# Feature clustering and ranking for selecting stable features from high dimensional remotely sensed data

# Abstract

High dimensional remote sensing data sets typically contain redundancy amongst the features. Traditional approaches to feature selection are prone to instability and selection of sub-optimal features in these circumstances. They can also be computationally expensive, especially when dealing with very large remote sensing datasets. This article presents an efficient, deterministic feature ranking method that is robust to redundancy. Average-linkage hierarchical clustering is used to group correlated features into clusters. A relevance criterion is evaluated for each feature. Clusters are then ranked based on the median of the relevance values of their constituent features. Individual features can then be selected from the best clusters. Other criteria, such as computation time or measurement cost, can be considered when making this selection. The proposed feature selection method is compared to traditional filter approach methods on a number of remote sensing data sets containing feature redundancy. Mutual information and naive Bayes relevance criteria were evaluated in conjunction with the feature selection methods. Using the proposed method it was shown that the stability of selected features improved under different data samplings, while similar or better classification accuracies were achieved compared to traditional methods.

## Index Terms: Feature selection, hierarchical clustering, high dimensionality, correlation, redundancy

# Introduction

In image classification, the amount of training data required to adequately represent class distributions in feature space increases exponentially as the number of features (variables) increases – a phenomena known as the “curse of dimensionality” (Bishop, 2003). For finite training samples, increasing the features beyond a certain point results in overtraining and a decrease in the classifier accuracy. This so-called “peaking phenomenon” (Jain et al., 2000) requires the size of the feature set to be reduced to a salient minimum in order to achieve an accurate classification. Support vector machine (SVM) (Burges, 1998) and random forest (Breiman, 2001) classifiers have become popular in remote sensing, partly because of their lack of sensitivity to the peaking phenomenon (Guyon et al., 2002), but several studies have demonstrated the benefits of feature reduction when these classifiers were applied to high-dimensional data (Guyon et al., 2002; Strobl et al., 2008; Tolosi and Lengauer, 2011). Reducing the number of features is also beneficial from the perspective of measurement costs and feature computation time. This is particularly relevant in large scale remote sensing studies involving Very High Resolution (VHR) imagery, as vast quantities of data require processing. A further motivation for reducing features to an informative minimum is the “ugly duckling theorem”, which implies that the more redundant features contained in a data set, the less separable classes become (Jain et al., 2000).

Two basic approaches to feature set reduction exist: feature selection and feature extraction. In feature extraction the feature set is mapped into a new feature space of reduced dimensionality (Webb, 2002). Various criteria, such as separability and variance, are used to define the dimensions of the new “optimal” space. Principal Components Analysis (PCA) (Webb, 2002) is an example of a popular feature extraction method. A disadvantage of the feature extraction approach is that it requires calculation of the full feature set.

Feature selection involves the selection of a subset of features from the original set according to some criterion of subset performance. The number of possible subsets increases combinatorially with the size of the feature set and it is seldom practical to evaluate all possible subsets (Jain et al., 2000). A variety of search methods exists for reducing the portion of feature space searched. Of these, only the branch and bound method is globally optimal, the rest achieve reduced computation at the price of optimality. The complexity of the branch and bound method increases exponentially with the size of the feature set and is as such still computationally impractical for large feature sets (Jain et al., 2000). The fastest and most straightforward search method is simply to rank features based on their individual performance and select the best *N*. However, feature ranking approaches are problematic for data sets containing feature redundancy. In these situations, correlated features are ranked similarly, resulting in sub-optimal and redundant feature sets.

More advanced search methods use greedy sequential approaches, such as forward selection and backward elimination. Compared to the feature ranking approach, greedy search methods are more likely to find the globally optimal feature set as they explore more of the search space and are less inclined to select multiple redundant features (Webb, 2002). The forward selection (FS) approach starts with an empty feature set; the feature from the set of unselected features that improves an accuracy criterion the most is then added to the model. This selection process is repeated for a set number of iterations or until a stopping criterion is reached (Bishop, 2003). The backward elimination (BE) method starts with the full set of features and the feature whose removal produces the best accuracy according to some criterion is eliminated from the candidate set. This process is repeated a set number of times or until a stopping criterion is reached (Bishop, 2003). BE is computationally more costly than FS, and requires sufficient reference data to be able to train and assess the classifier on the full feature set.

