Satellite Images Analysis with Symbolic Time Series: A Case Study of the Algerian Zone

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Abstract—Satellite Image Time Series (SITS) are an important source of information for studying land occupation and its evolution. Indeed, the very large volumes of digital data stored, usually are not ready to a direct analysis. In order to both reduce the dimensionality and information extraction, time series data mining generally gives rise to change of time series representation. In an objective of information intelligibility extracted from the representation change, we may use symbolic representations of time series. Many high level representations of time series have been proposed for data mining, including Fourier transforms, wavelets, piecewise polynomial models, etc. Many researchers have also considered symbolic representations of time series, noting that such representations would potentiality allow researchers to avail of the wealth of data structures and algorithms from the text processing and bioinformatics communities. We present in this work, one of the main symbolic representation methods "SAX"(Symbolic Aggregate Approximation) and we experience this method to symbolize and reduce the dimensionality of a Satellite Image Times Series acquired over a period of 5 years by characterizing the evolution of a vegetation index (NDVI).

Key Words—Satellite Image Time Series, symbolic representation, SAX.

I. INTRODUCTION

Satellite Images Time Series (SITS) are important information sources on the territory evolution. The study of these images allows to understand changes in specific zones but also to discover large-scale evolution patterns. However, discovering these phenomena imposes to respond to several challenges which are related to SITS characteristics and their constraints. Each pixel of a satellite image is described by several values and the evolution patterns are ported for very long a period which generates a very large volume of data which makes the information extraction complex and difficult. In order to both reduce the dimensionality of SITS and the information extraction, Time Series Data Mining generally gives rise to a change of time series representation. In this work, we present one of the main principal symbolic representation methods and we apply it on a SITS acquired over a period of 5 years. This representation will be used later in the change detection (such as vegetation evolution, buildings detection, etc.). We have used a vegetation index, NDVI (Normalized Difference Vegetation Index), which is related to the vegetation cover structure, particularly in the coverage rate of soil by vegetation, and its pigment content. Moreover, the NDVI vegetation index is the most widely used by the scientific community to study the vegetation. It is defined by

$$\text{NDVI} = \frac{(\text{PIR} - \text{R})}{(\text{NIR} + \text{R})}$$

PIR and R reflectance in the near infrared and red, respectively.

Fig. 1. Illustration of the studied problematic
II. TIME SERIES DEFINITION

A time series is a collection of observations made sequentially in time [6].

Examples of time series include voice data, historical stock prices, sales histories, records of tests of an engine, the seismic data, flight records of aircraft, weather data, environmental data, satellite data, astrophysics data, etc [4].

III. RELATED WORKS

Time series are data types that appear in many applications. Time series data mining includes many tasks such as classification, clustering, similarity search, motif discovery, anomaly detection, and others. Research in time series data mining has focused on two aspects; the first aspect is the dimensionality reduction techniques that can represent the time series efficiently and effectively at lower-dimensional spaces.

Different indexing structures are used to handle time series. Time series are high dimensional data, so even indexing structures can fail in handling these data because of what is known as the “dimensionality curse” phenomenon. One of the best solutions to deal with this phenomenon is to utilize a dimensionality reduction method to reduce the dimensionality of the time series, then to use a suitable indexing structure on the reduced space.

There have been different suggestions to represent time series in lower dimensional spaces. To mention a few; Discrete Fourier Transform (DFT) (Agrawal et al . 1993) and (Agrawal et al . 1995), Discrete Wavelet Transform (DWT) (Chan and Fu 1999), Singular Value Decomposition (SVD) (Korn et al . 1997), Adaptive Piecewise Constant Approximation (APCA) (Keogh et al . 2001), Piecewise Aggregate Approximation (PAA) (Keogh et al . 2000) and ( Yi and Faloutsos 2000), Piecewise Linear Approximation (PLA) (Morinaka et al . 2001), Chebyshev Polynomials (CP) (Cai and Ng 2004). [5]

Among the different representation methods, symbolic representation has several advantages, because it allows researchers to benefit from textretrieval algorithms and techniques that are widely used in the text mining and bioinformatics communities (Keogh et al . 2001).
IV. SYMBOLIC REPRESENTATION TIME SERIES

The purpose of changing the time series representation is often the dimensionality reduction. We seek to construct representation which preserves maximum information present in data without having any knowledge on what constitute this information.

We will present initially a generic framework of symbolic representation time series, before detailing the method which we have chosen for our experiments.

We have a given time series defined by $ST = \{(d_i, v_i)\}_{i \in \{1 \ldots N\}}$, with $d_i \in D$ et $v_i \in V$, with $D$ the temporal definition domain and $V$ is the digital space values of the time series.

