Application of Symmetric Uncertainty and Mutual Information to Dimensionality Reduction of and Classification Hyperspectral Images

ELkebir Sarhrouni*, Ahmed Hammouch** and Driss Aboutajdine*

*LRIT, Faculty of Sciences, Mohamed V - Agdal University, Morocco
**LRGE, ENSET, Mohamed V - Souissi University, Morocco
sarhrouni436@yahoo.fr, hammouch_a@yahoo.com, aboutaj@fsr.ac.ma

Abstract

Remote sensing is a technology to acquire data for disatant substances, necessary to construct a model knowledge for applications as classification. Recently Hyperspectral Images (HSI) becomes a high technical tool that the main goal is to classify the point of a region. The HIS is more than a hundred bidirectional measures, called bands (or simply images), of the same region called Ground Truth Map (GT). But some bands are not relevant because they are affected by different atmospheric effects; others contain redundant information; and high dimensionality of HSI features make the accuracy of classification lower. All these bands can be important for some applications; but for the classification a small subset of these is relevant. The problematic related to HSI is the dimensionality reduction. Many studies use mutual information (MI) to select the relevant bands. Others studies use the MI normalized forms, like Symmetric Uncertainty, in medical imagery applications. In this paper we introduce an algorithm based also on MI to select relevant bands and it apply the Symmetric Uncertainty coefficient to control redundancy and increase the accuracy of classification. This algorithm is feature selection tool and a Filter strategy. We establish this study on HSI AVIRIS 92AV3C. This is an effectiveness, and fast scheme to control redundancy.

Keywords: Hyperspectral images, Classification, Feature Selection, Mutual information, Redundancy.
1 Introduction

In the feature classification domain, the choice of data affects widely the results. The problem of feature selection is commonly reencountered when we have $N$ features (or attributes) that express $N$ vectors of measures for $C$ substances (called classes). The problematic is to find $K$ vectors among $N$, such as relevant and no redundant ones; in order to classify substances. The number of selected vectors $K$ must be lower than $N$ because when $N$ is so large that needs many cases to detect the relationship between the vectors and the classes (Hughes phenomenon) [10]. No redundant features (vectors) because they complicate the learning system and product incorrect prediction [14]. Relevant vectors means there ability to predicate the classes. The Hyperspectral image (HIS), as a set of more than a hundred bidirectional measures (called bands), of the same region (called ground truth map: GT), needs reduction dimensionality. Indeed the bands dont all contain the information; some bands are irrelevant like those affected by various atmospheric effects, see Figure.3, and decrease the classification accuracy. Finally there exist redundant bands, must be avoided. We can reduce the dimensionality of hyperspectral images by selecting only the relevant bands (feature selection or subset selection methodology), or extracting, from the original bands, new bands containing the maximal information about the classes, using any functions, logical or numerical (feature extraction methodology) [8][9][11]. Here we introduce an algorithm based on mutual information, reducing dimensionality in two steps: pick up the relevant bands first, and avoiding redundancy second. We illustrate the principle of this algorithm using synthetic bands for the scene of HIS AVIRIS 92AV3C [1], Figure.1. Then we approve its effectiveness with applying it to real datat of HSI AVIRIS 92AV3C. So each pixel is shown as a vector of 220 components. Figure.2. shows the vector pixels notion [7]. So reducing dimensionality means selecting only the dimensions caring a lot of information regarding the classes.

The Hyperspectral image AVIRIS 92AV3C (Airborne Visible Infrared Imaging Spectrometer)[2] contains 220 images taken on the region ”Indiana Pine” at ”north-western Indiana”, USA [1]. The 220 called bands are taken between 0.4 µm and 2.5 µm. Each band has 145 lines and 145 columns. The ground truth map is also provided, but only 10366 pixels (49%) are labeled from 1 to 16. Each label indicates one from 16 classes. The zeros indicate pixels how are not classified yet, Figure.1. The hyperspectral image AVIRIS 92AV3C contains numbers between 955 and 9406. Each pixel of the ground truth map has a set of 220 numbers (measures) along the hyperspectral image. Those numbers (measures) represent the reflectance of the pixel in each band. So the pixel is shown as vector off 220 components. Figure.2.

