Data fusion of hyperspectral and SAR images

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1 Introduction

The demands for higher classification accuracy of remote sensing images have encouraged an increasing usage of distinct characteristic information collected from different sources. Combining these multisource data is believed to offer strengthened capabilities for land cover classification.1,2 Synthesis of these datasets into composite images containing such complementary attributes in accurate registration would provide truly connected information about land covers for the remote sensing community. For example, hyperspectral and synthetic aperture radar (SAR) images show different advantages when they are used for land cover classification and object detection in earth remote sensing.

In the last decade, various hyperspectral (high-dimensional) image detection and classification techniques have been proposed. The most widely used techniques are the statistical approaches, even though neural network methods have the advantage of not needing a priori statistical information before a classifier is found. Statistical approaches overcome neural network methods in terms of classification accuracy as long as sufficiently statistical parameters can be obtained a priori. One of the well-known statistical approaches is orthogonal subspace projection.4,5 It projects all undesired pixels into a space orthogonal to the space generated by the desired pixels to achieve high-dimensionality classifications. Moreover, a decision fusion technique,6 which combines statistical schemes with neural methods, was proposed later for multisource and hyperspectral classifications. It first processes fused information from individual data sources separately, and then utilizes a decision fusion technique based on a consensus theory to make a decision level of data fusion.

In this work, a novel statistical feature selection algorithm applied to the greedy modular eigenspaces (GME)7 is proposed to explore a multiclass classification technique using data fused from hyperspectral and SAR images. The approach makes use of the GME feature extraction method,8 which tends to equalize all the bands in a subgroup with highly correlated variances to avoid a potential bias problem that may occur in conventional principal components analysis (PCA).9 This fast feature selection algo-

Abstract. A novel technique is proposed for data fusion of earth remote sensing. The method is developed for land cover classification based on fusion of remote sensing images of the same scene collected from multiple sources. It presents a framework for fusion of multisource remote sensing images, which consists of two algorithms, referred to as the greedy modular eigenspace (GME) and the feature scale uniformity transformation (FSUT). The GME method is designed to extract features by a simple and efficient GME feature module, while the FSUT is performed to fuse most correlated features from different data sources. Finally, an optimal positive Boolean function based multiclass classifier is further developed for classification. It utilizes the positive and negative sample learning ability of the minimum classification error criteria to improve classification accuracy. The performance of the proposed method is evaluated by fusing MODIS/ASTER airborne simulator (MASTER) images and the airborne synthetic aperture radar (SAR) images for land cover classification during the PacRim II campaign. Experimental results demonstrate that the proposed fusion approach is an effective method for land cover classification in earth remote sensing, and improves the precision of image classification significantly compared to conventional single source classification. © 2004 Society of Photo-Optical Instrumentation Engineers. [DOI: 10.1117/1.1768535]

Subject terms: data fusion; hyperspectral; synthetic aperture radar; greedy modular eigenspaces; feature scale uniformity transformation; positive Boolean function.

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2 Methodology

Referring to Fig. 1, there are five stages to implementing our proposed GME/FSUT/PBF-based multiclass classification scheme. 1. A GME transformation algorithm is applied to achieve dimensionality reduction and feature extraction. 2. The second stage is a GME/FSUT, which constructs an identical GME set for feature selection. 3. The third stage is to use a similarity measure for distance decomposition. 4. The fourth stage is a threshold decomposition, which normalizes and quantizes the distance computed from the third stage. Finally, a PBF-based multiclass classifier is performed for land cover classification.

