

IMMERSIVE VISUAL ANALYTIC OF EARTH OBSERVATION DATA

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ABSTRACT

New trends in exploration and visualization are highly demanded in dealing with the massive amount of collected Earth Observation (EO) data. In this work, we propose an immersive visual analytic of EO data utilizing *Virtual Reality* technology. Precisely, we introduce the visualization of large scale SAR images in an immersive 3D environment and also introduce an interactive learning algorithm for the data clustering using Nonnegative Matrix Factorization framework. We conduct our experiments on a dataset of SAR images represented by different features and show that the proposed interactive clustering outperforms the others.

Index Terms— Immersive, Visual analytic, Matrix factorization, Convex hull, Clustering

1. INTRODUCTION

The amount of collected earth observation data is increasing in the order of several Terra bytes per day. To deal with such a massive amount of data, Visual Analytics (VA) has gained a high attention in data mining. The VA is actually considered as a combination of visualization, interaction, and Machine Learning (ML). Here, the user is involved in knowledge discovery by observing the data and interacting with a visual interactive interface. Additionally, the user might interact with learning model by providing some feedbacks to leverage the performance of the system.

The Cave Automated Virtual Environment (CAVE) has been used intensively for the purpose of interactive visualization. However, It has not been used enough to build up an interactive machine learning system, in which the user plays a key role in the learning process. Precisely, the knowledge discovery is performed by visualization of data and the learning process is affected by the feedback that the user provides to the system. However, one challenge is to find a proper learning algorithm that can be adapted by the user's feedback. Additionally, the type of feedback and the way that the user interacts with the machine are also important issues that should be addressed properly.

In this paper, we propose an immersive visual analytics system with application to synthetic Aperture Radar (SAR) im-

ages. Virtual reality technology is used to create an immersive interactive visual interface. This is mainly composed of a visualization room, namely CAVE and a 3D interactive software [1]. A dataset of SAR images is represented by the Bag of Word model of local descriptors to create high-dimensional feature vectors. In order to position the images in 3D display space, dimensionality reduction techniques are used to reduce the dimension of feature vectors to 3D. The user is allowed to try out different techniques with different parameters to have an understandable visualization. In addition to the images, the neighborhood graph, the Minimum Spanning Tree (MST) of the data, the set of extracted local descriptors and visual words are also visualized. Finally, the user is allowed to do an interactive clustering based on drawing convex hulls around similar semantic images. For this, a regularized Nonnegative Matrix Factorization (NMF) framework is used to generate a new representation of the data based on the user's predefined convex hulls.

The rest of paper is organized as follows: In Section 2 the details of our proposed approach are provided. Here, we first explain the details of the CAVE as an immersive interface and then we discuss the proposed interactive learning algorithm for data clustering. Section 3 some preliminary experimental results applied on a dataset of SAR images are presented.

2. APPROACH

2.1. Immersive Visualization

The CAVE Automated Virtual Environment (CAVE) is used to visualize the SAR image collections in an interactive 3D virtual environment. The CAVE consists of four room-sized walls playing the role of display screen and one tracking system that has the ability to capture the motion of the user. The user inside the CAVE has the ability to have 3D impression of images positioned according to their 3D representations. Precisely, the position of images is determined by applying dimensionality reduction on the high-dimensional feature vectors. Fig. 1.a depicts a snapshot of visualized images in the CAVE. The user is able to navigate inside the data and observe the structure of the data by doing several interactive visualization approaches such as zoom in, zoom out, rota-



Fig. 1. (a) Immersive visualization of SAR images in the CAVE.

tion, translation, and navigation. The user interacts with the data by selecting a few images and creates a convex hull from them. Basically, it is assumed that the images inside a convex hull are very similar to each other. In order to facilitate the creation of convex hulls, the user tries out different combinations of features and dimensionality reduction techniques in order to see some clusters of images. Fig. 3.2 depicts several convex hulls created on a set of SAR images.