We can also note that not all classes are carrier of information. In Figure.5,
Figure 1: The Ground Truth map of AVIRIS 92AV3C and the 16 classes for example, we can show the effects of atmospheric effects on bands: 155, 220 and other bands. This Hyperspectral Image presents the problematic of dimensionality reduction.

Figure 2 shows the vector pixels notion [7]. So reducing dimensionality means selecting only the dimensions caring a lot of information regarding the classes.

Figure 2: The notion of pixel vector

2 Mutual Information Based Feature Selection

2.1 Definition of Mutual Information

This is a measure of exchanged information between tow ensembles of random variables A and B:

\[ I(A, B) = \sum p(A, B) \log_2 \frac{p(A, B)}{p(A)p(B)} \]

Considering the ground truth map, and bands as ensembles of random variables, we calculate their interdependence. Fano [14] has demonstrated that as soon as mutual information of already selected feature has high value, the error probability of classification is decreasing, according to the formula
The expression of conditional entropy $H(C/X)$ is calculated between the ground truth map (i.e. the classes $C$) and the subset of bands candidates $X$. $N_c$ is the number of classes. So when the features $X$ have a higher value of mutual information with the ground truth map, (is more near to the ground truth map), the error probability will be lower. But its difficult to compute this conjoint mutual information $I(C; X)$, regarding the high dimensionality [14].

Figure.4. shows the MI between the GT and synthetic bands. The figure .6 shows the MI between the GT and the real bands of HIS AVIRIS 92AV3C [1]. Many studies use a threshold to choice the relevant bands. Guo [3] uses the mutual information to select the top ranking band, and a filter based algorithm to decide if there neighbours are redundant or not. Sarhrouni et al. [17] use also a filter strategy based algorithm on MI to select bands. A wrapper strategy based algorithm on MI, Sarhrouni et al. [18] is also introduced.

By a thresholding, for example with a threshold 0.4, see Figure.5, we eliminate the no informative bands: $A_3$, $A_7$ and $A_9$. With other threshold, we can retain fewer bands. We can visually verify this effectiveness of MI to choice relevant features in Figure.4.

### 2.2 Symmetric Uncertainty

This is one of normalized form of Mutual Information; introduced by Witten and Frank, 2005 [19]. Its defined as bellow:

$$U(A, B) = 2 \cdot \frac{MI(A, B)}{H(A) + H(B)}$$

$H(X)$ is the Entropy of set random variable $X$. Some studies use this $U$ for recalling images in medical images treatment [9]. Numerous studies use Normalized Mutual Information [20][21][22].

Figure.3 shows that symmetric uncertainty means how much information is partaged between $A$ and $B$ relatively at all information contained in both $A$ and $B$. 
3 Principe of the Proposed Method and Algorithm

For this section we synthesize 19 bands from the GT, Figure 1, by adding noise, cutting some substances etc. see Figure 4. Each band has 145 lines and 145 columns. The ground truth map is also provided, but only 10366 pixels are labelled from 1 to 16. Each label indicates one from 16 classes. The zeros indicate pixels how are not classified yet, Figure 2. We can show the Mutual information of GT and the synthetic bands at Figure 5.

3.1 Principe to select relevant bands

With a threshold 0.4 of MI calculated in Figure 4 we obtain 16 relevant bands $A_i$:

with $i = \{1, 2, 3, 4, 5, 6, 8, 10, 11, 12, 14, 15, 16, 17, 18, 19\}$.

We can visually verify the resemblance of GT and the bands more informative, bout in synthetic and the real data bands of AVIRIS 92AV3C. See Figure 6.

3.2 Principe of no Redundant Bands Detection

First: We order the remaining bands, in increasing order of there MI with the GT. So we have:

$\{A_{12}A_8A_{15}A_6A_1A_3A_{14}A_{16}A_2A_{10}A_{17}A_4A_{19}A_5A_{11}A_{18}\}$

Second: We fixe a threshold to control redundancy, here 0.7. Then we compute the Symmetric Uncertainty: $U(A_i, A_j)$ for all couple $(i, j)$ of the ensemble:
Figure 4: The synthetic bands used for the study.