2.1 Greedy Modular Eigenspaces

In our previous work,7,8 we proposed a GME set \( \Phi^k \), which is composed of a group of modular eigenspaces, i.e., \( \Phi^k = (\Phi_1^k, \ldots, \Phi_i^k, \ldots, \Phi_m^k) \), for the class \( \omega_k \). Each modular eigenspace \( \Phi_i^k \) includes a set of highly correlated bands. Reordering the bands regardless of the original order in terms of wavelengths in high-dimensional datasets is an important characteristic of the GME. It utilizes the inherent separability of the different classes in high-dimensional data to reduce dimensionality and formulate a unique GME feature. In this approach, we first synthesize both hyperspectral and SAR datasets into precise registration and congruence composite images. In Fig. 2, a visual correlation matrix pseudocolor map (CMPM), which was proposed by Lee and Landgrebe12 to emphasize the importance of second-order statistics in hyperspectral data, is used to illustrate the magnitude of correlation matrices in our proposed GME method. We define a correlation submatrix \( c_{\Phi^k}(m_t \times m_i) \), which belongs to the \( l \)th modular eigenspace \( \Phi^k_l \) of a GME set \( \Phi^k = (\Phi_1^k, \ldots, \Phi_i^k, \ldots, \Phi_m^k) \) for a land cover class \( \omega_k \) in this fused dataset, where \( m_t \) and \( n_k \) represent, respectively, the number of bands (feature spaces) in modular eigenspaces \( \Phi^k_l \), and the total number of modular eigenspaces of a GME set \( \Phi^k \), i.e., \( l \in \{1, \ldots, n_k\} \) as shown in Fig. 2.

The original correlation matrix \( c_{\Phi^k}(m_t \times m_i) \), where \( m_t \) is the total number of original bands (i.e., \( m_t = \sum_{l=1}^{n_k} m_l \)), is decomposed into \( n_k \) correlation submatrices \( c_{\Phi_{t,l}^k}(m_t \times m_i), \ldots, c_{\Phi_{f,t}^k}(m_t \times m_i), \ldots, c_{\Phi_{t,n_k}^k}(m_t \times m_i) \) to build a GME set \( \Phi^k \) for the class \( \omega_k \). There are \( m_t! \) (the factorial of \( m_t \))
possible combinations to construct a candidate GME set. Only one of them can be chosen as the GME set. It is computationally expensive to make an exhaustive search to construct a GME set if $m_t$ is a large number. In Refs. 7 and 8, a fast greedy band reordering algorithm, called greedy modular eigenspace transformation (GMET), was proposed based on the assumption that highly correlated bands often appear adjacent to each other in high-dimensional data. In GMET, the absolute value of every correlation coefficient $c_{ij}$ in the correlation matrix $C$ is compared to a threshold value $t_c$ $(0 < t_c < 1)$. Those adjacent correlation coefficients $c_{ij}$ that are larger than the threshold value $t_c$ are used to construct a modular eigenspace $\Phi^l$ in an iterative mode. It performs a greedy iteration search algorithm, which reorders the correlation coefficients in the data correlation matrix row by row and column by column to group highly correlated bands as GME feature eigenspaces that can be further used for feature extraction.

Each land cover type or material class has a distinct set of GME-generated feature eigenspaces. A GME set $\Phi^k = (\Phi^1, ..., \Phi^l, ..., \Phi^n)$ is composed of land cover class $\omega_k$. Figure 2 illustrates the original correlation matrix map and the reordered one after a GMET. Each land cover type or material class has its uniquely ordered GME set $\Phi^k$. Three of these six classes are shown in Fig. 3. In this visualization scheme, we can build a GME efficiently and bypass the redundant procedures of rearranging the band order from the original high-dimensional datasets. Moreover, the GMET algorithm can reduce the eigen-decomposition computation significantly compared to the conventional PCA feature extraction. The computational complexity for the conventional PCA is of the order of $O(m^2 t)$ and it is $O(\sum_{l=1}^{n_k} m^2_l)$ for GME. The GME also preserves the original information of a data correlation matrix.

2.2 Feature Scale Uniformity Transformation

After a set of GME modules $\Phi^k$ for all classes $\omega_k$, $k \in \{1,...,N\}$, are found, a fast, simple, and effective GME/FSUT is then performed to fuse the feature scales of these GME sets into an identical GME set $\Phi_U$. We define two types of the GME/FSUT. They are GME/FSUT-union (GME/FSUT-U) and GME/FSUT-intersection (GME/FSUT-I). The first one applies union (OR) operations to the band numbers inside each GME module to fuse the feature scales of different classes produced by the GMET and construct an identical union GME (UGME) set $\Phi_U$. Figure 4 shows a union (OR) operation of the GME/FSUT-U, which generates an identical UGME set $\Phi_U$ for all classes $\omega_k$, $k \in \{1,...,N\}$. Every different class has the same UGME set $\Phi_U$ after the GME/FSUT-U. On the other hand, the second form of the GME/FSUT applies intersection (AND) operations to the band numbers inside each GME module of different classes to select an identical intersection GME (IGME) $\Phi_I$ set for all classes $\omega_k$, $k \in \{1,...,N\}$. A concept block diagram of GME/FSUT-I is depicted in Fig. 5.

