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DISCOVERING MOTIFS IN SPATIAL-TIME SERIES SEISMIC DATASETS

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Dissertação de Mestrado apresentada ao Programa de Pós-graduação em Engenharia de Produção e Sistemas, Centro Federal de Educação Tecnológica Celso Suckow da Fonseca CEFET/RJ, como parte dos requisitos necessários à obtenção do título de mestre.

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ABSTRACT

Discovering Motifs in Spatial-Time Series Seismic Datasets

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Abstract of dissertation submitted to Programa de Pós-graduação em Engenharia de Produção e Sistemas - Centro Federal de Educação Tecnológica Celso Suckow da Fonseca CEFET/RJ as partial fulfillment of the requirements for the degree of master.

Discovering motifs in time series data has been widely explored by recent researches. It is being motivated by the potential to identify relevant implicit information. Many time series data mining techniques were adapted to solve the problem regarding motif identification in time series. However, when it comes to spatial-time series, it is possible to observe an open gap according to the literature review. This work proposes a new approach to discover motif in spatial-time series. It is based on combining spatial-time series into a single time series. Then, Random Projection algorithm is applied in this transformed time series to identify candidate spatial-time motifs. Finally, candidates are aggregate and validate according to spatial-time constraints. The approach is evaluated in a seismic dataset. Identified motifs were able to identify seismic horizons, which is an important characteristics in seismic analysis.

Key-words:
Motifs; Spatial-Time Series; Seismic.

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Chapter I Introduction

Under the data deluge scenario, Data Scientists are continuously being stressed to provide new ways for efficiently collecting, storing, processing, and organizing large amount of data [Tsai et al., 2015]. We are immersed in a scenario with massive databases from many sources, types, and formats. However, such scenario opens a set of research opportunities involving knowledge discovery [Han, 2006; Shumway R. H. & Stoffer, 2006]. In this context, many phenomena can be observed and organized as a sequence of observations in time line that can be modelled as time series. There are many uses and applications for time series analysis. It can represent the behavior of process variables in a industrial plant, the price of stocks in financial market, economic and social indicators, medicine, weather conditions, and anything that can be measured and registered in time.

One of the areas that is being very often explored in time series analysis is finding patterns [Patel et al., 2002]. Patterns are sub-sequences of time series that can indicate some special properties or behaviors that are potentially important and should be more carefully observed and analysed [Han et al., 2007]. Pattern can be used in many applications, such as in medicine, to evaluate the health of a person based on an electrocardiogram; in financial market, to correlate stock prices, currencies, and commodities price; in weather prediction, to analyze meteorological phenomena that occurs recursively; in industry, to use the best combination of production factors to get the maximum efficiency with minimum cost based on historical records; in geophysics, to analyze seismograph data to detect anomalies, subsoil properties, and even earthquakes or tsunamis.

Finding those patterns may be a hard task to do without computational support. Trying to do it by graphical or visual analysis limits accuracy and restricts our ability to analyze only small set of data [Keogh and Kasetty, 2003]. On the other hand, the advances of computational resources provided the possibility to handle and process large amount of data in a feasible time with accuracy [Last et al., 2004]. Such scenario encouraged many researches in this area targeting to execute the pattern finding task more efficient [Agrawal et al., 1993].

One way to find patterns in time series is when a previously known behavior, represented as a sub-sequence, is used as a parameter to find similar occurrences in the analyzed time series [Ding et al., 2008]. It is known as pattern matching queries. It is done basically comparing the known sub-sequence to all sub-sequences in data set analyzed.

Another important time series pattern analysis is the identification of a particular behavior in time series that occurs a significant number of times but it is not previously known. This phenomenon is denominated *motif*. Identifying motifs is being intensely explored with different techniques, methods, and algorithms, such as finding motifs of a particular length [Li and Lin, 2010], finding motifs without any constraint (parameter free algorithms) [Madicar et al., 2014], finding motifs in multivariate time series [Minnen et al., 2007].

Motif discovery has important applications in many areas of knowledge. The term was originally coined in biology and represents the amino-acid sequence pattern in that context [Staden, 1989]. After that, the *motif* concept was generalized and expanded due to the possibility to understand and identify some specific behaviors based on patterns observed in the time series data. It allowed to apply these concepts to another interesting areas as weather prediction [McGovern et al., 2011], financial [Jiang et al., 2008], wind generation [Fan and Kamath, 2015], sea water level [Li and Nallela, 2009], image recognition [Chi et al., 2012], seismic amplitude [Cassisi et al., 2013].

The basic difference between traditional pattern mining and motif discovery is the parameter for computing similarity between sub-sequences [Lonardi and Patel, 2002]. While for pattern mining the objective is to find all sub-sequences in a the time series that are equal to a candidate frequent sub-sequence, in motif discovery, the goal is to find a set of similar sub-sequences that occurs in relevant number of times. Such threshold may vary according to the method used to find motifs.

A more complex problem involves the identification of patterns according to time and space. Many very important phenomena are modeled as a set of time series, where each one of them has an associated position in space. Such scenarios are known as spatial-time series and they bring challenges in both data management and in methods for knowledge discovery.

The seismic dataset is a good example of a spatial-time series. Figure I.1 presents a seismic shot. Each x is associated to a position in space and each y is associated to a time, which is also related to a depth in subsoil. A value in each x and y position is a seismic observation. The way in which observable values as spatially and timely distributed may give important information about soil. In Figure I.1 there are some important soil properties: (1) horizons; (2) faults; (3) gas reservoir, (4) igneous rock. Although specialists aim in find these patterns, they are not known beforehand and they need to be inspected and studied using visualization techniques and other complementary analysis.

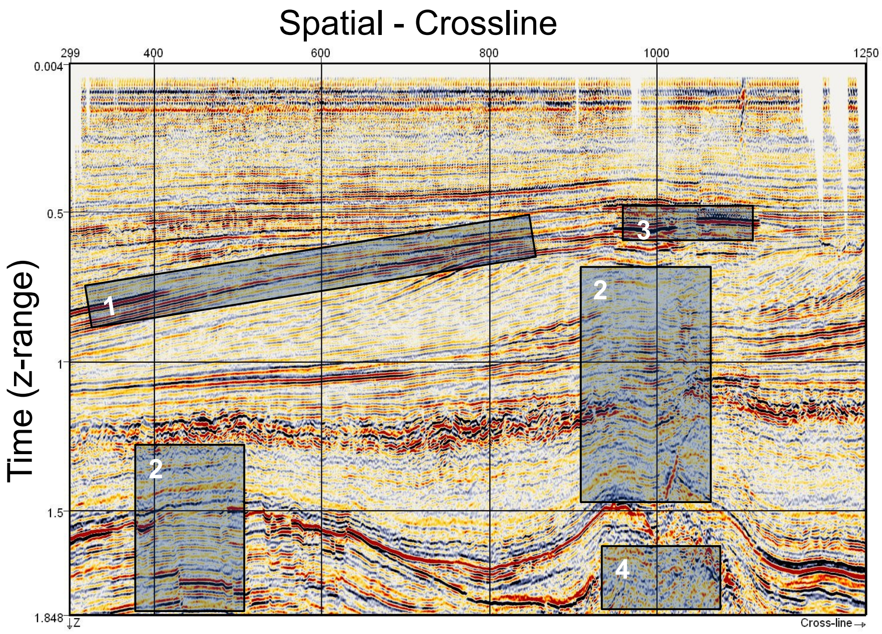


Figure I.1: Seismic Dataset

The spatial-time series characteristics of seismic dataset introduces, nevertheless, a new challenge for motifs identification, which corresponds to considering both space and time when identifying them. In this context, this work investigates the problem of *identifying motifs in spatial-time series*.

The goal of this work is to present an approach to identify and rank motifs in spatial-time series. The proposed approach, denominated Combined Series Approach (CSA), consists in a method that prepares the spatial-time data to apply the random projection algorithm and then organize the motifs in a meaningful manner. CSA partitions neighboring observations in space-time into blocks. Subsequences of time series inside these blocks are combined and transformed into a single time series. The latter is used as input for the random projection algorithm [Chiu et al., 2003], which computes candidate motifs. Finally, when considering the entire dataset, if the candidate motifs occur in a frequency greater than support thresholds, they are considered spatial-time motifs.

We have evaluated our approach using a Seismic Dataset. We applied it to a 2D seismic dataset set where some relevant patterns were known by seismic specialists, which works as a ground truth. The identified motifs were plotted over seismic pictures and the patterns that were unveiled from data were able to identify the majority of seismic horizons as top k identified motifs. We also identified some other non-mapped seismic horizons.

In addition to this introduction, this work is organized into more six chapters. Chapter II presents seismic background, including main concepts and characteristics, such as data acquisition, data processing, and interpretation. Chapter III presents time series data mining background. It includes a brief literature review about motifs in time series and the main concepts and techniques that support the motif discovering processes. Chapter IV presents the Related Works. Chapter V presents CSA. It formalizes the problem and describes the algorithm to find motifs in spatial-time series. Chapter VI describes and explains the experiments that were made using seismic dataset. Finally, Chapter VII concludes and discusses opportunities for improving our results.

