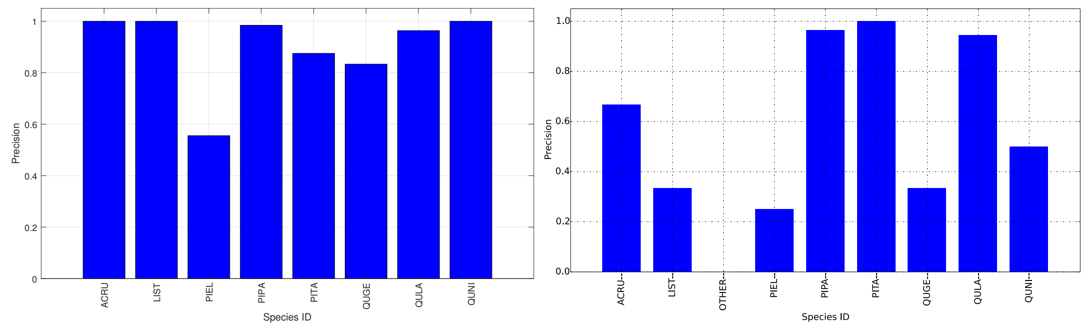
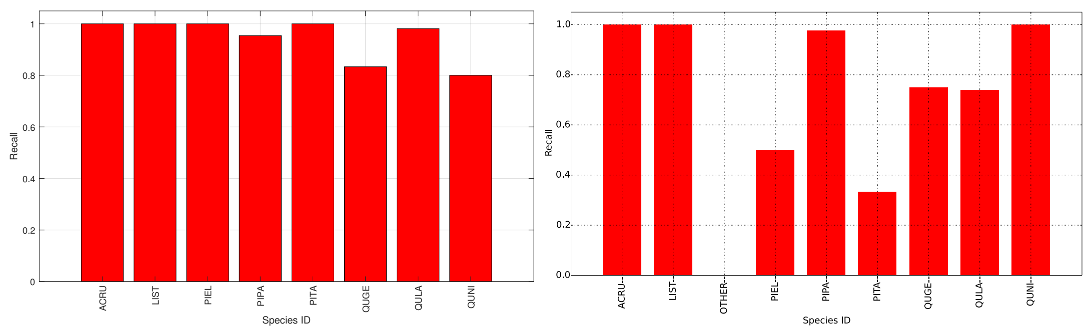


(a) training data (b) testing data

Figure 10. Precision (Per-Class) for training data (a) and testing data (b - provided by competition)



(a) training data (b) testing data

Figure 11. Recall (Per-Class) for training data (a) and testing data (b - provided by competition)

SUMMARY AND FUTURE WORK

A one-vs-one version of MI-ACE is proposed in the work to address the hyperspectral tree crown classification problem. The proposed method achieved a 86.4% overall classification accuracy on a blind testing dataset. Certainly, there are many improvements can be investigated in the future such as mechanisms to identify outliers and label them as members of the OTHERS class and estimate a likelihood of belonging to each class (as opposed to binary classification labels).

In the current implementation, only crisp binary classification results are estimated. However, competition organizers evaluated results using the cross entropy evaluation metric assuming probabilities of belonging to each class are estimated,

$$\text{cost} = -\frac{\sum_{n,k} \ln p_{n,k} \delta(g_n, k)}{N} \tag{6}$$

where g_n is the ground truth class of crown n, $p_{n,k}$ is the probability assigned that crown n belongs to class k. Class probabilities given the one-vs-one scheme can be estimated in the future using approaches such as those proposed by Wu et al. (2004). Furthermore, even if individual probabilities per data are not computed, an overall uncertainty value can be estimated from the training data. In other words, as opposed to assigning 0-1 probabilities for the crisp class labels. In our implementation data points were assigned to the estimated class label with probability 1 and all others with probability 0. Instead, we could pre-compute an optimal epsilon value, ε^*, to add to the '0' probabilities and subtract from the '1' probabilities to ensure values sum to one across classes to minimize cross entropy on the training data. For instance, we found that when $\varepsilon^* = 0.017$, the cross entropy for our results comes to 0.68, which is a smaller (i.e., better) than the cross entropy of 0.94 obtained using crisp labels and calculated by the competition organizers. The relationship between the cross entropy and epsilon value for the training data

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provided shown in Figure 12.

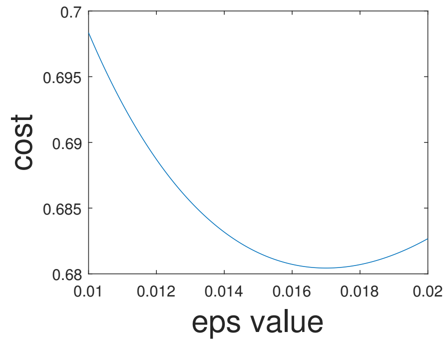

Figure 12. Cross entropy vs optimum epsilon value

In addition, in the current proposed framework, each one-vs-one classifier is equally weighted in final voting. However, the classification accuracies and the applicability of each classifier varies. For instance, if a tree crown is in class PI, the PI-vs-QU classifier should be more heavily weighted than the AC-vs-LI classifier. Investigation into whether this could be determined by considering the average confidence values estimated from the individual ACE detectors is needed. Furthermore, since some of the classes are more spectrally distinct, some one-vs-one classifiers have better prediction performances. One possible solution is to weight the classifiers based on the difference between the average confidence values of target and background classes for training data. Another possible solution is to weight based on the difference between the confidence value of testing point and threshold value of the classifier. In some scenarios, these two solutions might be equivalent. Finally, data fusion is also a promising approach for boosting the classification performance. For example, height information from Lidar data could be also incorporated into the training phase since different species generally have different average heights. In the current implementation, only hyperspectral information was leveraged.

ACKNOWLEDGEMENTS

This material is based upon work supported by the National Science Foundation under Grant IIS-1723891-CAREER: Supervised Learning for Incomplete and Uncertain Data. The National Ecological Observatory Network is a program sponsored by the National Science Foundation and operated under cooperative agreement by Battelle Memorial Institute. This material is based in part upon work supported by the National Science Foundation through the NEON Program. The ECODSE competition was supported, in part, by a research grant from NIST IAD Data Science Research Program to D.Z. Wang, E.P. White, and S. Bohlman, by the Gordon and Betty Moore Foundation's Data-Driven Discovery Initiative through grant GBMF4563 to E.P. White, and by an NSF Dimension of Biodiversity program grant (DEB-1442280) to S. Bohlman.

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