Figure 5: Mutual Information of GT and synthetic bands.

\[ S = \{8, 15, 6, 1, 3, 14, 16, 2, 10, 17, 4, 19, 5, 11, 18\}. \]

Observation 1: Figure 4 shows that the band \( A_{17} \) is practically the same at \( A_4 \). Table I shows \( U(A_{17}, A_4) \) near to 100% (0.95). So this indicates a high redundancy.

Observation 2: Figure 4 shows that the bands \( A_{16} \) and \( A_{18} \) are practically...
disjoint, i.e. they are not redundant. Table I. shows $U(A_{16}, A_{18}) = 0.07$. So this indicates no redundancy. So the ensemble of selected bands became $SS = \{16, 18\}$. $A_{16}, A_{18}$ will be discarded from the Table I. Algorithm 1 shows more details.

Now we can emit this rule:

**Rule:** Each band candidate will be added at $SS$ if and only if their Symmetric Uncertainty values with all elements off $SS$, are less than the thresholds (here 0.7).

Algorithm 1 shows more details implements this rule.

Table 1: THE SYMMETRIC UNCERTAINTY OF THE RELEVANT SYNTHETIC BANDS.

|   | 12  | 8   | 15  | 6   | 1   | 3   | 16  | 14  | 2   | 10  | 17  | 4   | 19  | 5   | 11  | 18  |
|---|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 12| 1   | 0.13| 0.14| 0.13| 0.17| 0.15| 0.17| 0.19| 0.20| 0.20| 0.20| 0.20| 0.20| 0.20| 0.20| 0.20|
| 8 | 0.13| 1   | 0.16| 0.17| 0.19| 0.19| 0.20| 0.20| 0.20| 0.21| 0.21| 0.22| 0.21| 0.21| 0.23| 0.27|
| 15| 0.14| 0.16| 1   | 0.17| 0.18| 0.19| 0.20| 0.20| 0.20| 0.20| 0.20| 0.21| 0.21| 0.21| 0.24| 0.27|
| 6 | 0.13| 0.17| 0.17| 1   | 0.19| 0.19| 0.21| 0.19| 0.20| 0.20| 0.20| 0.22| 0.22| 0.22| 0.24| 0.27|
| 1 | 0.17| 0.19| 0.18| 0.19| 1   | 0.20| 0.22| 0.22| 0.35| 0.23| 0.21| 0.22| 0.21| 0.21| 0.28| 0.32|
| 3 | 0.15| 0.19| 0.19| 0.19| 0.20| 1   | 0.21| 0.23| 0.24| 0.24| 0.22| 0.23| 0.24| 0.23| 0.28| 0.34|
| 16| 0.17| 0.20| 0.20| 0.21| 0.22| 0.21| 1   | 0.25| 0.22| 0.25| 0.25| 0.30| 0.35| 0.36| 0.33| 0.07|
| 14| 0.16| 0.20| 0.19| 0.19| 0.22| 0.23| 0.25| 1   | 0.25| 0.25| 0.26| 0.28| 0.28| 0.27| 0.30| 0.34|
| 2 | 0.17| 0.20| 0.20| 0.20| 0.35| 0.24| 0.22| 0.25| 1   | 0.26| 0.23| 0.25| 0.25| 0.24| 0.32| 0.37|
| 10| 0.18| 0.20| 0.20| 0.20| 0.23| 0.24| 0.25| 0.25| 0.26| 1   | 0.25| 0.27| 0.27| 0.26| 0.30| 0.37|
| 17| 0.16| 0.21| 0.20| 0.20| 0.21| 0.22| 0.26| 0.26| 0.23| 0.25| 1   | 0.35| 0.39| 0.36| 0.30| 0.34|
| 4 | 0.17| 0.22| 0.21| 0.22| 0.22| 0.23| 0.30| 0.28| 0.25| 0.27| 0.65| 1   | 0.44| 0.41| 0.33| 0.35|
| 19| 0.18| 0.21| 0.21| 0.22| 0.21| 0.24| 0.35| 0.28| 0.25| 0.27| 0.39| 0.44| 1   | 0.97| 0.34| 0.30|
| 5 | 0.17| 0.21| 0.21| 0.22| 0.21| 0.23| 0.36| 0.27| 0.24| 0.26| 0.36| 0.41| 0.97| 1   | 0.34| 0.28|
| 11| 0.20| 0.23| 0.24| 0.24| 0.28| 0.28| 0.33| 0.30| 0.30| 0.30| 0.33| 0.34| 0.34| 1   | 0.42|
| 18| 0.23| 0.27| 0.27| 0.27| 0.32| 0.34| 0.07| 0.34| 0.37| 0.37| 0.34| 0.35| 0.30| 0.28| 0.42| 1   |