The GME/FSUT-U, which performs a searching iteration to generate an identical UGME set $\Phi_U$, is initially carried out on a newly formed UGME feature module $\Phi_{U_l}$, where $l \in \{1,...,n_U\}$ and $\Phi_{U_l} \in \Phi_U$, in which the first band
Fig. 3  GME sets for the three land cover types used in the experiment. The squares on the left are the original correlation matrix maps. The crossed fine white lines in the maps divide the maps into the two datasets, hyperspectral and SAR data. The maps on the right are the reordered ones after a GMET. The GME feature modules ($\Phi_{1},...\Phi_{l},...\Phi_{n}$) of different GME sets $\Phi^{k}$, where $k=1,...,N$, are illustrated as the modular eigenspace boxes in the middle column.

Fig. 4  The proposed mechanism of GME/FSUT-union (GME/FSUT-U).

Fig. 5  The proposed mechanism of GME/FSUT-intersection (GME/FSUT-I).
where \( i = 1, \ldots, n \), of the largest GME module \( F_1^k \) is first chosen to form a UGME set \( F_U^k \). Each band \( b_i \) is assigned an attribute during a GME/FSUT-U. If the attribute of \( b_i \) is set as available, it means this \( b_i \) has not been yet assigned to any identical UGME set \( F_U^k \). If a \( b_i \) is assigned to a \( F_U^k \), the attribute of this \( b_i \) is set to used. All attributes of the original \( b_i \), \( i = 1, \ldots, n \), are first set as available. To conclude the most significant common bands features for UGME, the GME/FSUT-U accommodates each band \( b_i \) with a weighted merging factor \( WMF \) used to evaluate the correlation weighting of each band \( b_i \), and to carry out a feature selection from the GME sets \( F_k^i \) for different classes. A WMF corresponding with a selected band \( b_i \), denoted \( WMF_i^k \), is assigned a value. This value is equal to the number of bands of the GME module \( F_k^i \) to which the selected band \( b_i \) belongs. For example, the second modular eigenspace \( F_2^k \) of the first GME module \( F_1^k \), where \( k = 1 \), has a WMF equal to eight (+8), because this GME module \( F_2^k \) contains eight bands, as shown in Fig. 6(a). Thus all of the eight bands \( b_i \), \( i = 1, \ldots, 8 \), in this modular eigenspace have the same WMF value, i.e., \( WMF_i = 8 \), for \( i = 1, \ldots, 8 \). In this algorithm, the WMF value of each band \( b_i \) is cumulative across all classes \( a_k \), \( k = 1, \ldots, N \), and the WMF is updated to this accumulated value. The proposed GME/FSUT-U algorithm is as follows.

Step 1. Initialization: a new UGME feature module \( F_U^l \), where \( F_U^l \in F_U \), is initialized by a new band \( b_i \) inside a modular eigenspace \( F_i^k \), where \( b_i \) is defined as the first available band and \( F_i^k \) is the largest modular eigenspace of the class \( a_k \). This new band \( b_i \) is assigned to the newly created UGME feature module \( F_U^l \) and is then set as the current \( b_i \), i.e., the only one activated at the current time. Then, go to step 2. Note that this GME/FSUT-U algorithm is terminated if the last band \( b_i \) is already set to “used” and the last UGME feature module \( F_U^l \), \( F_U^l \in F_U \), has been obtained.

Step 2. If the current band \( b_i \) and all its related bands have all been set to used, then a UGME feature module \( F_U^l \) is constructed with all used bands, these used bands are removed from the band list, a maximum accumulated WMF value is determined for this identical UGME feature module \( F_U^l \), and the al-