Chapter II Seismic Background

An overview regarding seismic analysis is presented in this chapter. Such explanation is necessary to understand the experiment proposed and the effectiveness evaluation of the presented method in this work. It is not intended to be a complete survey about seismic. The main objective is to provide readers with a baseline knowledge that is used in experimental evaluation.

Seismology is the scientific study of the propagation of elastic waves through the Earth. Seismic waves produced by explosions (or vibrating controlled sources) are commonly produced to explore underground. Data is collected through sensors that measure waves responses from deep Earth layers. The interpretation of observations made at the surface provides useful information about the structure and composition of the inaccessible areas in great depths. Almost all knowledge about under wells and underground mines in deep depths comes from geophysical observations [Zhou, 2014].

Much of the tools and techniques developed for such studies have been applied in academic research on the nature of the Earth's interior. However, the breakthrough achieved in geophysical techniques is mainly due to its heavy use in the exploration of hydrocarbons and minerals. The development of technologies in the areas of acquisition, processing and interpretation of seismic data, combined with the study of the relationship between seismic properties, petrophysical properties, and environmental conditions have made this technique the most adopted exploration tool and one of the most important in characterization of oil reservoir [Yilmaz, 2001].

The seismic reflection method is based on generating artificial seismic waves through explosives, compressed air guns or other seismic sources and record the reflections from the various interfaces in the subsurface using as geophones receivers or hydrophones, which are devices analogous to microphones. The generated wave propagates through the interior of the Earth. The partial reflected waves are used to find interfaces between layers that have significant contrast elastic properties. The time of arrival of each reflection are related to the propagation velocities of the seismic wave in each layer. At first approximation, the recorded amplitude is related to the acoustic impedance contrast, compressional product of velocity and density of the layers defining the interface. This method is analogous to imaging the human body using ultrasound. However, unlike medicine, where the density contrasts are imaged, on seismic exploration, the effect of the speed difference is more studied [Zhou, 2014]. Figure II.1 shows an example of a seismic dataset represented in a seismic analysis software (OpendTect). Yilmaz [2001] describes the seismic analysis divided into three parts: data acquisition, seismic processing, and seismic interpreting.

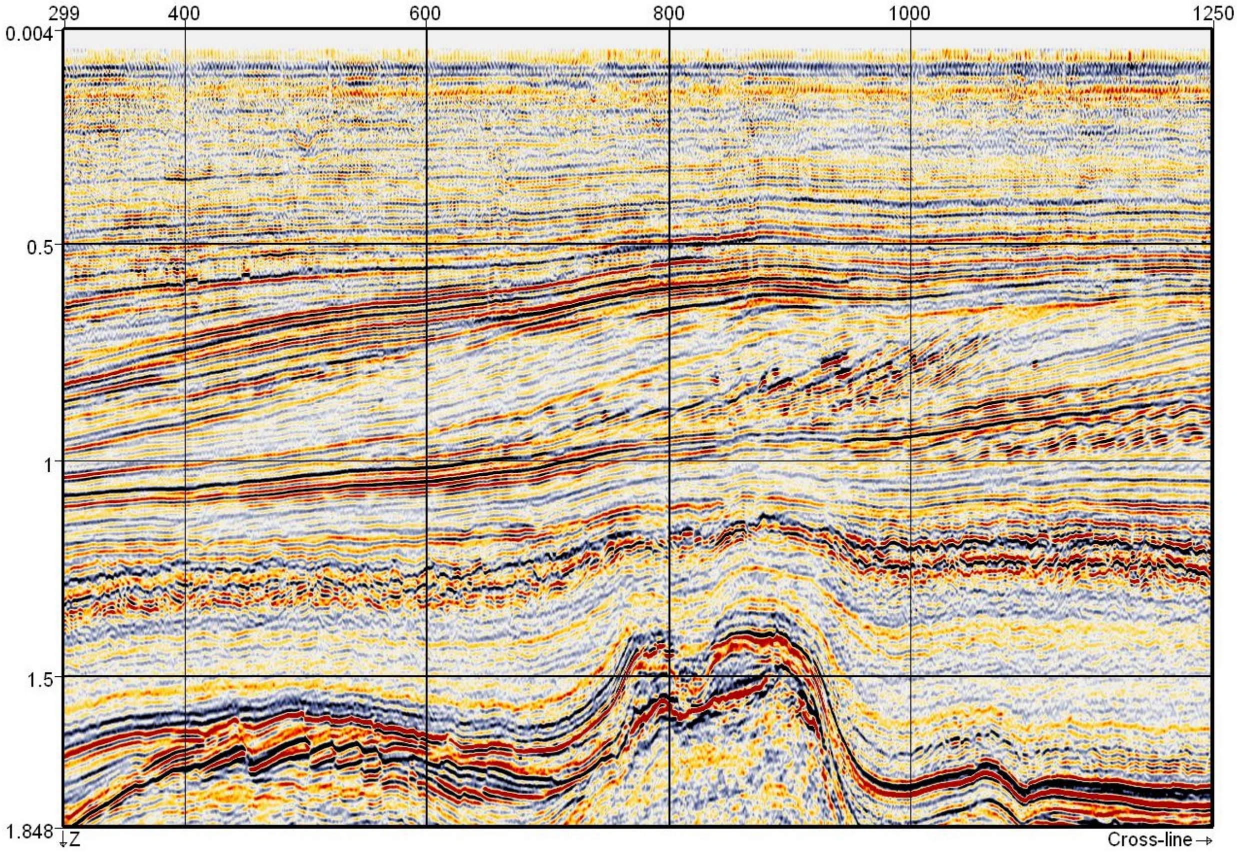


Figure II.1: seismic dataset Example

II.1 Data acquisition

A seismic survey is a set of several seismic shots performed in different locations. After propagation, the elastodynamics waves are reflected by the various layers of subsoil. They are measured and recorded by sensors on the surface. They are recorded at each receiver. Each measure is the time of wave return and is called a seismic trace, whereas the set of traces recorded for each generated waveform is called a seismic shot. When the seismic acquisition is performed through a single line, the seismic shot results in a two-dimensional image, and said acquisition is the 2D type. Conversely, when the acquisition is performed by a set of parallel lines or a two-dimensional sensor network is said that the acquisition is of the type 3D, the result is to obtain a seismic cube [Hatton et al., 1986].The figure II.2 is a representation of reflection method.

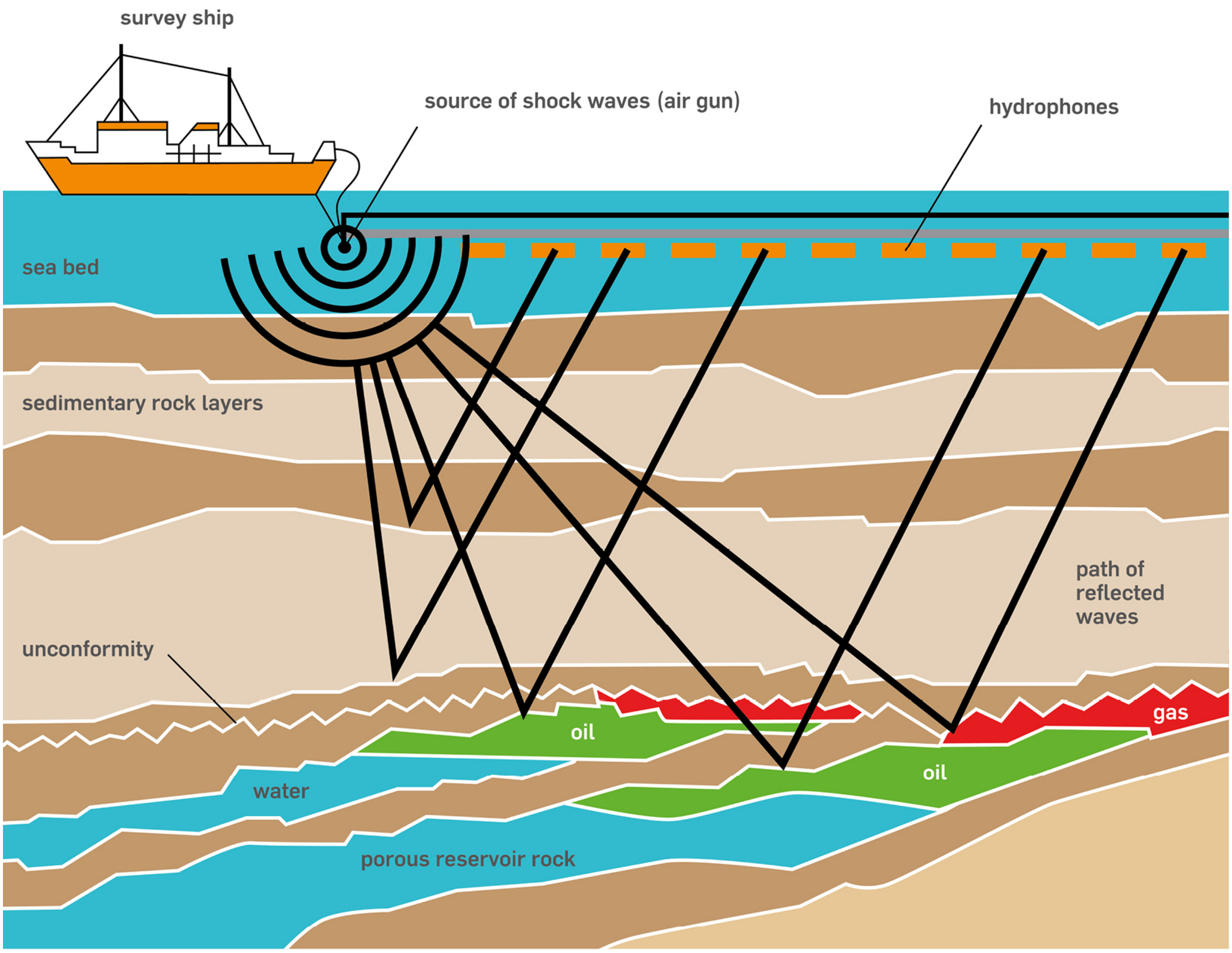


Figure II.2: Seismic Reflection Example - Source: https://krisenergy.com/company/about-oil-and-gas/exploration/