4 Application On HIS AVIRIS 92AV3C

The Algorithm 1 implement the proposed method.

We apply the proposed algorithm on the hyperspectral image AVIRIS 92AV3C [1], 50% of the labelled pixels are randomly chosen and used in training; and the other 50% are used for testing classification [3][17][18]. The classifier used is the SVM [5][12] [4].

Algorithm 1: \textit{Band} is the HSI. Let $Th_{relevance}$ the threshold for selecting bands more informative, $Th_{redundancy}$ the threshold for redundancy control.

1) Compute the Mutual Information (MI) of the bands and the Ground Truth map.
2) Make bands in ascending order by there MI value
3) Cut the bands that have a lower value than the threshold $Th_{relevance}$, the subset remaining is $S$.
4) Initialization: $n = \text{length}(S), i = 1, D$ is a bidirectional array values=1; //any value greater than 1 can be used, it’s useful in step 6)
5) Computation of bidirectional Data $D(n,n)$:
   \begin{verbatim}
   for 1:=1 to n step 1 do
   for j:=i+1 to n step 1 do
     D(i,j) = U(Band$_i$, Band$_j$);
     // with $U(A,B) = \frac{MI(A,B)}{H(A)+H(B)}$
   end for
   end for
   \end{verbatim}
6) $SS = \{\}$ ;
   \begin{verbatim}
   while $\min(D) < Th_{redundancy}$ do
     // Pick up the argument of the minimum of D
     (x, y) = argmin(D(.,.));
     if $\forall l \in SS \ D(x,l) < Th_{redundancy}$ then
       // x is not redundant with the already selected bands
       SS = SS $\cup \{x\}$
     end if
     if $\forall l \in SS \ D(y,l) < Th_{redundancy}$ then
       // y is not redundant with the already selected bands
       SS = SS $\cup \{y\}$
     end if
     D(x,y) = 1; D(x,y) = 1; // The cells $D(x,y)$ and $D(y,x)$ will not be checked as minimum again
   end while
7) Finish: The final subset SS contains bands according to the the couple of thresholds ( $Th_{relevance}, Th_{redundancy}$).
4.1 Mutual Information Curve of Bands

From the remaining subset bands, we must eliminate no informative ones, bay thresholding, see the proposed algorithm. Figure 6 gives the MI of the HSI AVIRIS 92AV3C with the ground truth GT.

Figure 6: Mutual information of GT and AVIRIS bands.

4.2 Results

From the remaining subset bands, we must eliminate redundant ones using the proposed algorithm. Table II gives the accuracy of classification for a number of bands with several thresholds.

4.3 Discussion

Results in Table II allow us to distinguish six zones of couple values of thresholds \((TH, IM)\):

- **Zone1**: This is practically no control of relevance and no control of redundancy. So there is no action of the algorithm.

- **Zone2**: This is a hard selection: a few more relevant and no redundant bands are selected.
Zone3: This is an interesting zone. We can have easily 80% of classification accuracy with about 40 bands.

Zone4: This is the very important zone; we have the very useful behaviours of the algorithm. For example with a few numbers of bands 19 we have classification accuracy 80%.

Zone5: Here we make a hard control of redundancy, but the bands candidates are more near to the GT, and they may be more redundant. So we can’t have interesting results.