Feature selection methods can be grouped into filter, wrapper and embedded approaches. In the filter approach, generic measures of separability or importance are used to evaluate feature subsets, while in the wrapper approach, the accuracy of a specific classifier trained on the feature subset is used as the selection criterion (Duin and Tax, 2005). An embedded approach is one where feature selection is incorporated into the classifier training procedure, such as with random forests (Breiman, 2001). Filter approaches have the advantage over wrapper and embedded approaches of making feature selection independent of the classifier, thus allowing for greater flexibility in the choice of classifier (Brown et al., 2012). In general, filter approaches are also computationally more efficient than wrapper approaches. This is an important consideration for large and high dimensional data sets such as those often encountered in remote sensing. This study focuses on filter approaches.

High dimensional feature spaces typically contain feature redundancy (Cukur et al., 2015; Tolosi and Lengauer, 2011; Yu and Liu, 2004). Although feature correlation and redundancy are related, they are not strictly the same thing (Brown et al., 2012; Guyon and Elisseeff, 2003). Features can help improve separability when the within class correlation is stronger than the between class correlation. We use the term “redundancy” to refer to correlation of features between classes. The raw bands of multispectral imagery often have significant spectral overlap and consequently are correlated with one another. This spectral overlap will exacerbate the redundancy amongst features derived from these raw bands (Cukur et al., 2015).

A number of authors have noted difficulties in selecting features from high dimensional data sets. Kononenko et al. (1997), Guyon et al. (2002), Yu & Liu (2004) and Yousef et al. (2007) noted that feature redundancy can have a negative impact on the optimality of feature selection. Feature redundancy not only leads to sub-optimal feature selection, but also makes selected features unstable and sensitive to small changes in the data used for selection (Guyon and Elisseeff, 2003; Kalousis et al., 2007; Li et al., 2011; Tolosi and Lengauer, 2011).

Redundancy can be effectively dealt with using a feature extraction approach, such as PCA, but this requires computation of the full feature set. This is not practical in computationally demanding applications such as analysing very high resolution (VHR) imagery over large areas. A number of feature selection approaches have been developed to address the issues of stability and sub-optimality encountered in high dimensional and redundant data. These methods consider the trade-off between feature relevance (i.e. how much information the feature contains about the class labels) and redundancy.

A means of selecting good features from redundant spaces was devised by Yousef et al. (2007). They used a k-means algorithm to produce a fixed number of clusters of correlated features. The accuracy of a SVM classifier is found for all the features of each cluster. The lowest performing clusters are eliminated, the remaining features combined, and the process is repeated until a desired number of clusters is reached. A related feature selection method that finds and removes redundancy by clustering features into similar groups was presented by Mitra et al. (2002). They used a novel clustering algorithm to group correlated features based on a similarity measure they call “maximal information compression index”, which is the smallest eigenvalue of the feature covariance. Sahu & Mishra (2011) also used k-means clustering to group redundant features. The best feature, according to an importance measure, is then selected from each cluster. Cukur et al. (2015) proposed a similar method, where redundant features are clustered and top ranked features selected from each cluster using an importance measure called “minimum redundancy maximum relevance” (mRMR).

A two-step procedure called the “Fast Correlation Based Filter” (FCBF), was developed by Yu & Liu (2004). It first creates a reduced set of relevant features, and then removes redundant features from this set using a search procedure based on Markov blanket filtering. A non-linear correlation measure, called symmetrical uncertainty, is used to measure both feature relevance and redundancy. Relevance is measured by how well features are correlated with class labels and redundancy is measured by how well features are correlated with each other.