II.2 Seismic Processing

In case of seismic shot, for example, the geophones are spaced every 50 meters and seismic trace was recorded for 4 seconds. As the seismic source is located in the center, possible reflectors appear distorted due to the displacement of receptors in relation to the seismic source. It is also observed the existence of a high level of noise in the signal. For the seismic acquisition to represent more realistically the geological structure of the subsurface, seismic shots must be adjusted. This adjustment process is called seismic processing and imaging. It is said that after the acquired data are properly processed it creates a 2D seismic line or 3D seismic cube.

II.3 Seismic Interpretation

The seismic interpretation comprehends the analysis of the images processed for exploration, characterization, and monitoring of oil reservoirs. These analyzes are very important to the oil industry, since it is from such analysis that the location of oil or gas reservoirs exploration is decided. Recently, it has also been used to monitor seismic reservoir to monitor oil exploitation.

In seismic exploration, seismic images are analyzed in detail by interpreters for signs that may indicate the presence of hydrocarbons. The seismic interpretation assumes that the contrast of acoustic impedance in the subsurface represented by seismic images has its origin in changes in the composition of the different layers of rocks. An important characteristic in understanding the underground consists in identifying seismic horizons. A horizon can be identified in the traces as an amplitude pattern in the vertical neighborhood. Moreover, such pattern occurs in the trace repeatedly where the horizon is defined [Zhou, 2014]. Real horizons can be represented by traces of the volume by a small set of vertically contiguous voxels. Seismic horizons help to understand the region. Some of them delimit the base and the top of a possible reservoirs [Zhou, 2014].

II.4 Final Comments

In this Chapter, we presented some seismic background which are relevant in understanding the use case scenario adopted in this dissertation. It was possible to see the importance of some characteristics in seismic analysis such as finding horizons, faults and potential hydrocarbon concentration zones. The focus of the analysis presented in this work is in finding seismic horizons.

Chapter III Time series data mining background

In this chapter, we introduce some background in time series data mining. We present a formalization and introduce some basic related concepts, including the definition for: time series, sub-sequences, and sliding windows. In addition, motif discovering mining process is described, including the activities of: normalization, data indexing, similarity measurements, and discovery algorithms.

III.1 Time series

A time series is a collection of observations of a phenomenon along a time-line [Hamilton, 1994]. Time series analysis is a large field of study and was intensively developed with the advances of computational resources. This allowed for handling a massive quantity of data [Cryer and Kellet, 1986]. The time series analysis is normally based on statistical references, including the extraction of time series properties such as average, median, variance, and distribution [Wei, 1994]. Formally:

Definition 1 *According to Box et al. [2008], a* ***time series*** t *is an ordered sequence of values in time , where each* t_i *is a value,* $|t| = m$ *is the number of elements in* t *and* t_m *is the most recent value in* t*.*

$$t =< t_1, t_2, \cdots, t_m >, t_i \in \mathbb{R}$$

III.2 Subsequence

A subsequence is a sample of a time series. It enables the analysis of a subset of the data to evaluate some local properties [Chiu et al., 2003]. A subsequence has a defined length and is necessarily smaller than the time series. Formally:

Definition 2 *According to Lonardi and Patel [2002], the* p*-th* ***sub sequence*** *of size* n *in a time series* t*, represented as* $t^{p,n}$*, is an ordered sequence of values* $< t_p, t_{p+1}, \ldots, t_{p+n-1} >$*, where* $|t^{p,n}| = n$ *and* $1 \leq p \leq |t| - n$*.*

$$t^{p,n} = subseq(t, p, n)$$

III.3 Sliding Windows

Sliding windows consists in extracting all possible subsequences of a time series [Lampert et al., 2008]. The sliding windows produces a set o subsequences with the same length. Such concept is widely used for time series analysis to make comparison between subsequences to find similarities between them [Van Hoan and Exbrayat, 2013]. Formally:

Definition 3 *A **Sliding Windows** [Keogh and Lin, 2005] is a function $sw(t, n)$ with arguments t and n that produces a matrix W of size $(|t| - n + 1)$ by n that contains all sub sequences of size n of time series t. Each line w_i in W is a sub sequence of t of size n. Given $W = sw(t, n)$, $\forall w_i \in W$, $w_i = t^{i,n}$.*

Figure III.1 depicts definitions 1, 2, and 3. The blue line represents the time series, the red line represents a subsequence from the time series, and the green dashed lines is an example of some of the subsequences extracted from time series based on sliding windows.

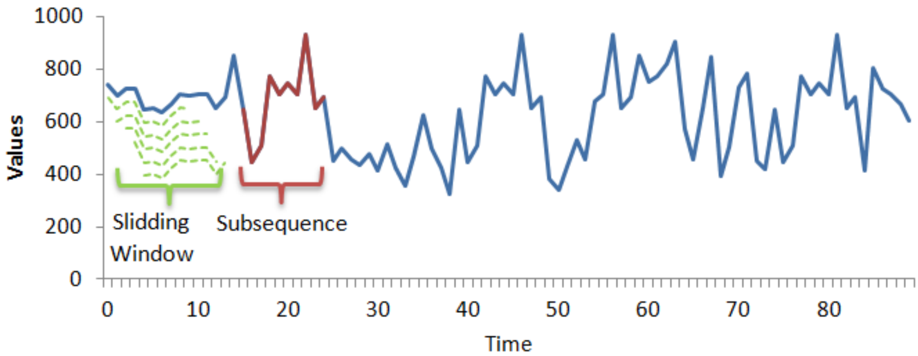


Figure III.1: An example of a time series with sub-sequence and sliding windows concepts

III.4 Spatial-time series

A spatial-time series can be described as a time series with an associated position [Chan, 2005]. Such position can be its geographical coordinates or any other reference that can represent the place where data was observed. If position is a function of time, it is a trajectory spatial-time series, otherwise it is a permanent spatial-time series. In this work, we are interested on permanent spatial-time series and for sake of simplicity, we are calling them spatial-time series. There are many applications which are indeed spatial-time series. Formally:

Definition 4 *Li [2014] defines a **Spatial-time series** s as a time series composed of coordinates x and y and $t =< v_1, v_2, \ldots, v_m >$ a sequence of observations. Then, $s.x$ e $s.y$ are the coordinates from s, and $s.t$ is the series of observations from s.*

III.5 Normalization

There are some different methods to compare time series, such as morphological comparison [Loh et al., 2000]. To apply such methods to compare them, it is necessary to verify some properties, such as scale. In this way, normalization becomes a fundamental step in data preprocessing to enable the effectiveness of time series comparison methods. One of the most common normalization methods is the amplitude normalization or z-score [Keogh and Ratanamahatana, 2005]. As result of this normalization method, the normalized time series has zero as average and one as standard deviation. The equation III.1 presents how to normalize a time series.

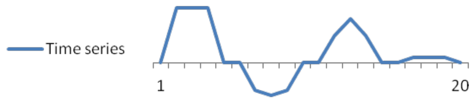
$$z_m = \frac{(t_m - \mu_t)}{\sigma_t} \tag{III.1}$$

where μ_t is the average and σ_t is the standard deviation of the time series.

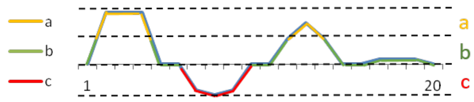
III.6 Symbolic Aggregation Approximation (SAX)

One of the data preprocessing activities in motif discovery consists in representing data in a manageable way [Lin et al., 2007]. Such representation is a complex task and depends on data domain [Shieh and Keogh, 2008]. In time series context, data is usually a continuous numerical value. For motif discovery, processing directly numerical representation is not an efficient way to adopt [Daw et al., 2003]. Some discretization methods, such as symbolic representation (also known as indexing) has been proposed. It consists basically in represent a range of values as a symbol. All values in such range are replaced by that symbol according to a defined alphabet.