Zone6: When we do not control properly the relevance, some bands affected by transfer affects may be non redundant, and can be selected, so the accuracy of classification is decreasing.

Partial conclusion: This algorithm is very effectiveness for redundancy and relevance control, in feature selection area.

The most difference of this algorithm regarding previous works is the separation of the two processes: avoiding redundancy and selecting more informative bands. Sarhrouni et al. [17] use also a filter strategy based algorithm on MI to select bands, and another wrapper strategy algorithm also based on MI [18], Guo [3] used a filter strategy with threshold control redundancy, but in those works, the two processes, i.e avoiding redundancy and avoiding no informative bands, are made at the same time by the same threshold.

Figure 7. illustrates the reconstruction of the ground truth map GT, for a redundancy threshold 0.56 and relevance threshold IM=0.9. The accuracy

Figure 7. In the middle the GT of AVIRIS 92AV3C. In the left: Reconstructed Truth map (GT) with the proposed algorithm for TH=0.56 and MI=0.9; the accuracy = 84.16 % for only 42 bands. In right the generalization of classification for all Indiana Pine regions.
Table 2: Classification Accuracy for several couples of thresholds (TH, IM) and their corresponding number of bands retained.

| N.B | TH: Threshold for control the redundancy | MI: Threshold for control the relevance (MI of bands with Ground Truth) |
|-----|------------------------------------------|---------------------------------------------------------------|
|     | MI = 0 | MI > 0.4 | MI > 0.45 | MI > 0.57 | MI > 0.6 | MI > 0.9 | MI > 0.91 | MI > 0.93 |
| N.B ac(%) | N.B ac(%) | N.B ac(%) | N.B ac(%) | N.B ac(%) | N.B ac(%) | N.B ac(%) | N.B ac(%) | N.B ac(%) |
| 0.10 | 26 | 37.68 | 3 | 46.31 | 3 | 46.62 | - | - | - | - | - | - | - | - |
| 0.15 | 30 | 44.40 | 6 | 49.52 | 6 | 60.65 | 2 | 43.74 | 2 | 43.25 | - | - | - | - |
| 0.20 | 34 | 45.31 | 10 | 64.70 | 10 | 65.44 | 6 | 59.69 | 5 | 51.61 | - | - | - | - |
| 0.25 | 40 | 46.44 | 13 | 67.27 | 13 | 68.13 | 8 | 56.63 | 8 | 61.82 | - | - | - | - |
| 0.30 | 47 | 47.50 | 20 | 75.32 | 18 | 74.67 | 15 | 66.63 | 14 | 67.60 | - | - | - | - |
| 0.35 | 59 | 47.13 | 29 | 77.77 | 29 | 77.67 | 25 | 73.33 | 23 | 71.03 | 18 | 65.58 | 2 | 55.48 | - |
| 0.40 | 70 | 46.76 | 40 | 81.41 | 38 | 80.34 | 32 | 77.48 | 30 | 77.34 | 27 | 71.73 | 4 | 63.80 | - |
| 0.43 | 78 | 46.35 | 47 | 83.21 | 46 | 82.82 | 37 | 77.21 | 32 | 77.40 | 6 | 73.29 | 4 | 63.80 | - |
| 0.45 | 90 | 45.92 | 56 | 84.08 | 54 | 83.44 | 45 | 80.65 | 41 | 80.19 | 11 | 75.86 | 7 | 65.69 | 2 | 52.09 |
| 0.46 | 93 | 45.68 | 61 | 84.69 | 58 | 84.32 | 48 | 81.45 | 44 | 80.89 | 13 | 78.28 | 10 | 69.02 | 2 | 52.09 |
| 0.47 | 102 | 45.12 | 68 | 85.25 | 61 | 84.57 | 52 | 82.10 | 50 | 81.38 | 16 | 79.82 | 12 | 71.75 | 2 | 52.09 |
| 0.48 | 109 | 45.10 | 71 | 86.42 | 65 | 85.43 | 56 | 82.04 | 54 | 82.14 | 19 | 80.38 | 14 | 72.73 | 2 | 55.19 |
| 0.49 | 115 | 44.77 | 76 | 86.89 | 71 | 86.19 | 61 | 83.07 | 59 | 82.74 | 23 | 81.39 | 18 | 74.38 | 2 | 55.19 |
| 0.50 | 121 | 44.57 | 80 | 86.69 | 75 | 86.40 | 64 | 83.97 | 62 | 83.73 | 25 | 81.73 | 20 | 75.04 | 4 | 56.65 |
| 0.51 | 127 | 44.15 | 87 | 87.51 | 82 | 87.14 | 68 | 84.34 | 65 | 84.40 | 29 | 82.70 | 23 | 75.67 | 6 | 57.82 |
| 0.52 | 135 | 43.74 | 89 | 87.59 | 84 | 87.38 | 73 | 85.02 | 71 | 85.04 | 30 | 83.28 | 25 | 76.89 | 7 | 58.08 |
| 0.53 | 141 | 43.46 | 96 | 87.63 | 91 | 87.43 | 75 | 85.21 | 74 | 84.86 | 34 | 82.93 | 27 | 77.36 | 10 | 59.75 |
| 0.54 | 147 | 43.22 | 104 | 87.94 | 99 | 87.61 | 84 | 85.82 | 81 | 85.42 | 39 | 83.99 | 34 | 78.32 | 11 | 60.78 |
| 0.55 | 154 | 42.55 | 108 | 87.94 | 103 | 87.78 | 84 | 86.23 | 82 | 85.68 | 46 | 83.64 | 35 | 78.67 | 15 | 61.84 |
| 0.56 | 158 | 42.35 | 110 | 87.78 | 105 | 87.63 | 85 | 86.07 | 83 | 86.11 | 43 | 84.16 | 36 | 78.49 | 16 | 61.72 |
| 0.60 | 220 | 38.96 | 173 | 88.72 | 163 | 88.41 | 128 | 87.88 | 126 | 87.55 | 67 | 86.71 | 54 | 81.77 | 22 | 63.72 |
| 0.70 | 220 | 38.96 | 173 | 88.72 | 163 | 88.41 | 128 | 87.88 | 126 | 87.55 | 67 | 86.71 | 54 | 81.77 | 22 | 63.72 |