We propose to define a symbolic representation of $ST$ by:

- A division into $P$ episodes.
- $E = \{e_j = [d_{j\text{debut}}, \ d_{j\text{fin}}] \in \mathbb{D}^2 \ and \ d_{j\text{debut}} < d_{j\text{fin}}\}_{j \in \{1 \ldots P\}}$ and $d_{j\text{debut}} < d_{j\text{fin}}$
- An alphabet of symbols $K \Lambda = \{s_m\}_{m \in \{1 \ldots K\}}$.
- Symbolic representation called $SR : E \rightarrow \Lambda \ \ e_j \mapsto RS(e_j)$ is then the application associating each episode of $E$ a symbol of $\Lambda$.

A symbolic representation will be relevant if it best satisfies the following contradictory imperatives:

- Maximum concision representation: with cardinality of $E$, minimal $\Lambda$ and symbols as simple as possible.
- Maximum fidelity: it allows a reconstruction as near as possible to the original series [2]

V. TIME SERIES SYMBOLIC REPRESENTATION BY SAX (SYMBOLIC AGGREGATE APPROXIMATION)

In order to reduce the dimensionality, it is important to define time units for grouping the time series points. We generally define episodes like intervals of time definition domain of time series to be represented. Generally, because of the minimal cost of acquisition and storage data, time series are stored in databases in the most detailed possible form, regardless of the time scale at which develop behaviors to identify. We can then group the points to episodes without losing essential information. This is the principle of symbolic representation SAX presented by Lin et al. (2003).

SAX is a time series symbolic representation univariate centered reduced:

- The time domain is divided into episodes of equal size.
- The equivalence classes of the time series values are set in advance according to the number of symbols to be used, so as to obtain a cutting of the same effective classes provided that the distribution centered and reduced values is normal [2].
- It allows a time series of arbitrary length $n$ to be reduced to a string of arbitrary length $w$ ($w < n$) [6].

The SAX method is based on two main steps

A. Step 1: Dimensionality Reduction via PAA (Piecewise Aggregate Approximation)

A time series $C = c_1 \ldots c_n$ of length $n$ can be represented in a $w$-dimensional space by a vector $\vec{c} = \vec{c}_1 \ldots \vec{c}_w$.

The $i$-th element of $\vec{c}$ is calculated by the following equation:

$$
\vec{c}_i = \frac{1}{n} \sum_{j=\frac{i-1}{w}+1}^{\frac{i}{w}} c_j
$$

Fig. 4. The PAA representation can be visualized as an attempt to model a time series with a linear combination of box basis functions. In this case, a sequence of length 128 is reduced to 8 dimensions [8].
The PAA dimensionality reduction is intuitive and simple, yet has been shown to rival more sophisticated dimensionality reduction techniques like Fourier transforms and wavelets.

B. Step2 : Discretization
SAX makes the assumption that time series values follow a Gaussian distribution. The quantization step makes use of \((N-1)\) breakpoints (Gaussian quantiles) that divide the area under the Gaussian distribution into \(N\) equiprobable areas. These breakpoints can be found in lookup tables. Hence, the average values computed for each segment of the time series (step 2 above) are then quantized according to the breakpoints of the Gaussian distribution. Figure 5 shows an example of the SAX representation of a time series.

The figure 6 shows in details the SAX method working:

1. The original time series
2. Converting the time series to PAA
3. Choosing the breakpoints
4. Discretizing PAA

SAX method’s advantages are:
- The construction of representations is extremely efficient in computation time \((O(N))\) for a time series representation of \(N\) points.
- All representations (based on the same number of symbols and episodes of the same size) are trivially commensurable. [2]
- Simplicity
- Need any a priori knowledge on data
- For two sets \(S1, S2\) and their SAX representation \(\hat{S}1, \hat{S}2\), we have \(\text{dist}(\hat{S}1, \hat{S}2) \leq \text{dist}(S1, S2)\)
• Well adapted and efficient for classification, clustering and indexing. [3]

However, this performance suffers of disadvantages which are intrinsically linked:
• The modeling error for a given dimensionality reduction is not minimal since the model is not locally adapted to the data.
• Equivalence classes which symbols are associated, are not necessarily relevant because they are not adapted to the data. [2]
• Few semantics symbols. [3]

VI. IMPLEMENTATION

Our approach proposed seeks to build Symbolic Satellite Images Time Series (SITS) using SAX method, in order to reduce the dimensionality of the original SITS and make them easier to interpret. The set of images constitute a SITS, and each pixel is associated to a time series. As shown in Figure 7 (Above, vision of layers images, and below, transversal vision of a pixel in the form of time series).

A. Data

Satellite images used in this implementation are NDVI images of the satellite Terra/MODIS (Moderate Resolution Imaging Spectroradiometer) based on the evolution of vegetation indices (NDVI). These images are available in five years with important acquisition frequency (one image every sixteen days) and form so satellite image time series (SITS), which extends from the year 2000 to 2005 covering the same scene representing a part of an east Algerian city "Batna". Each image has 521X455 pixel's size with a spatial resolution of 250mX250m. In total, our database contains 135 images.