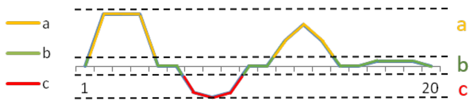
The simplest method of discretization is the Uniform Partitioning which the region between the top and bottom limits are split uniformly and each region receives a tag that replaces all value in such region [Keogh and Pazzani, 1998]. Figure III.2a is a example of a numerical time series. Figure III.2b shows the same time series after uniform partitioning. Another method is Maximum Entropy Partitioning [Daw et al., 2003], which is similar to the previous method, but instead of splitting uniformly the regions, the division consider some criteria to address important regions. Figure III.2c presents the result of maximum entropy partitioning. The last and most important method considering the scope of this work is the Symbolic Aggregation approXimation (SAX) [Lin et al., 2003]. This method is derived from the previous ones, but consider time series data distribution to define the size and position of regions. It was shown in Lin et al. [2003] that subsequence observations trend to follow a normal distribution. In SAX, the regions are divided according to Gaussian function with different sizes, but same probability. Figure III.2d is an example of time series indexed by SAX.



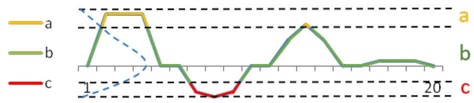
(a) Time Series



(b) Uniform partitioning



(c) Maximum entropy partitining



(d) SAX (Symbolic Aggregation Approximation)

Figure III.2: Symbolic Indexing methods

In figure III.2d, SAX transformation divides the time series plot area in three regions. The number of regions is defined as input. Based on data distribution, the range of each region are defined and tagged with a letter that will represent any value in such range.

III.7 Motif

In time series context, a motif can be described as a subsequence that occurs a determined number of times in a time series in different time windows [Mueen, 2014]. An important property regarding motifs is that the repeated subsequence is not previously known and is identified by means of scanning the entire data. It can be discovered by making comparison between subsequences that are obtained using sliding windows [Lonardi and Patel, 2002]. Such process requires some data preprocessing such as normalization and indexing prior the running of motif discovery algorithms to increase the performance and precision of results [Mueen, 2014]. Formally:

Definition 5 *Let* $q =< q_1, q_2, \ldots, q_n >$ *and* $t =< t_1, t_2, \ldots, t_m >$ *be two time series, such that* $|q| = n$*,* $|t| = m$*, and* $m > n$*.* q *is* ***included*** *in* t *(*$q \prec t$*) if and only if* $\exists\, w_i \in W$ *such that* $w_i = q$*.*

Definition 6 *Given two time series* q *and* t*,* q *is a* ***motif*** *[Mueen, 2014] with support* σ*, if and only if* q *is included in* t *at least* σ *times. Formally, given time series* q *and* t *such that* $W = sw(t, |q|)$*,* $motif(q, t, \sigma) \leftrightarrow \exists\, R \subseteq W$*, such that* $\forall w_i \in R$*,* $w_i = q \wedge |R| \geq \sigma$*.*

According to Definition 6, a motif is a set of similar subsequences that occur in time series. Many methods proposed in literature to discover motifs in time series are computational intensive [Patel et al., 2002]. Due to that, many methods aim to improve the effectiveness in motif identification and reduce the computational resources needed.

To make comparison between subsequences, a common approach is to compute dissimilarity between them. Approaches are commonly grouped into: (i) *Shaped-based*, which compares the shape of subsequences; (ii) *Edit-Based*, which counts the minimum number of interactions to transform one subsequence in another, (iii) *Feature-based*, which extracts properties from subsequences to compare them using another metric, and (iv) *Structure-based*, which try to find high level structures in subsequences to compare them using a global scale [Esling and Agon, 2012].

An example of Edit-Based method is to compute the Hamming distance. The Hamming distance consists in comparing each position of one string to another. For each position with different symbol, it adds one in the distance. The total distance is computed as the sum of comparison in all positions of the string. Table III.1 presents an example of hamming distance. In this case, the Hamming distance is 2, due to a mismatches in positions two and three. Edit-Based motif discovery methods can use a tolerance level for Hamming distance that is according to the domain of data, considering as similar strings with low Hamming distance.

string (aabde)	a	a	b	d	e
string (abdde)	a	b	d	d	e
Hamming Distance	**0**	**1**	**1**	**0**	**0**

Table III.1: Hamming distance example

Considering the concepts of indexing, sliding windows, and comparison between subsequences, another important element is the actual motif discovery searching algorithm. To find similar subsequences with such data, there are basically two main approaches: brute force and random projections algorithms.

III.7.1 Brute-force algorithm

The brute force approach is the simplest method, but it has a high computational cost, specially when used for large dataset [Mueen et al., 2009]. It is indicated for low dimensional data [Li and Nallela, 2009]. In this method the coverage and accuracy is complete since it makes all possible comparisons between all subsequences of a time series.

Each word that matched considering the Hamming distance tolerance parameters is grouped and classified as a potential motif. More than one motif can be found in the same time series. This method consumes a lot of computational resources due to the number of comparisons needed to cover such combinations.

III.7.2 Random Projection algorithm

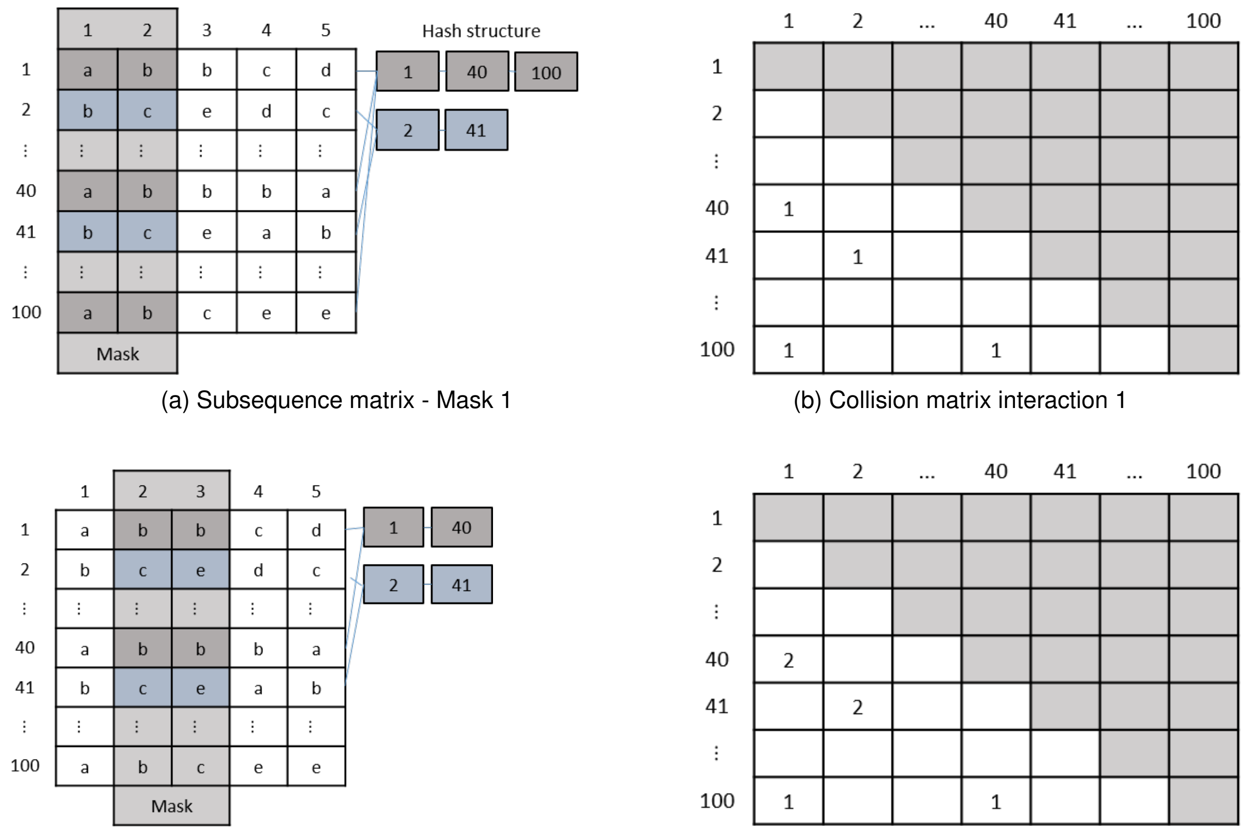
The random projections approach was proposed to handle large dataset reducing dimensionality taking samples of data aleatory. [Li and Nallela, 2009]. It optimizes the execution time and reduces the computational consumption in identifying motifs [Buhler and Tompa, 2002; Chiu et al., 2003]. In random projection, the data preprocessing is similar to brute-force method. It includes indexing and sliding windows.

