The principal component method consists of calculating eigenvectors and eigenvalues of the covariance matrix of the data space, then constructing projections in such a way that the direction of the maximum dispersion of the projection always coincides with the eigenvector having the maximum eigenvalue equal to the value of this dispersion. The covariance matrix after PCA processing can be seen in Figure 4.

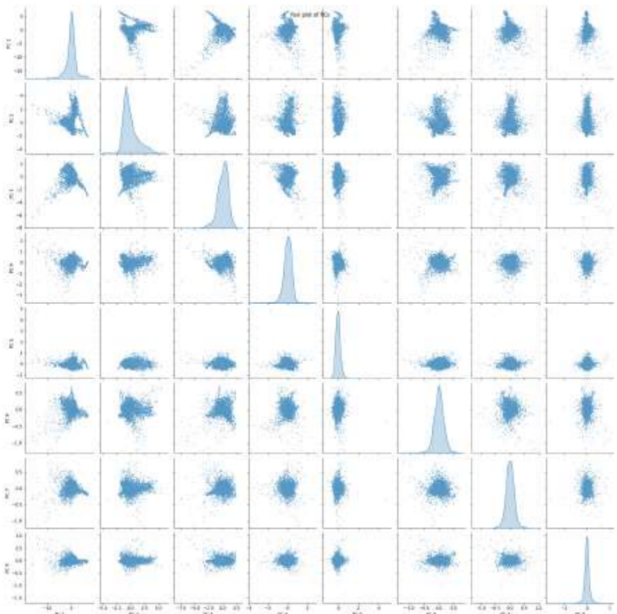

Figure 4: Visualization of the image covariance matrix with 8 spectral bands.

The next step of the algorithm is to reduce the dimension of the data space, but in the case of multispectral images this is not a necessary step: each projection is a new image layer that stores the necessary data. Instead, in [9] it is proposed to work only with the most informative image from the resulting projections.

Different images of the same class will have almost identical spectral data ratios. Indeed, for Forest class images the frequencies of 560 nm will prevail. and 842 nm., when for the SeaLake class 490 nm. and 945 nm. As a consequence, since each cell of the covariance matrix denotes either the variance of some layer of the multispectral image if that cell lies on the diagonal, or the covariance of two specific layers if it does not lie on the diagonal, the covariance matrices for each class will have the same patterns of dominant relationships.

V. Construction of a semantic form of the area

If we consider the matrix as a vector, then using the Word2vec technology from [10], from the previous statements we can conclude that the image is converted into a word that has metric characteristics, as shown in Figure 5.

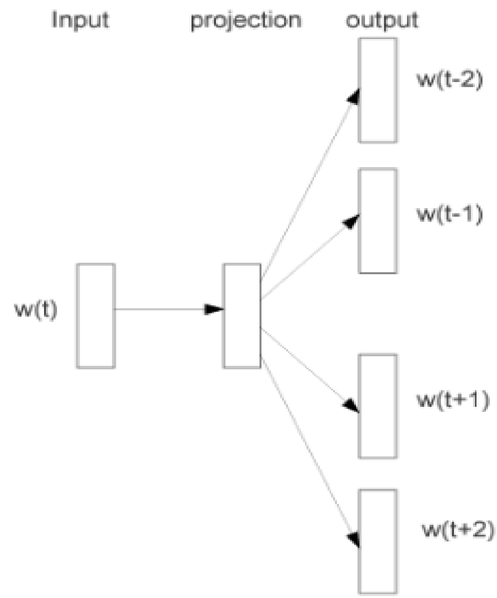

Figure 5: Illustration of how Word2vec technology works.

Following the Word2vec principle, we can build a semantic model to determine the semantic image of an image. Thus, the image is converted into a covariance ratio vector, where each cell uniquely defines the covariance of the two spectral layers. Consequently, if defining vectors are selected for each class, then by the difference between the vectors of the vector space, the dimension of which is n*n, where n is the number of spectral bands in the image, it will be possible to predict which class the image belongs to by the semantic difference of the vectors.