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**Fig. 6** (a) An example of the proposed GME/FSUT-U method. The numbers with plus signs outside every GME modular eigenspace box denote the WMF. The UGME modules \( F_U^k \) are obtained in the final column (inside the gray bold GME modular eigenspace boxes). (b) An example of the proposed GME/FSUT-I method. The IGME modules \( F_I^k \) are obtained in the final column (inside the gray bold GME modular eigenspace boxes).
Eventually, an identical UGME set \( \Phi_{U_l} \) is composed of a group of identical modular eigenspaces \( \Phi_{U_l} = (\Phi_{U_{l1}}, \ldots, \Phi_{U_{l n_U}}) \) for all classes \( \omega_k \), \( k \in \{1, \ldots, N\} \), as shown in Fig. 4. Here, \( n_U \) represents the total number of modular eigenspaces of an identical UGME set \( \Phi_{U_l} \) for all classes \( \omega_k \) after the GME/FSUT-U. For convenience, we sort these identical UGME feature modules \( \Phi_{U_l} \), where \( l \in \{1, \ldots, n_U\} \), \( n_U \leq n_k \), according to the number of their feature bands, i.e., the number of feature spaces, in descending order. In Fig. 6(a), each identical UGME feature module \( \Phi_{U_l} \) has one/many maximum accumulated WMF_max value(s) inside a circle in gray. An example of the proposed GME/FSUT-U method is illustrated in Fig. 6(a). GME/FSUT-U is applied to the land cover types shown in Fig. 3. The numbers with plus signs outside the GME modular eigenspace boxes are the WMF values. The identical UGME set \( \Phi_{U} = (\Phi_{U_{1}}, \ldots, \Phi_{U_{n_U}}) \) is obtained in the final column inside the gray bold rectangles with a maximum accumulated WMF_max value on the right.

In a similar manner to GME/FSUT-U, the GME/FSUT-I uses the intersection (AND) operation to create an identical IGME \( \Phi_{I_l} \), as shown in Fig. 5. An identical IGME set \( \Phi_{I_l} \) is composed of a group of identical modular eigenspaces \( \Phi_{I_{l1}}, \ldots, \Phi_{I_{l n_I}} \) for all classes \( \omega_k \), \( k \in \{1, \ldots, N\} \), where \( n_I \leq n_k \) represents the total number of modular eigenspaces of an identical IGME set \( \Phi_{I_l} \) for all classes \( \omega_k \), after the GME/FSUT-I. Each identical IGME feature module \( \Phi_{I_l} \) has a unique band set inside a box in gray. The GME/FSUT-I mechanism is demonstrated in Fig. 6(b).

### 2.3 Distance Measures

The UGME/IGME can distinguish different classes well by the highly correlated features of GME. It makes use of the Euclidean distance (ED) and the PCA, also known as the Karhunen-Loève transform, to extract the most significant features of the UGME/IGME from the proposed GME/FSUT-generated bands. If we assume an identical UGME/IGME set \( \Phi_{U_l}/\Phi_{I_l} \) has \( n_U/n_I \) identical UGME/IGME feature modules (feature bands), as shown in Figs. 4 and 5, an ED of the identical UGME/IGME set with \( n_U/n_I \) feature bands for class \( \omega_k \) is defined as:

\[
\mathbf{e}_{U_l}(x) = \left( \sum_{i=1}^{n_U} \frac{x_i^2}{\bar{x}_i^2} \right)^{1/2},
\]

where \( \bar{x} = x - \bar{x} \) is the mean-normalized vector of sample \( x \). Note that only one band for each UGME/IGME feature module \( \Phi_{U_l}/\Phi_{I_l} \), \( l \in \{1, \ldots, n_U/n_I\} \) is selected for the ED decomposion. In Fig. 6, we choose one band with the maximum WMF_max (WMF_max) of each identical UGME feature module \( \Phi_{U_l} \) and any one arbitrary band of IGME feature module \( \Phi_{I_l} \) for the ED decomposion. Here, \( \mathbf{e}_{U_l}(x) \) represents the distance between the query sample \( x \) and the mean vector of training samples based on the identical UGME/IGME feature modules \( \Phi_{U_l}/\Phi_{I_l} \). This distance decomposion is applied to all classes \( \omega_k \) to generate an ED vector \( \mathbf{e}_{U_l} = (e_{1,1}, \ldots, e_{n_U/n_I, n_k}) \) for all classes \( \omega_k \).