With the set of words resulted from such data preprocessing, each symbolic subsequence is inserted in a subsequences matrix. Each line index corresponds to the initial position of subsequence in time axis. The next step is to build the collision matrix which is used to indicated potential motifs in the time series. The collision matrix is initially null and has the same quantity of lines and columns that correspond to the total number of subsequences identified. The collision matrix is built from the random projection process where two columns of the subsequence matrix are randomly selected and mask and for each position in mapped as a hash structure that has as input the symbolic values that correspond to position of selected columns. If two subsequences has the same symbolic value in the mask position then it is placed in hash structure.

As an example, consider a time series with 100 observations, normalized and indexed using SAX with alphabet size composed of five letters a,b,c,d,e. In such data, sliding windows of size five is applied to create subsequence matrix as presented in Figure III.3a. It also shows the mask selecting the columns 1 and 2. In such matrix there are two mapped subsequences that are placed in hash structure [1, 40, 100] and [2, 41]. The occurrences mapped in hash structure are marked in collision matrix according to the their positions as shown in III.3b.

Just applying one interaction is not enough to guarantee that subsequences mapped are motifs, since it covers only a small part of subsequence. It is possible to find different motifs according to the mask chosen. To address this problem, random projection process is applied many times. The III.3c is the second interaction of random projection, where a different mask is considered, selecting the columns 2 and 3. They are mapped to hash structure the subsequences [1, 40] and [2, 41]. Such appointment is used to update the value of collision matrix incrementing the previous value.

After performing certain number of interactions, it is necessary to verify the collision matrix. The motif identification is done by selecting the indexes with highest values in collision matrix. If the value in the collision matrix is relevant, it may represent a motif, but since it is a probabilistic method, this property is not guaranteed. The number of interactions can be defined by previously definition based fixing the number of interactions and stopping the process when it achieves a predetermined value [Chiu et al., 2003]. As result, it generates a list of motifs with their position occurrence in the time series analyzed.



(a) Subsequence matrix - Mask 1 (b) Collision matrix interaction 1

(c) Subsequence matrix - Mask 1 (d) Collision matrix interaction 2

Figure III.3: Collision matrix construction

III.8 Ranking motifs

After motif discovering process, an important task in motif analysis is how to sort the motifs according to their relevance [Castro and Azevedo, 2012]. A common classification method is $k-motif$ which considers the total number of occurrences in time series. For this method the $1-motif$ is the motif which has more occurrences observed [Lonardi and Patel, 2002].

Another property to be considered in motif sorting is the relevance degree. Some motifs can be similar to a straight line and depending of the data domain it can bring a not relevant information. Such motifs can be low qualified or discarded to avoid distorting the analysis [Chiu et al., 2003].

Some approaches to evaluate the significance and relevance of motifs were proposed in literature. A statistical approach to assess statistical relevance of motifs is called information gain which measures how expected is the motif to occurs [Krogh, 1998]. The Log-odds considers the degree of how rare is the motif by comparison between the chance of occurrence with the expectation chance of occurrence based on probabilistic distribution [Yang et al., 2004]. Castro and Azevedo [2012], proposes the estimation of expectation for frequency of a motif based on Markov Chain models. The value is assessed making the comparison between actual frequency and estimated based in hypothesis tests.

Another important approach that may be used to rank motifs is to cluster the occurrences of each motif and compute some quality measures. The general approach for clustering are described as follows.

III.9 Final Comments

In this Chapter, we discussed the main concepts and techniques used to develop the CSA such the basic concepts in time series analysis regarding motif identification such, subsequence and Sliding Windows. We defined the spatial-time series as a time series with a position associated. We presented the data treatment by normalization and SAX indexing process. We explored the motif definition and described the brute-force and Random Projection algorithm. At last, brought a ranking motifs description and methods presented in literature.

Chapter IV Related Works

This chapter presents a brief review regarding the most relevant works performed in time series motif discovery. The first approach regarding motif discovery in time series was proposed in Lonardi and Patel [2002]. In their approach, it is necessary to choose some parameters, such as motif length, size of SAX alphabet, and similarity tolerance between subsequences to classify them as a motif. It also describes the concept of k-motifs, which corresponds to the k most significant motifs.

Lonardi and Patel [2002] proposed a brute-force algorithm called EMMA (Enumeration of Motifs through Matrix Approximation) . Brute-force algorithms have quadratic complexity for processing. Since then, the task to identify motifs in time series has been widely explored. Recent researches focus on either improving the quality or reducing computational costs to find them. Chiu et al. [2003], for example, proposed a optimized method, extended from Buhler and Tompa [2002], aiming to reduce the computational cost to identify motifs.

Considering the exact motif discovery approach, some specific method to address the dimensionality and motif length problem were proposed. For univariate data with fixed-length motif, Jiang et al. [2008] proposed an efficient motif discovery algorithm PMDGS (P-Motif Discovery based on Grid Structure) that processes data streams. Mueen et al. [2009] proposed an exact time series motif discovery algorithm called MK (Mueen-Keogh) and observed that MK was faster than brute-force presented by Lonardi and Patel [2002]. Narang and Bhattacherjee [2010] introduce the Par-MK, Par-MK-SLB, and Par-MK-DLB. They are parallel multi-threaded algorithms for exact motif discover that focus on load balancing. Mueen et al. [2011] proposed a disk-aware algorithm to exact identify motifs in large time series databases. Cassisi et al. [2013] applies an exact time series motif discovery technique to study recurrent patterns in seismic amplitude time series of the Etna 2011 periodic eruptive activity. Chi and Wang [2013] introduced a method based on cloud model theory to extract the top k-motifs. Truong and Anh [2015] proposed a fast method for motif discovery in time series based on Dynamic Time Warping distance.

When it comes to approximated motif discovery methods, they aim to reduce the complexity and consequently the computational cost. Some work proposed approaches to improve the accuracy and efficiency of Random Projection Algorithm proposed in Chiu et al. [2003]. For univariate data with fixed-length motif, Lin et al. [2007] created a new symbolic representation for time series

(SAX) for indexing. Mohammad and Nishida [2009] proposed two algorithms called MCFull and MCInc that addresses constrained motif discovery problem. Castro and Azevedo [2010] addresses motif discovery problem as an approximate top k frequent subsequence discovery problem. Lin et al. [2010] presented an approach that uses subseries joins to get similarity among subseries of the time series. Armstrong and Drewniak [2011] developed the algorithm MD-RP for unsupervised motif discovering in time series. Narang and Bhattcherjee [2011] designed the new sequential and parallel Motif discovery and data de-duplication algorithms based on bloom filters.

For univariate data and variable-length motif discovery, Wilson et al. [2007] proposed the Motif Tracking Algorithm (MTA) that uses a small number of parameters based on implementation of the Bell immune memory theory. Yankov et al. [2007] presented a novel algorithm that discover motifs in time series with invariance to uniform scaling. This enables to reduce parameters such as motif length. In Nunthanid et al. [2011], a new motif discovery algorithm that do not requires motif length parameter called VLMD is introduced. Such algorithm automatically returns motif lengths from all possible sliding window lengths reducing a set of possibilities of the sliding window lengths. Nunthanid et al. [2012] presented the k-Best Motif Discovery (kBMD), a new time series motif discovery algorithm that is free of parameter produces a set of the best motif that are ranked by a scoring function based on similarity of motif locations and shapes. Mueen [2013] proposed the MOEN, an exact free-parameter algorithm to enumerate motifs that is faster than brute-force approach due to a novel bound on the similarity function that uses only linear space. Mohammad and Nishida [2014a] proposed an extension of the MK algorithm called MK++ to handle multiple motifs of variable lengths considering maximum overlap of subsequences. Mohammad and Nishida [2014b] presented a new algorithm, derived from MK++ to find the top K similar subsequence pairs at multiple lengths efficiently using scale invariant distance functions.

In the approximated approach for univariate time series with variable-length, Tang and Liao [2008] presented a new k-motif-based algorithm that is able to discover approximated motif with no need to define the length of motif. Li and Lin [2010] proposed the Sequitur, a new approximated approach based on grammar induction considering variable-length time series motif discovery with improvement of discovering hierarchical structure, regularity and grammar from data. Mohammad et al. [2012] proposed the G-Tex algorithm that can discover multiple motifs of multiple lengths with good performance. Truong and Anh [2013] developed the EP-BIRCH algorithm that is more efficient than MK algorithm finding motifs in large time series datasets and has low sensibility regarding the input parameters as motif-length.

In multivariate time series with fixed motif length, Tanaka and Uehara [2003] and Tanaka et al. [2005] showed how to dynamically determine the optimum period length using the Minimum Description Length (MDL) principle and apply the method to the multidimensional time-series transforming into one dimensional time-series using the Principal Component Analysis. Liu et al. [2005] proposed heuristic approach that can significantly improve the quality of motifs in m-dimensional time series. Lam et al. [2011] proposed two algorithms for solving multivariate time series called nmotif and kmotif. McGovern et al. [2011] introduced an approach to mining multidimensional motif in temporal streams of real-world data. Son and Anh [2016] proposed two new algorithms for motif discovery in time series data, first based on R-tree and the other is based on dimensionality reduction through Skyline index.