Wu et al. (2013) compared a number of filter approach feature selection methods based on their application to three hyperspectral data sets. They used a number of performance measures for comparison, including classifier accuracy, feature stability, and their own criterion called the maximal minimal associated index quotient (MMAIQ). MMAIQ uses Cramer’s *V*-test values to trade feature relevance against redundancy and is applied in a forward selection type routine. While the authors concluded that MMAIQ provided the best overall performance, it did not provide good stability for high dimensional data.

A number of feature importance measures (including the FCBF) were incorporated by Brown et al. (2012) into a common theoretical framework. These measures all consider both relevance and redundancy in some way. A comprehensive empirical study was used to compare the performance (in terms of stability and classifier accuracy) of these measures. The study tested the criteria in a FS approach, under varying conditions, including redundancy in high dimensional feature spaces. They concluded that joint mutual information (JMI) (Yang and Moody, 1999) provides the best feature selection performance overall.

With the exception of FCBF, the above feature selection procedures can be grouped into two categories:

1. Approaches that use some form of clustering of similar features to identify and remove redundancy, usually followed by a ranking of cluster relevance to choose features from the most informative clusters.
2. Approaches that use a single measure of feature importance that incorporates the trade-off between feature relevance and redundancy, after which a FS or simple ranking procedure is used to select the best features.

In gene expression studies, such as DNA microarray studies, all features have similar measurement costs and computation times (Inza et al., 2004), but this is not the case for remote sensing problems, where some features might carry significantly larger computation time or measurement cost burdens than others (Blaschke, 2010). Where a group of correlated features are similarly relevant, it is beneficial to select the feature with the lowest computation time or measurement cost. Consideration of these costs can potentially result in a substantial reduction in classification computation time for this form of remote sensing problem.

The availability of high resolution imagery and associated feature extraction and classification techniques are rapidly increasing (Chi et al., 2016). With the advent of “big data” in remote sensing (large quantities of high resolution spatial and spectral data requiring interpretation), computationally efficient feature selection techniques robust to high dimensional redundant spaces will become increasingly important. In this paper we propose a filter approach feature selection method for addressing the problem of high dimensional, redundant feature spaces of remotely sensed data. We adopt the filter approach due its relative speed and separation of feature selection and classification tasks. The method follows the clustering and ranking approach (category 1 above) and employs hierarchical clustering. This has the advantage of producing deterministic results, not requiring prior knowledge of the number of clusters and allowing user selection of the final partitioning. We compare the performance of the proposed method to popular feature selection approaches, on a number of remote sensing data sets. The proposed method also allows consideration of computation time and measurement cost in selecting features from correlated clusters of similarly relevant features. While many feature selection evaluations only consider classification accuracy (Mitra et al., 2002; Strobl et al., 2008; Yu and Liu, 2004), we present measures of computation time, classification accuracy and stability of selected features under different data samplings.

# Methods

## Formulation

The proposed method is described as follows:

1. Perform average-linkage hierarchical clustering (Szekely and Rizzo, 2005) of the feature set using the correlation coefficient as the dissimilarity metric.
2. Select a dissimilarity threshold at which to extract a natural number of clusters containing high correlation (in this study it is done by visual inspection of the dendrogram, but selection can conceivably also be automated).
3. Rank each cluster’s importance by finding the value of a relevance criterion for each individual feature and then finding the median of the feature relevance values in the cluster.
4. Select a single feature from each of the *N* clusters with best importance scores.

Hierarchical clustering provides a simple way of grouping features and does not require prior knowledge of the number of clusters (Webb, 2002). The method begins with each individual feature in its own cluster and proceeds in a number of steps. At each step, the pair of clusters that minimise a cluster dissimilarity criterion are merged into a single cluster. The hierarchy of clusters can be graphically represented with a dendrogram (MathWorks, 2016), as illustrated with an example in Figure 1. The inverted U-shaped lines show which clusters are combined into new clusters. The height of the horizontal line indicates the magnitude of the dissimilarity between clusters.