The second similarity measure to be used is the PCA-based method, also known as the GME projection.\(^2\textsuperscript{8}\) The basis functions in the PCA are obtained by solving the eigenvalue problem: \( \Lambda = \phi_i^T \Sigma \phi_i \), where \( \Sigma \) is the covariance matrix of \( \phi_i^T \), \( \phi_i^* \) is the eigenvector matrix of \( \Sigma \) and \( \Lambda \) is the corresponding diagonal matrix of eigenvalues. Moghadam and Pentland\(^1\textsuperscript{4}\) decomposed the vector space \( \mathbb{R}^W \) into two exclusive and complementary subspaces: the principal subspace (W feature spaces) \( \phi_i^W = (\phi_i^W)_{i=1}^W \) and orthogonal complement subspace \( \phi_i^C = (\phi_i^C)_{i=1}^{W-1} \), where \( \phi_i^C \) is the \( i \)th eigenvector of \( \phi_i^W \). A residual reconstruction error (RRE) of the GME feature modules \( \phi_i^W \) for class \( \omega_k \) is defined as:

\[
\mathbf{e}_i^W(x) = \sum_{i=W+1}^{m} y_i^2 = \| \tilde{x} \|^2 - \sum_{i=1}^{W} y_i^2,
\]

where \( \tilde{x} = x - \bar{x} \) is the mean-normalized vector of sample \( x \) and \( y_i \) is the projected value of sample \( x \) by the eigenvector corresponding with the \( i \)th largest eigenvalue. Here, \( \mathbf{e}_i^W(x) \) represents the distance between the query sample \( x \) and the GME feature module of the training samples. This GME projection is applied to all the GME feature modules to generate an RRE vector \( \mathbf{e}_i^W = (e_{1,1}^W, \ldots, e_{n_U/n_I, n_k}^W) \) for all classes \( \omega_k \), \( k \in \{1, \ldots, N\} \). For convenience, we redefine these two types of distance measure, ED and RRE, as an ED/RRE decomposion (distance decomposion) shown in Fig. 7.

### 2.4 Threshold Decomposions

After finding the ED/RRE vector \( \mathbf{e}_{U_l}/\mathbf{e}_i^W \) from the previous stage, the threshold decompositions described next are performed to create normalized and quantized ED/RRE vectors \( \mathbf{e}_{U,l}^N \) for all classes, \( k \in \{1, \ldots, N\} \). The \( \mathbf{e}_i^W \) is first normalized to the range \((0,1)\) by the nonlinear sigmoid function:
Fig. 7 Determination process of GME/FSUT/PBF-based multiclass classification scheme for high-dimensional imagery classification.

$$\xi_i^k = \frac{e_i^k - \mu_i^k}{\sigma_i^k},$$ \hspace{1cm} (3)

and

$$e_i^k(\xi_i^k) = \frac{1}{1 + \exp(-t \xi_i^k)}.$$ \hspace{1cm} (4)

where $\mu_i^k$, $\sigma_i^k$, and $t$ denote the mean and the standard deviation of the ED/RRE vector $e_{ui}^k$ and a threshold value, respectively. This new normalized ED/RRE $e_{NQ}^k$ is then uniformly quantized into $L$ levels. Finally, these distance vectors $e_{NQ}^k = (e_{NQ1}^k, e_{NQ2}^k, ..., e_{NQn}^k)$ are converted into binary vectors $e_{NQ} = (e_{NQ1}^k, e_{NQ2}^k, ..., e_{NQn}^k)$. In Fig. 7, the threshold decomposition function $T(\cdot)$ transforms the ED/RRE vector $e_{ui}^k$ into the binary ED/RRE vectors $e_{NQ}^k$ for all classes $\omega_k$.

2.5 Stack Filter and Positive Boolean Function

The PBF proposed in Refs. 7 and 8 was developed from a stack filter. Each stack filter corresponding to a PBF possesses the weak superposition property (the threshold decomposition) and the ordering property (the stacking property).\(^{15,16}\) Recently, Han\(^{11}\) further proposed a PBF-based multiclass classification scheme based on the MCE criterion to resolve multiclass problems. The MCE criterion has the ability to learn from both positive samples and negative samples of the binary ED/RRE generated simultaneously from UGME/IGME feature vectors. It not only improves the classification accuracy, but also overcomes the restriction of a limited number of training samples, which is one of the most common problems in high-dimensional classification of remote sensing.