In multivariate time series with fixed-length, Vahdatpour et al. [2009] proposed a new model based on Random Projection to find approximately motif in multivariate time series data by combining motifs discovered and grouping them. Wang et al. [2010] developed the AMG method to list the motifs candidates by scanning the entire series and then filling a matrix for similarity comparison to verify the real motif. Son and Anh [2012] presented a R*-tree together with early abandoning based approach that stores Minimum Bounding Rectangles (MBR) of data in memory. Regarding the variable-length, the work of Minnen et al. [2007] proposed a method based on Random Projections for motif finding high density regions in the space of time series.

There are many works that proposes algorithm, methods and approaches to handle with motif discovery task with different characteristic such exactness, dimensionality and motif length. Table IV.1 summaries a comparison between works that contributed to motif discover, according to the following properties: exactness of algorithm (Exact or Approximated); dimensionality of data (Univariate or Multivariate); and length of motif (Fixed-length or Variable-length).

Table IV.1: Comparison of Works regarding motif discovering in times series

Reference	Exact	Approx-imated	Univari-ate	Multi-variate	Fixed-length	Variable-length
[Lonardi and Patel, 2002]	x		x		x	
[Patel et al., 2002]	x		x		x	
[Chiu et al., 2003]		x	x		x	
[Tanaka and Uehara, 2003]	x			x	x	
[Liu et al., 2005]	x			x	x	
[Tanaka et al., 2005]	x			x	x	
[Ferreira et al., 2006]		x	x		x	
[Lin et al., 2007]		x	x		x	
[Minnen et al., 2007]		x		x		x
[Wilson et al., 2007]	x		x			x
[Yankov et al., 2007]	x		x			x
[Jiang et al., 2008]	x		x		x	
[Tang and Liao, 2008]		x	x			x
[Fuchs et al., 2009]	x		x		x	
[Mohammad and Nishida, 2009]		x	x		x	
[Mueen et al., 2009]	x		x		x	
[Vahdatpour et al., 2009]		x		x	x	
[Castro and Azevedo, 2010]		x	x		x	
[Li and Lin, 2010]		x	x			x
[Lin et al., 2010]		x	x		x	
[Narang and Bhattacherjee, 2010]	x		x		x	
[Wang et al., 2010]		x		x	x	
[Armstrong and Drewniak, 2011]		x	x		x	
[Lam et al., 2011]	x			x	x	
[McGovern et al., 2011]	x			x	x	
[Nunthanid et al., 2011]	x		x			x
[Mueen et al., 2011]	x		x		x	
[Narang and Bhattcherjee, 2011]		x	x		x	
[Mohammad et al., 2012]		x	x			x
[Nunthanid et al., 2012]	x		x			x
[Son and Anh, 2012]		x		x	x	
[Mueen, 2013]	x		x			x
[Cassisi et al., 2013]	x		x		x	
[Chi and Wang, 2013]	x		x		x	
[Truong and Anh, 2013]		x	x			x
[Mohammad and Nishida, 2014a]	x		x			x
[Mohammad and Nishida, 2014b]	x		x			x
[Truong and Anh, 2015]	x		x		x	
[Son and Anh, 2016]	x			x	x	

Chapter V Combined Series Approach

V.1 Problem Definition

The motif discovery approaches presented in literature review basically propose to solve the problem considering time series. In the context of spatial-time series where exists a neighborhood relationship among time-series, we observe a more complex scenario due to spatial constraints.

In order to highlight how challenging the problem is, consider a set of spatial-time series dataset where each spatial-time series has a position. Such scenario is depicted in Figure V.1. If we apply to this scenario a known motif discovery method, such as Random Projection Algorithm, on each spatial-time series, we can observe that no motif is found in five spatial-time series. Also, even when some motifs are identified, considering the entire data set, those motifs are not fully explored. It is possible to observe that similar shapes appearing in neighboring spatial time series are not identified as motifs when running the algorithm on each time series separately.

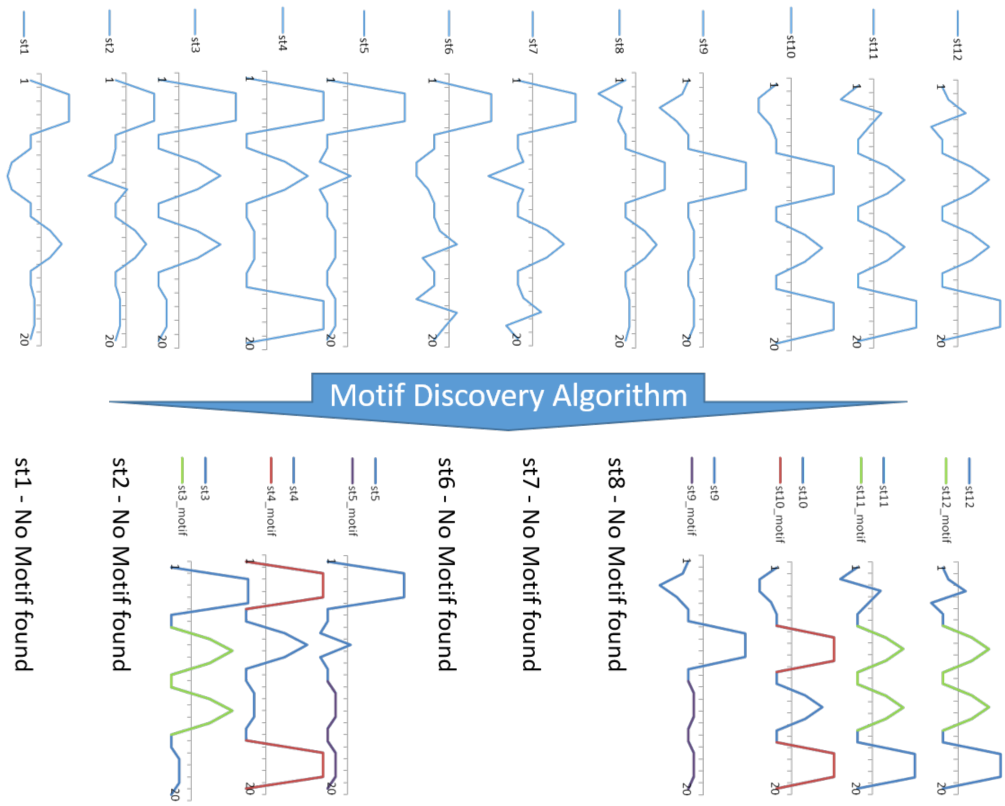


Figure V.1: Traditional motif discovery algorithm applied in spatial-time series dataset. (i) red trapeziums and green triangles are identified motifs; (ii) blue trapeziums are not identified and not linked with red ones; (iii) blue triangles are not identified and not linked with green ones; (iv) purple shapes are not identified motifs.

Depending on the data set, such shape similarities in neighboring time series can correspond to some relevant information. Identifying and grouping motifs in spatial-time series datasets can address some real-world problems, such as in seismic analysis. Such scenario was not studied in previous works as discussed in Chapter IV. The problem formalization for this new scenario is presented as follows.

Definition 7 *A **spatial-time series dataset** (for short, dataset) S is a set of spatial-time series $\{s_z\}$. We define $t_{max}(S)$ as the maximum number of observations for all spatial series s_z inside dataset S. Formally, $t_{max}(S) = max(\{|s_z.t|\}), \forall s_z \in S$.*

Definition 8 *Let σ and κ be two support values such that $\sigma \geq \kappa$. A subsequence q is a **spatial-time motif** if and only if q is included at least σ times in D and q occurs in at least κ different spatial-time series.*

From the aforementioned definitions, the problem is *to discover spatial-time motifs in spatial time series dataset*.

V.2 Combined Series Approach

To address such problem, we developed a data mining process that is organized in five steps: (i) Normalization & SAX Indexing; (ii) Partition of Spatial-Time Series; (iii) Combination of Blocked Spatial Time Series and Motif Discovery Algorithm; (iv) Aggregate Motifs and evaluate Spatial Time Constraints; (v) Rank Spatial-Time Motifs. The process is depicted in Figure V.2. The next sections explain these steps in details.

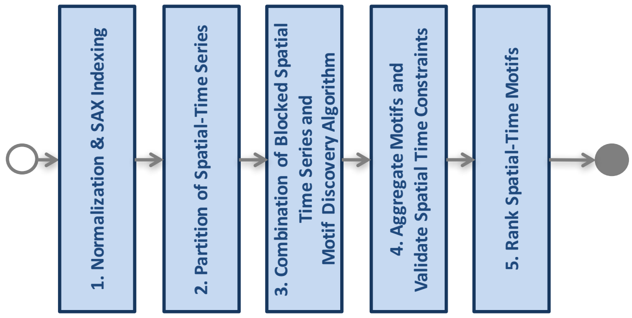


Figure V.2: Spatial-time series motif discovery process

For a better understanding of the steps, consider a toy synthetic dataset D as example, where all steps can be applied to explain the entire process. Table V.3.a presents dataset D, where each column is a spatial-time series (varying from positions 1 to 12) and rows represent observations that occur in a specific time. The example dataset can be represented as a set of line plots (Figure V.3.b).