The average-linkage criterion, which is the average of the pairwise distances between the objects in two clusters, was used to measure cluster dissimilarity. The pairwise object distances were calculated as , where is the Pearson correlation coefficient between two objects. Cluster stability and strength of correlation within each cluster are the key factors to consider when choosing the number of clusters and can be visually interpreted from the dendrogram. In Figure 1, the dotted line shows an example dissimilarity threshold at which to extract clusters from the hierarchy. At this threshold, the clusters are highly correlated (i.e. the dissimilarity is small) and the cluster contents are stable (i.e. the next level in the hierarchy only occurs at a substantially larger dissimilarity).

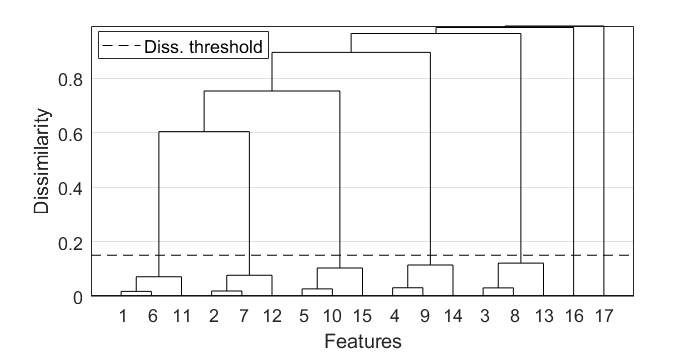


Figure 1 Example dendrogram showing chosen threshold at which to extract clusters

We investigated the performance of two different feature relevance measures: the accuracy of a naive Bayes classifier and the mutual information (MI) between the feature and the class labels. The naive Bayes classifier, using a histogram to model class densities, was chosen primarily because it makes no assumptions about the form of the class distributions and can thus provide a generic measure of separability. It is simple, fast and recognised as being accurate for a variety of problems (Hand and Yu, 2001). The “naive” assumption of feature independence is of no consequence when testing individual features.

MI is a measure of the dependence between two random variables (Brown et al., 2012). Given two random variables and , with probability distributions and and joint probability distribution , the MI between and is defined as:

|  |  |  |  |
| --- | --- | --- | --- |
|  |  |  | (1) |

The MI between a feature and the class labels gives a useful indication of that feature’s relevance or importance (Brown et al., 2012). The probability distributions in Equation (1) are not known and are estimated using histograms.

The number of clusters to select, *N*, can be specified by the user based on the size of the training set or by using a grid search with the final classifier accuracy as performance measure. To avoid biased accuracy estimates, all classifier accuracy evaluations, for cluster ranking or selection of *N*, are done on unseen test data using a five-fold cross validation (Bishop, 2003).

## Data Sets

Five remote sensing and one synthetic data set were used for comparing the proposed method against popular existing feature selection methods. The data sets are detailed in Table 1. The “difficulty” in the last column is calculated as , as in Brown et al. (2012), where is the number of objects, the number of features and the number of classes. Smaller values indicate that the data is less representative of the underlying class distributions, which results in more challenging feature selection and classification tasks. The Spekboom set consists of 46 spectral and textural features derived from four band multispectral, 0.5 m spatial resolution aerial imagery. The classes represent three types of vegetation found in the Little Karoo, a semi-arid region in South Africa. It was created as part of a vegetation mapping project being conducted by the authors.

The two class synthetic data set was generated to have redundancy amongst the features. The first five features for class were generated from a normal distribution, , with mean mean and standard deviation of one (). The mean, , of each distribution, was generated from the standard normal distribution, . The same number of objects were generated for each class. To introduce redundancy, an additional five features were generated by adding normally distributed noise, , to the original five features. A further five redundant features were similarly generated, but by adding normally distributed noise, , to the original features. Finally, two spurious features, sampled from a standard normal distribution, , were added to the data set.

The Statlog Landsat and Urban Land Cover data sets were obtained from the UCI Machine Learning Repository (Lichman, 2013). The Statlog Landsat features are generated from six band multispectral pixel values in three by three neighbourhoods. The data set consists of six land cover classes. The features of the Urban Land Cover data set are comprised of multi-scale spectral, size, shape and textural measures, derived from high resolution aerial imagery (Johnson and Xie, 2013).