Using this semantic approach, we convert the image into a covariance ratio vector. Each element in this vector encapsulates the covariance between the two spectral layers, encoding not only spectral information but also semantic nuances. By selecting definition vectors for each terrain category, we create a semantic reference frame. Subsequently, using the semantic differences between these vectors within a vector space (which is expanded according to the number of spectral bands in the image), images can be accurately classified based on their semantic properties. By leveraging semantic techniques, we overcome the limitations of traditional pixel-based analysis and gain a deeper understanding of the semantic landscape of multispectral images.

VI. Demonstration of the method

To demonstrate how the method works, consider matrices for three different classes: Industrial, Forest, SeaLake. All three classes have different spectral characteristics that will uniquely determine the covariance matrix for the images representing the class. By calculating the average value of the covariance matrix for classes whose sample included 1000 images, as well as the vector of eigenvalues of these matrices.

A. Calculation of class matrices

Matrix for class Industrial:

[[1 0.981 0.971 0.839 0.328 0.33 0.583 0.676]
[0.981 1. 0.976 0.876 0.414 0.426 0.64 0.696]
[0.971 0.976 1. 0.877 0.347 0.348 0.653 0.738]
[0.839 0.876 0.877 1. 0.549 0.45 0.823 0.823]
[0.328 0.414 0.347 0.549 1. 0.886 0.59 0.323]
[0.33 0.426 0.348 0.45 0.886 1. 0.504 0.255]
[0.583 0.64 0.653 0.823 0.59 0.504 1. 0.903]
[0.676 0.696 0.738 0.823 0.323 0.255 0.903 1.]]

Eigenvalues:

[5.566 1.449 0.706 0.145 0.059 0.012 0.024 0.041]

Matrix for class Forest:

[[1. 0.878 0.907 0.853 0.724 0.75 0.841 0.854]
[0.878 1. 0.907 0.888 0.805 0.856 0.861 0.863]
[0.907 0.907 1. 0.917 0.738 0.731 0.882 0.907]
[0.853 0.888 0.917 1. 0.888 0.793 0.972 0.976]
[0.724 0.805 0.738 0.888 1. 0.898 0.901 0.857]
[0.75 0.856 0.731 0.793 0.898 1. 0.794 0.755]
[0.841 0.861 0.882 0.972 0.901 0.794 1. 0.992]
[0.854 0.863 0.907 0.976 0.857 0.755 0.992 1.]]

Eigenvalues:

[5.568 1.259 0.627 0.218 0.015 0.066 0.136 0.112]

Matrix for class SeaLake:

[[1. 0.492 0.446 0.366 0.27 0.23 0.295 0.289]
[0.492 1. 0.477 0.408 0.32 0.26 0.329 0.296]
[0.446 0.477 1. 0.532 0.418 0.394 0.402 0.373]
[0.366 0.408 0.532 1. 0.583 0.552 0.537 0.501]
[0.27 0.32 0.418 0.583 1. 0.582 0.585 0.519]
[0.23 0.26 0.394 0.552 0.582 1. 0.54 0.482]
[0.295 0.329 0.402 0.537 0.585 0.54 1. 0.561]
[0.289 0.296 0.373 0.501 0.519 0.482 0.561 1.]]

Eigenvalues:

[4.047 1.147 0.589 0.506 0.492 0.383 0.413 0.425]

And also consider two images from the dataset, Industrial-1011, shown in Figure 2, and SeaLake-1016, shown in Figure 6.

Figure 6: SeaLake-1016 in RGB spectral bands.

B. Calculation of image matrices

The first proposed method for determining the class of an image will be the difference in the metrics of the matrix space L0. This method allows you to quickly and even visually determine whether an image belongs to a class. The main problem of this method is reducing the dimension of space from eight stripes to one number, as a result of which collisions arise when semantically different vectors return a measure that is close in value. Because of this, a significant number of errors arise when determining the class of an image.

The second method for determining the class membership of an image is the nearest neighbor search algorithm. This algorithm consists of three steps:

1) The distance between each image and the eigenvectors of each class is calculated. The distance is taken to be the quadratic difference of vectors.
2) Find the minimum distance for each image.
3) The class to which the image belongs is determined by comparing the minimum distances.