An optimal stack filter $S_f$ is defined as a filter whose MCE value between the filter’s output and the desired signals is minimum. At the supervised training stage, each level of the training samples is assigned to true (1) or false (0). We assume there are $N$ ground cover classes. We extract only the first $n$ elements of $e_{NQ}^k$, $(e_{NQ1}^k, ..., e_{NQn}^k)$, as a window of fixed length $n$ for all classes, where $n \leq n_k$ for all classes $\omega_k$ and $k \in \{1, ..., N\}$, to develop a PBF-based multiclass classifier. A PBF is exactly one sum-of-product form without any negative components. The classification errors can be calculated from the summation of the absolute errors incurred at each level. The proposed PBF-based multiclass classification scheme is constructed by minimizing the classification error rate using the training samples. In Fig. 7, we assume there are $N$ classes of training samples. $M$ stands for a fixed number of training samples for each class $\omega_k$. $MN$ training samples are applied to $N$ UGME/IGME datasets and then decomposed into $MN^2$ binary ED/RRE vectors $e_{NQ}^k$. Let $x_{ij}$ and $e_{NQij}^k$ represent $MN$ training samples and $MN^2$ binary vectors $e_{NQj}^k$ of length $n$, respectively. The desired value of an occurrence $e_{NQij}^k$ can be treated as the error value of sample $x_{ij}$ at class $\omega_k$. If sample $x_{ij}$ belongs to class $\omega_k$, it means that no error occurs, i.e., the desired value of $e_{NQij}^k$ is 0. Otherwise, it is equal to 1.

$$d(e_{NQij}^k) = \begin{cases} 0 & \text{if } i = k, \ x_{ij} \in \omega_k \\ 1 & \text{if } i \neq k, \ x_{ij} \notin \omega_k \end{cases}.$$ \hspace{1cm} (5)

According to the PBF criteria,\(^{11}\) a Boolean function $B_f^k(\cdot)$ is defined as an occurrence $e_{NQij,\ell, p}^k$ at level $\ell$ in a window of fixed length $n$ (the number of Boolean binary variables) for the class $\omega_k$, as shown in Fig. 8, where $k \in \{1, ..., N\}$, $i \in \{1, ..., N\}$, $j \in \{1, ..., M\}$, $\ell \in \{1, ..., L - 1\}$, and $p \in \{1, ..., n\}$.

Based on the threshold decomposition property, an occurrence of binary ED/RRE vector $e_{NQij}^k$ as an input of PBF...
can be decomposed into binary vectors $e^{k}_{NQ,t}$ with a window of fixed length $n$ (n dimensions). Let us consider two samples $u$, $v$, and a class $w_k$. We assume that $e^{k}_{NQ,u,t} \leq e^{k}_{NQ,v,t}$ for all dimensional elements as indicated before. If sample $u$ does not belong to class $w_k$ (an error occurs), sample $v$ does not belong to class $w_k$. On the other hand, if sample $v$ is an element of class $w_k$ no error!, sample $u$ should be an element of class $w_k$. Here, we define $E_f(\cdot)$ as an error function. Thus, $E_f(u) \leq E_f(v)$, if $e^{k}_{NQ,u,t} \leq e^{k}_{NQ,v,t}$ for all dimensional elements. We further define $E_f(x)$ to be PBF $B_f^1(\cdot)$ of an occurrence $e^{k}_{NQ,t}$ of the class $w_k$ at each level $\ell$. If $e^{k}_{NQ,u,t} \leq e^{k}_{NQ,v,t}$, then $B_f^1(e^{k}_{NQ,u,t}) \leq B_f^1(e^{k}_{NQ,v,t})$, satisfying the stacking property. This gives an indication that the stacking property offers the ability to solve the classification problems.

The $MN^2$ occurrences are treated as the training occurrences of the PBF-based multiclass classifier. They are decomposed into $MN^2(L-1)$ binary vectors of length $n$. The desired value $d(e^{k}_{NQ,t})$ for each occurrence $e^{k}_{NQ,t}$ is determined by Eq. (5). The classification error (CE), which is defined as the expected value $E[\cdot]$ of the differences between the desired values $d(e^{k}_{NQ,t})$ and the stack filter’s binary outputs $S_f(e^{k}_{NQ,t})$, is determined by