Kennedy Space Centre (KSC) and Botswana are public hyperspectral data sets with vegetation and land cover classes (GIC, 2014). The Botswana data were acquired by the Hyperion sensor on board the NASA EO-1 satellite and consist of 145 bands in the 400-2500 nm portion of the spectrum, at a 30 m pixel resolution. The KSC data were acquired by the NASA AVIRIS (Airborne Visible/Infrared Imaging Spectrometer) sensor and consist of 176 bands in the 400-2500 nm range, acquired at a spatial resolution of 18 m.

Table 1 Data sets

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Name | Abbrev. | Features | Objects | Classes | Difficulty |
| Spekboom | Spekboom | 46 | 57877 | 3 | 419.40 |
| Synthetic | Synthetic | 17 | 10000 | 2 | 294.12 |
| Statlog Landsat | Landsat | 36 | 3756 | 6 | 17.39 |
| Urban Land Cover | Urban | 147 | 261 | 9 | 0.20 |
| Botswana | Botswana | 145 | 1330 | 14 | 0.66 |
| Kennedy Space Centre | KSC | 176 | 1365 | 13 | 0.60 |

## Evaluation

The proposed Feature Clustering and Ranking (FCR) method was compared to a number of other established feature selection methods. We adopted a similar, although reduced, evaluation approach to that of Brown et al. (2012) and Wu et al. (2013). The compared methods included the standard selection approaches of ranking, FS and BE. These standard approaches and FCR, were each evaluated with two different feature relevance criteria: MI and the naïve Bayes classification accuracy. The MI relevance criterion for FCR and ranking approaches finds the MI between individual features and the class labels. To integrate the MI relevance criterion into FS and BE, it is necessary to compute the MI of a set of multiple candidate features with the class labels. In this situation, the candidate features are first merged into a joint variable and then the MI of the class labels with this joint variable is computed (Brown et al., 2012). We used histograms with ten bins along each dimension to approximate probability densities for both the MI and naive Bayes criteria (Webb, 2002). This approximation is made to avoid difficulties and inefficiencies associated with estimating probability densities for continuous variables (Brown et al., 2012).

Brown et al. (2012) compared the performance of a several feature selection criteria in redundant high dimensional spaces, and found the JMI criterion gave the best overall performance in terms of classification accuracy and stability. Based on these results, FS with the JMI criterion was included in our study to represent the “state of the art” performance. The JMI measure for feature is

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| --- | --- | --- | --- |
|  |  |  | (2) |

where are the class labels and is the set of previously selected features. JMI considers the MI between the class labels and the joint variables , which are the pairwise combinations of the candidate feature with each feature already selected. It measures how well the candidate feature complements selected features in describing the class labels. The evaluated methods and their criteria are detailed in Table 2.

Table 2 Method and criteria combination

|  |  |  |
| --- | --- | --- |
| Method | Criterion | Abbreviation |
| Forward selection | Joint Mutual Information | FS-JMI |
| Feature Clustering and Ranking | Naive Bayes | FCR-NaiveBC |
| Ranking | Naive Bayes | Rank-NaiveBC |
| Forward selection | Naive Bayes | FS-NaiveBC |
| Backward elimination | Naive Bayes | BE-NaiveBC |
| Feature Clustering and Ranking | Mutual information | FCR-MI |
| Ranking | Mutual information | Rank-MI |
| Forward selection | Mutual information | FS-MI |
| Backward elimination | Mutual information | BE-MI |

To quantify the stability of the selected features, we used the consistency index developed by Kuncheva (2007). If and and are subsets of the full feature set , with , and , the consistency index is

|  |  |  |  |
| --- | --- | --- | --- |
|  |  |  | (2) |

It’s value lies in the range , where positive values indicate similar sets, zero indicates a random relation and negative values indicate an anti-correlation between the feature sets (Kuncheva, 2007). To evaluate stability for a particular method, we select features from bootstrap samples of the data. The consistency index is found for each pairwise combination of selected features over ten bootstraps of the data and averaged to give a measure of overall stability.