2.2. Semantic Regularized NMF

$$R = \frac{\lambda_1}{2} \sum_{i,j} \|v_i - v_j\|^2 W_{ij} = \lambda_1 \text{Tr}(V^T L V) \quad (1)$$

where $L = D - W$ and D is a diagonal matrix, whose entries are column sums of W , $D_{jj} = \sum_i W_{ij}$. Such as cost function has been used before for the purpose of structure preservation in [2].

$$O = \|X - UV^T\|^2 + \lambda_1 \text{Tr}(V^T L V) \quad (2)$$

where X , the original data, is decomposed to U and V , where V is the new representation of the data. Using the KKT-conditions [3], we arrive at the following update rules for U and V :

$$u_{ik} \leftarrow u_{ik} \frac{(XV)_{ik}}{(UV^T V)_{ik}} \quad (3)$$

$$v_{jk} \leftarrow v_{jk} \frac{(X^T U)_{jk} + \lambda_1 (L^- V)_{jk}}{(V U^T U)_{jk} + \lambda_1 (L^+ V)_{jk}} \quad (4)$$

where we introduced the term $L = L^+ - L^-$ with $L_{ij}^+ = (|L_{ij}| + L_{ij})/2$, $L_{ij}^- = (|L_{ij}| - L_{ij})/2$.

3. EXPERIMENTS

3.1. Data sets

The used SAR dataset contains 3434 TerraSAR-X satellite images of size 160×160 pixels, which are grouped in 15

Set	Img	C1	C2	C3	C4	C5	C6
1	16	93.75	6.25	0	0	0	0
2	59	1.69	23.73	74.58	0	0	0
3	45	2.2	95.56	2.22	0	0	0
4	266	6.39	4.89	2.26	67.29	1.13	18.05
5	292	14.38	.34	85.27	0	0	0
6	91	87.91	6.59	1.1	3.3	1.1	0
7	147	8.84	2.04	4.08	6.12	3.4	75.51

Table 1. The statistics of created convex hulls. The percentage of similar images ($C1 - C6$) in each convex hull is presented. Additionally, the total number of images in each set is given in the second column.

classes. The images are represented by vectors of their most representative features, so-called feature vectors. For each image, the Bag-of-Word model of different local descriptors such as Gabor [4], and SIFT [5] is used as feature vector.

3.2. Setup

We used a library of Dimensionality Reduction (DR) to reduce the dimension of feature vector to 3D for visualization [6]. Here, we combine different features with different DR techniques to reveal different aspects of the data. Fig. 2 shows the 3D visualization of SAR images using two different dimensionality reduction techniques applied on two different features. Once the dataset is visualized in such a way as some clusters are visible, the user starts interacting with data by creating convex hulls around similar images. Once a few convex hulls are created, these are used to create a similarity matrix. Precisely, those images which are inside the same convex hulls are considered as similar items in the similarity matrix. The similarity matrix is used in SRNMF algorithm to create a new representation of the data. Additionally, we also use PCA and NMF to create new representations. In the experiments, we choose at each time a subset of K clusters and set the dimension of PCA, NMF, and SRNMF equal to K . The Kmean algorithms is applied to do the clustering on these new representations. The clustering accuracy are used to demonstrate the performance of each representation.

3.3. Evaluation metrics

In order to evaluate the clustering results, we employ two evaluation metrics, namely Accuracy (AC) and normalized Mutual information (nMI) of clusters [9]. The accuracy is obtained by computing the percentage of correctly predicted cluster labels, provided the true labels are available. The nMI measures the similarity of ground true clustering and the obtained clustering. The details of these two metrics can be found in [2].