This method requires a little more calculations, but it takes into account the ratio of the spectral bands of the matrices in a certain order, as well as the difference between the corresponding bands.

The image Industrial-1011 obtained the following values of the covariance matrices and eigenvectors:

Matrix for class Industrial-1011:

[[1. 0.982 0.957 0.841 0.136 0.195 0.564 0.774]
[0.982 1. 0.975 0.873 0.214 0.275 0.604 0.778]
[0.957 0.975 1. 0.899 0.18 0.216 0.63 0.818]
[0.841 0.873 0.899 1. 0.383 0.321 0.816 0.929]
[0.136 0.214 0.18 0.383 1. 0.925 0.69 0.36]
[0.195 0.275 0.216 0.321 0.925 1. 0.608 0.302]
[0.564 0.604 0.63 0.816 0.69 0.608 1. 0.894]
[0.774 0.778 0.818 0.929 0.36 0.302 0.894 1.]]

Eigenvalues:

[5.47 1.862 0.487 0.089 0.042 0.032 0.006 0.014]

Based on the calculation results, image Industrial1011, the quadratic distance between the image vector and the

Industrial class vector is 0.482, the Forest class vector is 0.662, and the SeaLake class vector is 1.839. For clarity, distances are rounded to the third decimal place. The probability of an image belonging to the Industrial class is 84%, to the Forest class is 78%, and to the SeaLake class is 38%. Thus, we can conclude that the image belongs to the Industrial class, but it is worth noting the presence of local vegetation in the image.

The SeaLake-1016 image obtained the following values of covariance matrices and matrix space norms:

Matrix for class SeaLake-1016 :
[[1. 0.465 0.383 0.433 0.409 0.306 0.316 0.124]
[0.465 1. 0.56 0.621 0.605 0.459 0.477 0.137]
[0.383 0.56 1. 0.546 0.512 0.439 0.386 0.172]
[0.433 0.621 0.546 1. 0.647 0.51 0.481 0.202]
[0.409 0.605 0.512 0.647 1. 0.553 0.562 0.238]
[0.306 0.459 0.439 0.51 0.553 1. 0.42 0.174]
[0.316 0.477 0.386 0.481 0.562 0.42 1. 0.095]
[0.124 0.137 0.172 0.202 0.238 0.174 0.095 1.]]

Eigenvalues:
[3.981 0.955 0.746 0.611 0.553 0.453 0.371 0.331]

Based on the calculation results, image Industrial1011, the quadratic distance between the image vector and the Industrial class vector is 1.902, the Forest class vector is 1.823, and the SeaLake class vector is 0.310. For clarity, distances are rounded to the third decimal place. The probability of an image belonging to the Industrial class is 47%, to the Forest class is 49%, and to the SeaLake class is 92%. Thus, we can conclude that the image belongs to the SeaLake class, and unambiguously.

Diagram of the algorithm

The general diagram of the algorithm is presented in Figure 7.

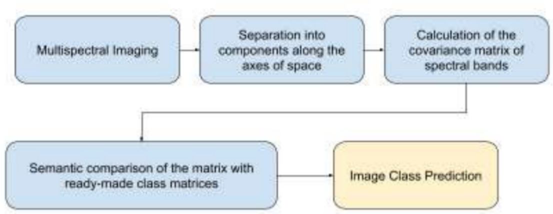

Figure 7: General diagram of the algorithm.

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ОПРЕДЕЛЕНИЕ КЛАССА МУЛЬТИСПЕКТРАЛЬНОГО ИЗОБРАЖЕНИЯ ПО СЕМАНТИЧЕСКОЙ РАЗНОСТИ КОВАРИАЦИОННЫХ МАТРИЦ

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Аннотация: В данной статье проведено исследование спутниковых мультиспектральных изображений, спектральных данных местности, а также представлен метод определения принадлежности изображений к классам местности с использованием семантического анализа вектора собственных значений ковариационной матрицы спутникового мультиспектрального изображения.

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