A k-nearest-neighbour (k-NN) classifier (with ) was used to evaluate the accuracy of the features selected by each method. k-NN is a generic classifier that makes no assumptions about the data and requires no tuning. While other classifiers may be more accurate in particular situations, k-NN allows a relative comparison of the feature selection methods, independent of the influence of classifier tuning for specific data. For each of the feature sets found from the bootstrap samples, the k-NN accuracy was found as the average per-class accuracy from a ten-fold cross validation. For each method and data set combination, an overall accuracy was computed as the average of the bootstrap accuracies.

The number of features to select for each data set was fixed across methods. This parameter was selected by using the accuracy of a k-NN classifier (), trained on the first *N* features selected by FS-NaiveBC, as the criterion in a grid search. A low value of *N* that achieved good accuracy was selected for each data set.

The FCR methods (FCR-MI and FCR-NaiveBC) required some specific treatment to integrate them into the evaluation. The dissimilarity threshold at which to extract the feature clusters from the hierarchy was determined by visual inspection of the dendrogram for each dataset. Thresholds at which the clusters were both stable and strongly correlated were favoured (see section 2.1 for a description of these concepts). The chosen threshold was used across all bootstraps of the data set. After bootstrapping, clusters were assigned unique indices, ensuring identical clusters had the same index. The consistency index was then found using the selected cluster indices rather than feature indices. This was done to simulate hand-selection of preferred features from the best clusters for each bootstrap, while, in practice, allowing the FCR algorithm to automatically choose the top ranked feature from each cluster (for the sake of simplicity and speed). In other words, the cluster index was used to represent the index of the preferred feature that could otherwise have been selected by hand from the cluster contents. The clusters represent a reduced set of possible indices compared to the features. This reduced set in turn reduces the possibility of stability errors. It is acknowledged that this formulation of the consistency index may favour FCR, but it was regarded as a necessary modification to allow comparison of the different methods.

We followed a similar approach to that of Brown et al. (2012), for computing a single “non-dominated” ranking of the methods that considers stability and accuracy performance simultaneously. The concept of “Pareto optimality”, is used to find a single optimal solution in terms of multiple criteria. In the context of our evaluation, the “Pareto front” is the set of methods on which no other method can improve without degrading either the accuracy or stability. The methods in this set are called “non-dominated” (Mishra and Harit, 2010). Successive Pareto fronts can be formed iteratively by finding the current Pareto front of the set of methods that excludes members of the previous fronts. A method was thus given a non-dominated rank of *N* if it was a member of the *N*th Pareto front. The average of the non-dominated ranks for each method over the six data sets was used to produce an overall ranking.

The bulk of the software implementation was done in MatlabTM, making use of the PRTools toolbox (TU Delft, 2015). The MI and JMI criteria were computed using the FEAST (FEAture Selection Toolbox) C++ implementation (Brown et al., 2012).

# Results and Discussion

The chosen FCR correlation dissimilarity thresholds and corresponding number of features selected for each data set are detailed in Table 3.

Table 3 Feature selection parameters

|  |  |  |
| --- | --- | --- |
| Data Set | Num Features to Select | FCR Dissimilarity Threshold |
| Spekboom | 6 | 0.2 |
| Synthetic | 5 | 0.15 |
| Statlog Landsat | 4 | 0.2 |
| Urban Land Cover | 4 | 0.3 |
| Botswana | 7 | 0.03 |
| Kennedy Space Centre | 7 | 0.05 |