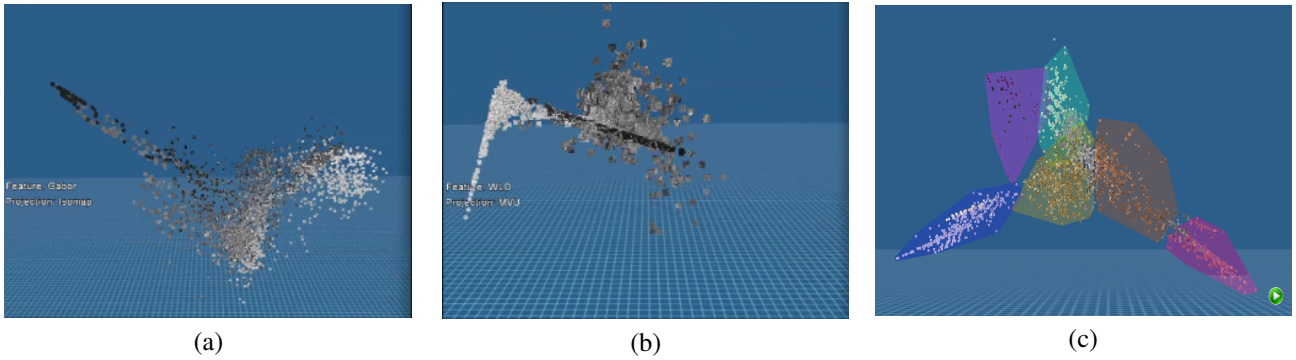


Fig. 2. 3D visualization of SAR images. (a) Images are positioned as the result of Isomap [7] applied on the corresponding Gabor features. (b) Images are positioned as the result of Maximum Variance Unfolding (MVU) [8] applied on the corresponding Weber features. (c) Created six convex hulls over the dataset. Each convex hull is represented by different colors.

3.4. Discussion

As it can be inferred from the results, PCA works well when the dimension of the data is small. However, when the complexity of data increases, by increasing the number of clusters and also the dimension of the representation, the proposed method outperforms the others in terms of clustering accuracy. Additionally, the accuracy decreases by increasing the dimension and also the number of clusters for all methods, which is logical. The results confirm that representations based on Gabor features are more discriminative than SIFT features. For instance, the accuracy of clustering of whole dataset is 53% for Gabor and 46% for SIFT features. But, SRNMF shows much more improvements on SIFT features over the other two methods by an improvement of roughly 10%. Finally, Although we have tested our algorithm on two kinds of features, it is not absolutely dependent on the kind of the used feature. For instance, the raw data (i.e., pixel values) can be used as features. For future works, it could be interesting to find out other methods to cluster/learn features in this immersive environment.

4. CONCLUSION

In this paper, we introduced an immersive visual analytics system in order to visualize and process the SAR image repository. The CAVE visualizes the SAR images by applying dimensionality reduction on the high-dimensional feature vectors extracted from the content of the images. The user can change the visualization by trying out different features and dimensionality reduction techniques. Additionally, we proposed an interactive algorithm in order to increase the accuracy of clustering. The user inside the CAVE creates several convex hulls over the similar items to build a regularization of an NMF algorithm. The results confirmed that the proposed method outperformed the others in terms of accuracy of clustering results.

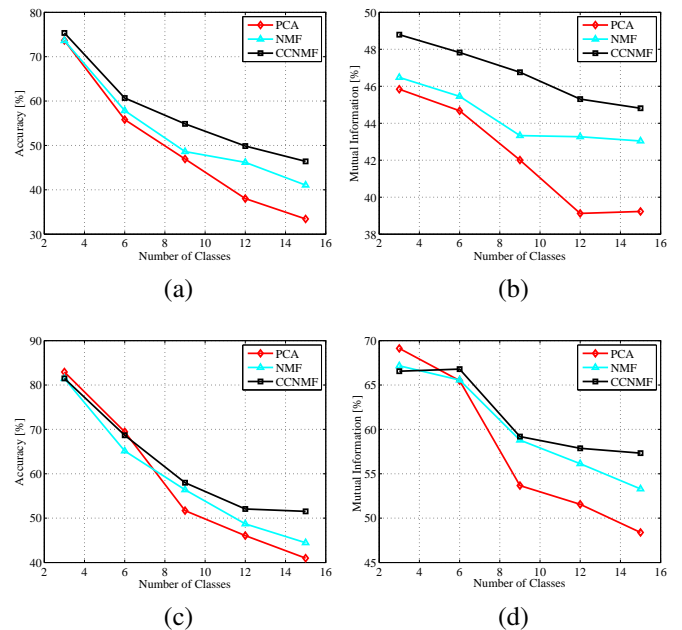


Fig. 3. Clustering results on the SAR dataset. (a), (b) are the accuracy and normalized mutual information of clustering on SIFT features, respectively. (c), (d) show the accuracy and normalized mutual information of clustering on Gabor features, respectively.

5. REFERENCES

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