$$CE = E[|d(e^{k}_{NQ,t}) - S_f(e^{k}_{NQ,t})|]$$

$$= E \left[ \sum_{\ell=1}^{L-1} T_{\ell}(e^{k}_{NQ,t}) - B_f^1(T_{\ell}(e^{k}_{NQ,t})) \right]$$

$$= \sum_{\ell=1}^{L-1} \sum_{i=1}^{N} \sum_{j=1}^{M} \sum_{k=1}^{N} |d(e^{k}_{NQ,t}) - B_f^1(e^{k}_{NQ,t})|,$$

where a stack filter $S_f(\cdot)$, a threshold function $T_{\ell}(\cdot)$ at level $\ell$, and a Boolean function $B_f^1(\cdot)$ are used at each level. The mechanism illustrated in Fig. 8 is an example of the use of the proposed PBF-based multiclass classifier to process a map classification. All PBF $B_f^1(\cdot)$ of different classes at each level can simultaneously calculate the PBF binary outputs to classify a test sample. The outputs of the stack filter, i.e., the summations of the PBF binary outputs at each level for each class $w_k$, are compared to each other and the one that has the smallest value is chosen as the final decision class for that test sample. This shows that our proposed PBF-based method can be used as a basis for a multiclass classifier.

Fig. 8 An example of the use of the proposed PBF-based multiclass classifier corresponding to a stack filter for processing a map classification.

Fig. 9 The map of the Au-Ku test site used in the experiment.
3 Experimental Results

A plantation area in Au-Ku on the east coast of Taiwan, shown in Fig. 9, was chosen for study. The image data were obtained by the MODIS/ASTER airborne simulator (MASTER) instrument, a hyperspectral sensor, and an airborne synthetic aperture radar (AIRSAR) instrument as part of the PacRim II project. A ground survey was made of the selected six land cover types at the same time. The proposed PBF-based multiclass classification method was applied to 35 bands selected from the 50 contiguous bands (excluding the low signal-to-noise ratio mid-infrared channels) of MASTER and nine components of AIRSAR. Nine components in the polarimetric SAR covariance matrix are preprocessed. The MASTER and AIRSAR images had different spatial resolutions and different number of bytes of pixel values. The SAR data was registered to the same resolution of MASTER data using an averaging algorithm. Both of them were also linearly rescaled to the same number of bytes of pixel values. Six land cover classes, sugar cane A, sugar cane B, seawater, pond, bare soil, and rice \((N = 6)\) were used in the experiment. The criterion to measure classification accuracy was based on exhaustive test cases. 150 labeled samples were randomly collected from ground survey data sets by iterating every fifth sample interval for each class. 30 labeled samples were chosen as training samples, while the rest were used as test samples. Namely, the studied samples were partitioned into 30 (20%) training and 120 (80%) test samples \((M = 120)\) for each test case. Three correlation coefficient threshold values, \(r_c = 0.75, 0.80, \) and \(0.85,\) were selected to carry out the GMET. Four windows of fixed length three, four, five, and six \((n = 3, ..., 6)\) were chosen for each class. Based on PBF-based multiclass classification criteria, there were \(NM\) test samples \((NM = 720)\) for each class. Finally, the accuracy was obtained by averaging the combined results.

We compared several different configurations. Four main groups were compared in Fig. 10. The first group is for IGME (the bolder lines in gray in Fig. 10). In this group, the same GME/FSUT-I was applied to three different datasets to generate the IGME. They were MASTER, SAR, and the datasets fused from SAR and MASTER images. One band was arbitrarily selected for each IGME feature module \(\Phi_{l1}, l \in \{1, ..., n\}\), to calculate the ED. The PBF-based multiclass classifier was then applied to these selected bands. The accuracy using the fused datasets was superior to those using single separate datasets. Comparison of these results showed the advantage of fusing SAR and MASTER images. For the second group, the same datasets were used as the first group, but instead, the UGME was applied. Once again, the fused datasets produced better results, but the overall accuracy was not as good as that obtained from the first group (IGME). The IGME features were always better than the UGME. Here, we also applied two different feature extraction techniques, conventional PCA and the GME projection, as proposed in our previous work, to the same PBF-based multiclass classifier for accuracy comparison. Thus the third group was designed to make such a comparison between the conventional ED and our proposed UGME/IGME methods. The Euclidean upper bound, Euclidean average bands, and Euclidean lower bound represent, respectively, the best upper bound feature bands, the average bands (between upper bound and lower bound), and the worst lower bound feature bands obtained from original datasets. Euclidean PCA stands for the primary principal components of PCA resulting from the original datasets. Compared to the results from the third group, the first group and the second group (the IGME and UGME features) were more suitable for the PBF-based multiclass classifier.
An interesting case is the fourth test group, in which there was a difference in classification accuracy between ED and RRE (GME projection method)\(^7,8\) distance measures. Despite the fact that the feature module of GME has better accuracy than UGME/IGME feature modules when they were all applied to the same RRE distance decomposition, the proposed GME/FSUT algorithm provided an efficient way to select the most significant feature channel (band) and to speed up the distance measure-based decomposition process compared to GME features before applying the PBF-based multiclass classifier. Table 1 summarizes the evaluation of classification accuracy under different conditions to illustrate the validity of these unique properties of the proposed GME/FSUT/PBF-based multiclass classification method. These encouraging results showed that satisfactory classification accuracy could be achieved with only a few training samples.