B. Results

We present in this part the implementation steps of the application “SAX” on our base of SITS:

1) Step 1: Data Storage
This step consists to create a MySQL database in which all satellite MODIS NDVI images will be stored. Images are identified principally by their acquisition date and size.

2) Step2 : Images Time Series Representation
This step is to represent the NDVI change in time of each pixel's time series, we obtained a total of 237055 time series of the same size (135 points). At each time \( t_i \) representing the image acquisition date, NDVI value is affected.
3) Step 3: Symbolic Representation Time Series by SAX method

In this step, each time series of length \( n \), such that \( n = 135 \), is transformed into SAX symbolic sequence of length \( w \) as \( w \ll n \).

The SAX parameters choice was defined as mentioned below:

The alphabet used is a finite set of natural numbers \( \{1, 2, 3, 4, 5, \ldots, 20 \ldots\} \).

Alphabet size named Code Book (CB) will be selected by user, for example from the even numbers: 2, 4, 6… to 64, such as \( CB \geq 2 \). For example, for the alphabet size \( CB = 4 \), symbols are selected from the set \( \{1, 2, 3, 4\} \). The Word Code (CW) size for which the time series will be divided into the same size segments will be selected by user from even numbers: 2, 4, 6… 32.

Then we combine the two parameter values, this gives the resolution \( (CB \times CW) \): 2x2, 2x4, 2x6, 2x8 …… 64x28, 64x30, 64x32. For each \( CB \times CW \) resolution, the steps of the SAX method are applied to all SITS and we get in results SAX sequences.

First, the division of all SITS (obtained in step 2) into subsequences of equal length, for each time series \( C = c_1, c_2, \ldots, c_n \) (where \( c_i \) represents NDVI), a sliding window CW traverses all points of the series and the division into the same CW intervals size. In each position \( ((i+1)*CW+1, i*CW) \), the average values of the points located in the current interval is calculated. And we get in result PAA vector \( \vec{C} = [\vec{c}_1, \ldots, \vec{c}_w] \).

The second step consists to quantifying the PAA vectors by a symbol of our alphabet. This transformation is performed by assigning a symbol with equal probability to each element of PAA vector by referring to a Gaussian distribution. This is the assumption of the SAX method which suggests that the values of the time series are in \( \mathbb{N}(0,1) \).

Examples of Results:

- **CBXCW = 10X4**
  - Pixel position “1”:
    - SAX sequence is 6 5 5 5 5 7 6 5 5 5 5 5 5 5 5 5 5 6 6 5 5
  - Pixel position “203743”:
    - SAX sequence is 7 7 6 6 6 7 8 7 7 6 6 6 8 7 5 6 6 7 7 7 5 5 5 6 6 6 7 6 6 5 5 5 5
  - Pixel position “237055”:
    - SAX sequence is 7 7 7 7 7 8 7 7 6 6 6 8 8 8 7 6 6 7 8 8 8 8 8 7 7 7 7 7 5 5 5 5

- **CBXCW = 10X2**
  - Pixel position “1”:
    - SAX sequence is 6 5 5 5 5 5 5 5 5 5 6 5 5 6 7 6 6 6 7 7 7 5 5 5 5 5 5 6 6 6 7 6 6 5 5 5 5
  - Pixel position “203745”:
    - SAX sequence is 7 7 7 7 7 7 8 8 8 8 8 8 7 7 7 7 7 8 8 8 8 8 8 7 7 7 7 8 8 8 8 8 8 8 8 8
  - Pixel position “237055”:
    - SAX sequence is 7 6 7 7 7 8 8 8 8 8 8 8 8 8 7 7 7 7 8 8 8 8 8 8 7 7 7 7 7 8 8 8 8 8 8 8

- **CBXCW = 32X10**
  - Pixel position “1”:
    - SAX sequence is 1 9 1 8 2 3 1 8 1 9 1 8 1 9 1 8 2 3 1 8 1 9 1 8 2 3 1 8
  - Pixel position “203745”:
    - SAX sequence is 2 3 1 8 2 3 1 8 2 3 1 8 2 3 1 8 2 3 1 8 2 3 1 8 2 3
  - Pixel position “237055”:
    - SAX sequence is 2 3 1 8 2 3 1 8 2 3 1 8 2 3 1 8 2 3 1 8 2 3 1 8 2 3

VII. CONCLUSION

In order to better exploitation an important volume of satellite data, we applied the SAX method on satellite images time series (SITS) MODIS based on the vegetation index (NDVI) with an acquisition frequency of 16 days in a period of 5 years. First, SAX proceeds to transforming the SITS to PAA representation, then to symbolizing PAA representation to a discrete representation using numbers alphabet \( \{1, 2, 3, \ldots\} \), and in function of CB and CW parameters choice, several tests were performed and results are satisfactory and show that SAX is effective to reducing the dimensionality of SITS size and also fast even in the treatment of long time series.

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