The results of the stability and accuracy evaluations for each method and data set combination are shown in Figure 2 and Figure 3 respectively. The methods appear along the x axis in order of their mean stability in Figure 2, and mean accuracy in Figure 3, over the six data sets. FS-MI was the most stable overall, but had one of the poorest accuracies. Similarly, FS-NaiveBC is the most accurate overall, but is the least stable. While neither FCR-NaiveBC nor FCR-MI achieve the best overall accuracy or stability, they are amongst the top three methods for both performance measures. The wide range of stabilities confirms the sensitivity of some methods to variations in the data. The method accuracies span a smaller range than the method stabilities. Nonetheless, there are substantial differences in accuracy between the best and worst methods. Compared to the other data sets, the stability of the Spekboom, Synthetic and Landsat data is noticeably superior. As reflected in the “difficulty” values in Table 1, these data sets are more representative of the underlying distributions and are thus less sensitive to disturbances.

The ranking methods, Rank-MI and Rank-NaiveBC both have poor accuracy performance. This is expected as these methods do not consider feature complementarity and only measure relevance of features in isolation. The relatively poor accuracy and stability of FS-JMI was surprising in the context of the results of Brown et al. (2012), where it produced the best overall performance. Perhaps FS-JMI is more competitive when applied to higher dimensional data sets, containing hundreds or thousands of features, such as those that were used in Brown et al. (2012). The FS-JMI results nevertheless provide a benchmark that helps confirm the usefulness of the FCR method for the type of data investigated in our study.

As with classifier design, there is a “curse of dimensionality” problem with computing the MI of joint variables. As the number of features increases, the number of objects needed to adequately represent the feature distribution increases exponentially (Brown et al., 2012). For this reason, the MI criterion is not well suited for evaluating the BE method, which requires computation of the relevance criterion for the full feature set. This likely explains the poor performance of BE-MI in terms of both accuracy and stability. Note that part of the motivation for the JMI formulation is to circumvent this kind of representivity issue by using a low dimensional approximation to MI.



Figure 2 Method stability per data set (methods along the x axis are ordered by their mean stability over the data sets)



Figure 3 Method accuracy per data set (methods along the x axis are ordered by their mean accuracy over the data sets)

The method execution times, summed over the six data sets, are provided for reference in Table 4. The execution time of FCR competes well with the other methods. The NaiveBC criterion is slower to compute than the MI criterion as it uses a five-fold cross-validation, implemented in MatlabTM, to evaluate the classification accuracy. MI is computed once-off using the efficient FEAST C++ implementation. Methods using the NaiveBC criterion are consequently slower than their MI counterparts. JMI is faster than the related FS-MI method, as the criterion only requires MI computations between pairwise combinations of features and the class labels, while the MI criterion is evaluated on the combination all selected features. BE is known to be less efficient than FS (Guyon and Elisseeff, 2003), and is slowest of the tested methods.

Table 4 Method cumulative execution time over all data

|  |  |
| --- | --- |
| Method | Time (s) |
| Rank-MI | 5.77 |
| JMI | 6.25 |
| FCR-MI | 6.46 |
| FS-MI | 24.71 |
| FCR-NaiveBC | 122.23 |
| Rank-NaiveBC | 145.55 |
| BE-MI | 815.23 |
| FS-NaiveBC | 831.99 |
| BE-NaiveBC | 5726.67 |

Table 5 presents the non-dominant ranking of the methods, in terms of both accuracy and stability. The best ranked method overall is FCR-MI, with FCR-NaiveBC, FS-MI and FS-NaiveBC occupying the second rank position. While the FS-MI and FS-NaiveBC produced the best performance for stability and accuracy respectively, FCR-MI and FCR-NaiveBC achieved a better compromise between these two measures. The Rank-NaiveBC, Rank-MI and BE-MI methods are ranked lowest due to the known limitations of these methods.

If the clustering step were omitted, FCR-MI and FCR-NaiveBC would simplify to Rank-MI and Rank-NaiveBC respectively. FCR-MI and FCR-NaiveBC show a substantial improvement in performance compared to Rank-MI and Rank-NaiveBC which lends support to the effectiveness of the clustering step. Considering the combination of the MI and naive Bayes criteria with each method in isolation, there is a general trend for MI to produce better stability and naive Bayes to produce better accuracy. While FCR works well with either criterion, the results favour the use of MI as it is faster and produces a better non-dominant ranking than naive Bayes. On the whole the evaluation study shows the FCR method to be effective at selecting accurate and stable features from high dimensional remote sensing data containing redundancy.