### Table 1
Summary evaluation of classification accuracy for different feature selection methods, distance measures, number of classes, and datasets.

<table>
<thead>
<tr>
<th>Feature selection methods (distance measures)</th>
<th>Datasets</th>
<th>Number of classes</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>3</td>
</tr>
<tr>
<td>Group one: (ED)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>IGME</td>
<td>MASTER and SAR</td>
<td>89.44%</td>
</tr>
<tr>
<td>IGME</td>
<td>MASTER</td>
<td>85.37%</td>
</tr>
<tr>
<td>IGME</td>
<td>SAR</td>
<td>85.09%</td>
</tr>
<tr>
<td>Group two: (ED)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>UGME</td>
<td>MASTER and SAR</td>
<td>86.20%</td>
</tr>
<tr>
<td>UGME</td>
<td>SAR</td>
<td>79.37%</td>
</tr>
<tr>
<td>UGME</td>
<td>MASTER</td>
<td>74.44%</td>
</tr>
<tr>
<td>Group three: (ED)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Euclidean upper bound</td>
<td>MASTER</td>
<td>89.06%</td>
</tr>
<tr>
<td>Euclidean average bound</td>
<td>MASTER</td>
<td>69.55%</td>
</tr>
<tr>
<td>Euclidean lower bound</td>
<td>MASTER</td>
<td>52.85%</td>
</tr>
<tr>
<td>Euclidean PCA</td>
<td>MASTER</td>
<td>59.00%</td>
</tr>
<tr>
<td>Group four: (RRE)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>GME</td>
<td>MASTER</td>
<td>95.93%</td>
</tr>
<tr>
<td>IGME</td>
<td>MASTER</td>
<td>85.37%</td>
</tr>
<tr>
<td>UGME</td>
<td>MASTER</td>
<td>88.80%</td>
</tr>
</tbody>
</table>

### 4 Conclusions

We present a novel supervised classification technique to fuse hyperspectral and SAR images. The GME/FSUT makes use of the GME developed by grouping highly correlated bands into a small set of bands, regardless of the original order of wavelengths. It applies union (OR) and intersection (AND) operations to the band numbers inside each GME module to fuse the feature scales of GME and construct an identical UGME/IGME feature module set. It can be implemented as a feature selector to generate a particular feature set for each of the material classes present in the fused images. The features selected by the GME/FSUT algorithm contain discriminatory properties crucial to subsequent classification. It makes use of the potential significant separability of GME to find a unique set of the most important features with little computational complexity. It can also speed up the distance decomposition compared to GME features.

The PBF is a stack filter built by using the binary ED/RRE as classifier parameters for supervised training. The advantages of the proposed PBF-based multiclass classifier are its discrete and nonlinear binary properties. It can effectively find nonlinear boundaries of different classes. It utilizes the MCE learning ability to improve the classification accuracy, particularly in dealing with high-dimensional datasets in which training data are always inadequate and knowledge of the data distribution is usually incomplete.

Experimental results demonstrate that the proposed GME/FSUT feature selector fits the nonlinear PBF-based multiclass classifier well for classification. Furthermore, it can improve computational performance by the parallel properties of the PBF-based multiclass classifier. This parallel structure also allows us to explore the possibility of real-time operation.

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### References

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