#	st1	st2	st3	st4	st5	st6	st7	st8	st9	st10	st11	st12
1	0	0	0	0	0	0	0	0	0	0	0	0
2	10	10	10	10	10	10	10	-7	-1	-3	-3	1
3	10	10	10	10	10	10	10	-1	-5	-3	4	4
4	10	10	10	10	10	10	10	-2	-2	-1	2	-2
5	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0
7	-5	-1	5	5	-1	-3	1	10	10	10	5	5
8	-6	-7	8	8	3	-3	-5	10	10	10	8	8
9	-5	3	5	5	-1	-1	1	10	10	10	5	5
10	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0
12	5	5	5	1	1	1	5	5	1	5	5	5
13	8	8	8	1	1	4	8	8	1	8	8	8
14	5	5	5	1	1	-2	5	5	1	5	5	5
15	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0
17	1	1	1	10	1	-3	1	1	1	10	10	10
18	1	1	1	10	1	4	4	1	1	10	10	10
19	1	1	1	10	1	2	-2	1	1	10	10	10
20	0	0	0	0	0	0	0	0	0	0	0	0

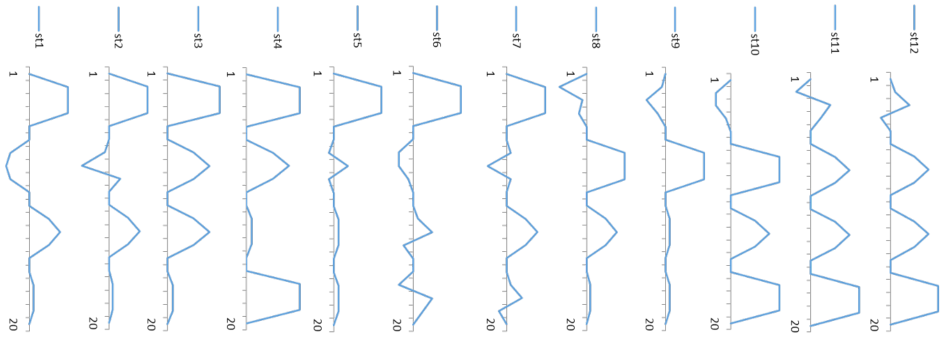


Figure V.3: Toy dataset (a); Graphical representation (b)

V.2.1 Normalization & SAX Indexing

The first step is to apply a data normalization in the entire dataset using z-score method Han [2006]. To normalize the data we apply the equation V.1.

$$Z_{i,j} = \frac{D_{i,j} - \mu_D}{\sigma_D} \tag{V.1}$$

Immediately after normalization, it is possible to apply *Symbolic Aggregate ApproXimation (SAX)* indexing method. This process has the size of alphabet *alpha* as input. It transform the numeric data into indexes defined by letters according to the data distribution, so that each letter of the alphabet has similar amount of data. For example, considering an alphabet size of 5, values are be replaced by letters (a,b,c,d,e). In this case, central values are tagged as ”c”, low positive values as ”d”, high positive as ”e”, low negative as ”b” and high negative as ”a”. Figure V.4 presents a SAX indexed spatial-time series database.

V.2.2 Partition of Spatial-Time Series and Motif Discovery Algorithm

The second step is to partition the spatial-time series dataset into blocks. Blocks are created based on $sslice$ (spatial slice) $tslice$ (time slice). $sslice$ is the number of neighbors series inside each block and $tslice$ is length of subsequences of the spatial time series. In this way, each block contains $sslice \cdot tslice$ observations.

Considering our example, Figure V.4 depicts the partition of the dataset, where each blue box corresponds to a block. In this example, the input threshold *sslice* is 4 and *tslice* is 10. Since the dataset has 12 columns and 20 rows, the dataset is divided into 6 blocks.

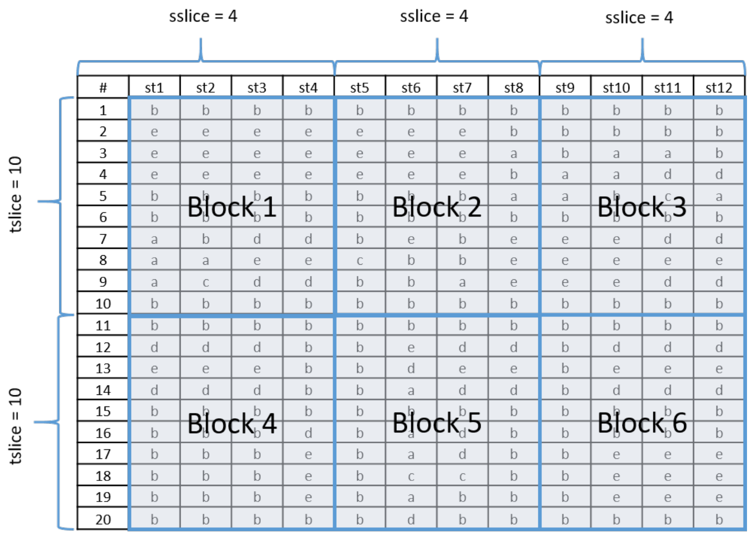


Figure V.4: Toy dataset partitioned into blocks

Once the partitioning of the data has been applied, each block is used for motif discovery algorithm. This is an important step in Combined Series Approach to identify motifs in spatial-time series since it combines observations with different space and time. This partitioning groups spatial-time series in different positions according to a fixed time window. Another important characteristics of this procedure is to reduce the computational complexity when processing large datasets.

In each block, we concatenate the spatial-time subsequences into a single time series t. The concatenation occurs linearizing the block connecting all columns inside the block by the last element of previous column to first element to next column consideration orientation left-to-right. After concatenation, the problem becomes a traditional motif discovery problem. It is possible to directly apply the random projection algorithm to identify time series motifs. Once at least one motif is found, the step returns a list of motifs and their occurrences that includes the word that represent the motif and a vector of initial positions where the motif is found.

Figure V.5 shows CSA applied to our toy dataset. Considering a $sslice$ and $tslice$ of 4 and 10, respectively, we obtain 6 combined series, each one with 40 observations. According to Figure V.5, the combined series is represented as blue line. After applying the motif discovery algorithm, we obtain the motifs identified with line colors red, green, and purple.