Table 5 Non-dominated ranking of methods by accuracy and stability

|  |  |
| --- | --- |
| Method | Rank |
| FCR-MI | 1.50 |
| FCR-NaiveBC | 1.83 |
| FS-NaiveBC | 1.83 |
| FS-MI | 1.83 |
| BE-NaiveBC | 2.83 |
| JMI | 3.00 |
| Rank-NaiveBC | 3.33 |
| Rank-MI | 3.50 |
| BE-MI | 3.50 |

# Conclusions

Feature redundancy was identified as a source of instability and inaccuracy in feature selection. A method for ranking correlated clusters of features was presented. Using hierarchical clustering, a natural number of clusters can be selected by observing the stability of correlation relationships in the data using a dendrogram. Clusters are then ranked using an importance measure, calculated as the median of a relevance criterion evaluated on each individual feature in the cluster. By selecting individual features from the best clusters, a set of informative features is found while simultaneously removing redundancy from the data. The ability to hand-pick features is beneficial as it allows other factors, such as speed of computation and physical interpretability, to be considered when determining an effective feature set.

The effectiveness of the proposed FCR method was evaluated by comparing its accuracy, stability and execution time to a set of popular feature selection methods. A set of five remote sensing and one synthetic data set, all containing redundancy, were used to compare the methods. The feature selection methods were each tested in combination with two criteria for feature relevance: the MI between the candidate feature(s) and the class labels, and the accuracy of a naive Bayes classifier trained on the candidate feature(s). FS-NaiveBC provided the best accuracy performance but the worst stability performance. In a similar vein, FS-MI provided the best stability performance but the second worst accuracy performance. The FCR method performed well overall, with both naive Bayes and MI criteria. Although FCR did not quite achieve the best performance in accuracy or stability alone, it was the highest ranked method when considering the accuracy and stability measures in combination. Another benefit of FCR is its relative speed compared to greedy search FS and BE type methods. Ever increasing quantities of high spatial and spectral resolution remote sensing data are being produced and require interpretation (Chi et al., 2016). In this context, instability and sub-optimality associated with feature selection from high dimensional redundant data will become increasingly critical issues. Computationally efficient techniques, such as FCR, are required to address these challenges.

The need for user specification of dissimilarity threshold is a weakness of the FCR method. This is a subjective choice and different thresholds can lead to different sets of selected features. A possible way to automate this choice would be to extract clusters from all levels in the hierarchy, select a set of features from the best clusters at each level, and then use a performance measure such as the accuracy of a k-NN classifier to choose the best set of features overall. The need for visual inspection of the dendrogram to make the choice of dissimilarity threshold also limits the dimensionality of data that the FCR method can practically be applied to. For data sets of hundreds or thousands of features, the dendrogram would likely be too cluttered to make a sensible choice and a feature selection algorithm other than FCR may be more appropriate. It is worth noting that for problems where feature stability and user specification of preferred variables are not required, FS-NaiveBC may be a more sensible choice of feature selection method. It achieved the best accuracy results and does not require any user intervention as with FCR.

Our reasoning for the choice of dissimilarity metric for clustering, clustering algorithm and feature relevance measure was loose and other options could also prove effective. Another aspect of our method that could benefit from further investigation is the correlation coefficient dissimilarity metric. It would be preferable to use a metric that can describe non-linear correlation, such MI or the symmetrical uncertainty used in Yu & Liu (2004).

Despite these shortcomings, FCR performed well on a diverse range of high dimensional and redundant data. It achieved the best overall performance, in terms of combined stability and accuracy measures, compared to existing feature selection methods. It is also achieved similar or superior computation times relative to existing methods. For these reasons, FCR is considered a sensible. It was shown that redundancy is prob for rsa

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