N.B : Number of Bands retained for the couple of threshold (MLTH)
ac(%) : The accuracy of classification calculated for the couple of threshold (MLTH)

classification is 84.16% for 42 bands selected. The figure 7 gives also a general classification of the entire scene Indiana Pin [1]; the pixels not labelled in GT, are here classified. This illustrates the power of generalisation of the proposed method.

We can not here that Hui Wang [15] uses two axioms to characterize feature selection. Sufficiency axiom: the subset selected feature must be able to reproduce the training simples without losing information. The necessity axiom "simplest among different alternatives is preferred for prediction". In the algorithm proposed, reducing error uncertainty between the truth map and the estimated minimize the information loosed for the samples training and also the predicate ones. We not also that we can use the number of features selected like condition to stop the search. [16].
5 Conclusion

Until recently, in the data mining field, and features selection in high dimensionality the problematic is always open. Some heuristic methods and algorithms have to select relevant and no redundant subset features. In this paper we introduce an algorithm in order to process separately the relevance and the redundancy. We apply our method to classify the region Indiana Pin with the Hyperspectral Image AVIRIS 92AV3C. This algorithm is a Filter strategy (i.e. with no call to classifier during the selection). In the first step we use mutual information to pick up relevant bands by thresholding (like most method already used). The second step introduces a new algorithm to measure redundancy with Symmetric Uncertainty coefficient. We conclude the effectiveness of our method and algorithm the select the relevant and no redundant bands. This algorithm allows us a wide area of possible fasted applications. But the question is always open: no guaranties that the chosen bands are the optimal ones; because some redundancy can be important to reinforcement of learning classification system. So the thresholds controlling relevance redundancy is a very useful tool to calibre the selection, in real time applications. This is a very positive point for our algorithm; it can be implemented in a real time application, because in commercial applications, the inexpensive filtering algorithms are urgently preferred.

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