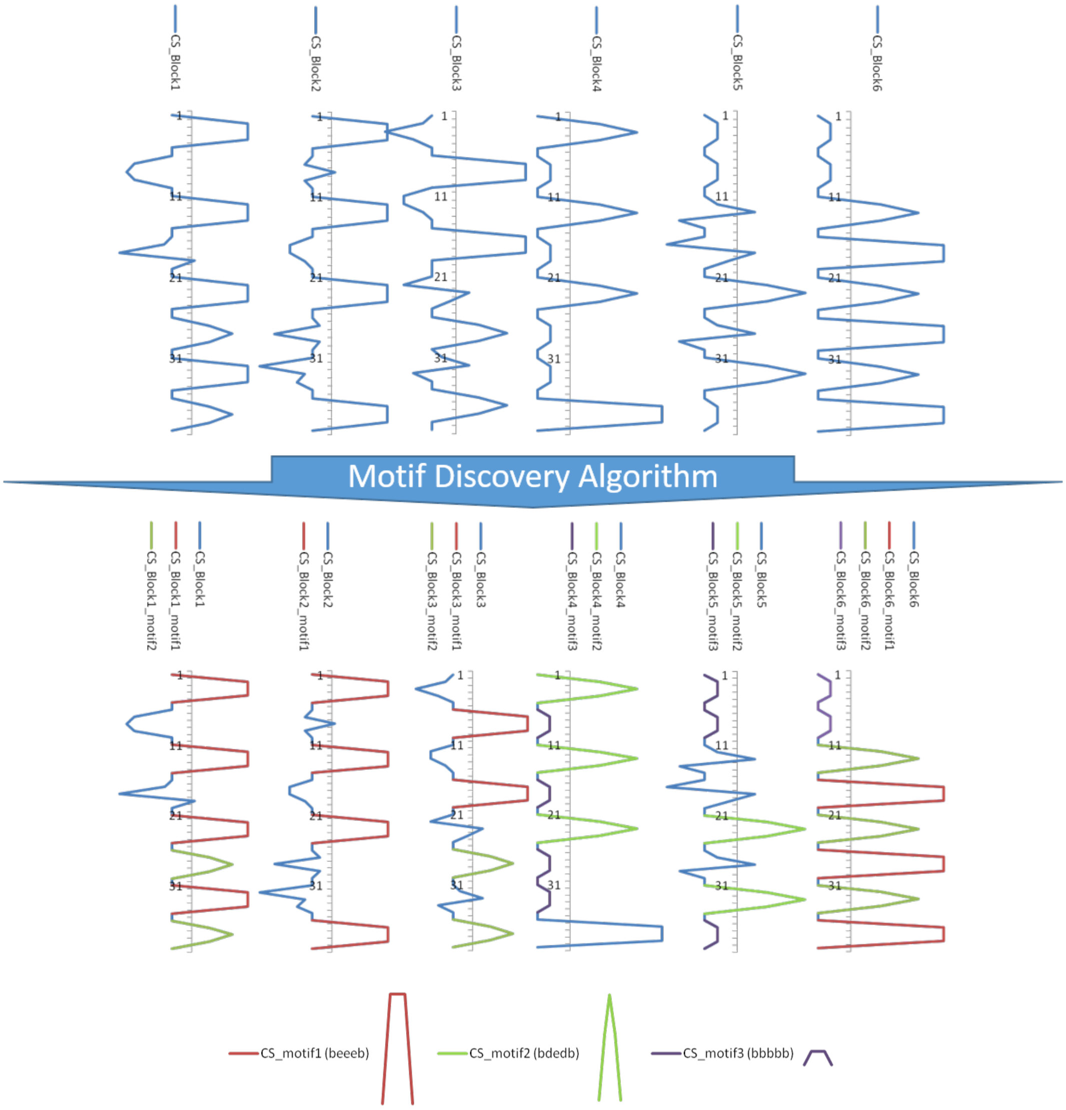


Figure V.5: Motif Discovery Algorithm to Combined Series

Analyzing the output of Figure V.5, some occurrences of motifs found using CSA were not found when we simply apply traditional motif discovery algorithm in each spatial time series. Figure V.5 also presents the shape of motifs found in the example data considering the combined series, their SAX representation (word), the number of occurrences and the initial positions of each occurrence.

Another main difference between traditional and combined series approach is in the number of occurrences observed. In combined series we obtained a representative higher number of occurrences than in traditional method. Table V.1 presents the comparison of number occurrences observed in both methods. This is due to the advantage of combining different spatial-time series.

Table V.1: Global Occurrences - Combined Series x Traditional Method

Motif	Combined Series	Traditional
motif1 (beeeb)	13	4
motif2 (bdedb)	12	6
motif3 (bbbbb)	9	4

V.2.3 Aggregate Motifs and Evaluate Spatial Time Constraints

The motifs identified in previous steps are motifs for the combined time series. However, in order to be *de facto* spatial-time motifs, we need to verify if support κ and σ stands for the data according to Definition 8. Due to that, we call the motifs identified during previous phase as candidate spatial-time motifs.

From the candidate spatial-time motifs, we rolled-out the combined series in all blocks to original spatial-time space. An important measure considering the spatial characteristic of the data is in how many positions in space the motif occurs. It can help to define how wide is the behavior and can represent a relevant information for analysis. We aggregate motifs in entire dataset mapping their positions of occurrence and counting the number of occurrences (global occurrences) $GO(motif)$ of the motifs and the number of spatial-time series (spatial occurrences) $SO(motif)$ in which these motifs appears.

The support validation consists in verifying each motif so that it can be classified as spatial-time motif. The first verification is to check if $GO(motif) \geq \sigma$ and if $SO(motif) \geq \kappa$. If both constraints are satisfied, then it is a spatial-time motif.

Figure V.6.a shows the aggregated motifs of our toy example. Similar motifs are colored with same color. We can observe the spatial occurrences of the motifs. For motif1 (beeeb), motif2 (bdedb), motif3 (bbbbb) there are, respectively, 12, 9 and 7 occurrences. Figure V.6.b and Figure V.6.c present 3 scenarios to evaluate the minimum support. Scenario 1 considers $\sigma \geq 4$ and $\kappa \geq 4$ and all three motifs satisfies such condition. Scenario 2 considers $\sigma \geq 8$ and $\kappa \geq 8$. In this case, all motifs satisfied the σ constraint, but motif3 did not satisfy κ constraint. Scenario 3 considers $\sigma \geq 12$ and $\kappa \geq 12$.In this scenario, motif3 does not satisfy both σ and κ constraints.

#	st1	st2	st3	st4	st5	st6	st7	st8	st9	st10	st11	st12
1	b	b	b	b	b	b	b					
2	e	e	e	e	e	e	e					
3	e	e	e	e	e	e	e					
4	e	e	e	e	e	e	e					
5	b	b	b	b	b	b	b					
6			b	b				b	b	b	b	b
7			d	d				e	e	e	d	d
8			e	e				e	e	e	e	e
9			d	d				e	e	e	d	d
10			b	b				b	b	b	b	b
11	b	b	b	b	b		b	b	b	b	b	b
12	d	d	d	b	b		d	d	b	d	d	d
13	e	e	e	b	b		e	e	b	e	e	e
14	d	d	d	b	b		d	d	b	d	d	d
15	b	b	b	b	b		b	b	b	b	b	b
16	b	b	b		b			b	b	b	b	b
17	b	b	b		b			b	b	e	e	e
18	b	b	b		b			b	b	e	e	e
19	b	b	b		b			b	b	e	e	e
20	b	b	b		b			b	b	b	b	b

Scenario 1	word	Global Occurrences		Support (σ)	Check
Motif1	beeeb	13			OK
Motif2	bdedb	12	>=	4	OK
Motif3	bbbbb	9			OK

Scenario 2	word	Global Occurrences		Support (σ)	Check
Motif1	beeeb	13			OK
Motif2	bdedb	12	>=	8	OK
Motif3	bbbbb	9			OK

Scenario 3	word	Global Occurrences		Support (σ)	Check
Motif1	beeeb	13			OK
Motif2	bdedb	12	>=	12	OK
Motif3	bbbbb	9			No

Scenario 1	Spatial Occurrences		Spatial Validation (k)	Check
Motif1	12			OK
Motif2	9	>=	4	OK
Motif3	7			OK

Scenario 2	Spatial Occurrences		Spatial Validation (k)	Check
Motif1	12			OK
Motif2	9	>=	8	OK
Motif3	7			No

Scenario 3	Spatial Occurrences		Spatial Validation (k)	Check
Motif1	12	>=	12	OK
Motif2	9			No

Figure V.6: Aggregated Motifs (a); Support constraint (σ) (b); Spatial constraint (κ)(c)

V.2.4 Rank Spatial-Time Motifs

From a list of identified motifs and their occurences, it is possible to apply a ranking function so that we can provide specialists an ordered list of motifs ranked by their interests. There are many ranking functions that are described in time series, such as presented section III.8. When it comes to spatial-time series, the number of possible ranking functions may increase considerably.

Given a set of identified motifs, one may observe that is not going to exist a silver bullet ranking function. The adequacy of a ranking function is driven by the research questions that specialists may be interested on. Despite such alternative, our method assumes that every function rf may be a ranking function as long as it receives as input a motif and its occurrences. Function rf needs to return a value greater or equal to 0. The lower the result of rf , the better a motif is ranked.

A deeper discussion on specifying ranking functions and their properties is outside the scope of this dissertation. However, for sake of exploring seismic dataset, we provided in Appendix I an ad-hoc ranking function that prioritizes motifs whose occurrences produces horizontal shapes.

V.3 CSA Algorithm

The entire data mining process can be summarized by Algorithm 12. It takes as input a spatial-time series dataset D, a word size w, an alphabet size a, $slice$ and $tslide$ corresponding to spatial and temporal block sizes, a σ and κ constraints, and, finally a ranking function rf.

function STMOTIF($D, w, a, sslice, tslice, \sigma, \kappa, rf$)
  $D_s \leftarrow norm\_sax(D, a)$
  $b \leftarrow partition(D_s, sslice, tslice)$
  for each $b_i \in b$ **do**
    $t \leftarrow combine(b_i)$
    $motifs \leftarrow identify(t, w) \cup motifs$
  end for
  $cand\_motifs = aggregate(motifs)$
  $st\_motifs = evaluate(cand\_motifs, \sigma, \kappa)$
  $topst\_motifs = rank(st\_motifs, rf)$
  return $topst\_motifs$
end function

Chapter VI Experimental Evaluation

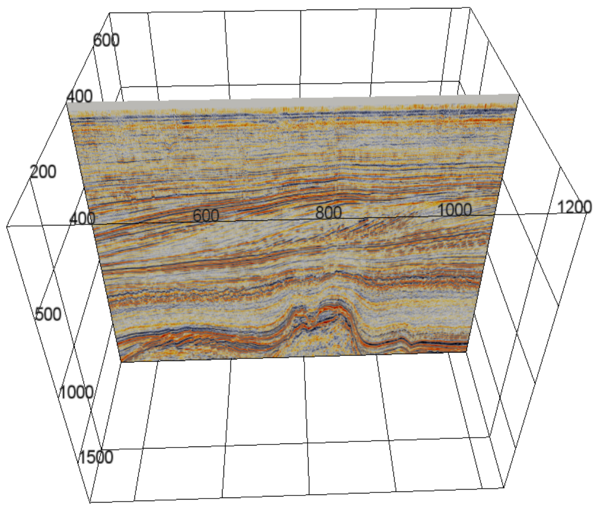
This chapter addresses experimental evaluation using seismic datasets. Initially, it is presented an overview about the Netherlands seismic dataset used in this dissertation. Then, both the methodology and scenarios considered for analysis are presented. Finally, the results are summarized and evaluated according to the ground truth for the Netherlands seismic dataset.

VI.1 Dataset description

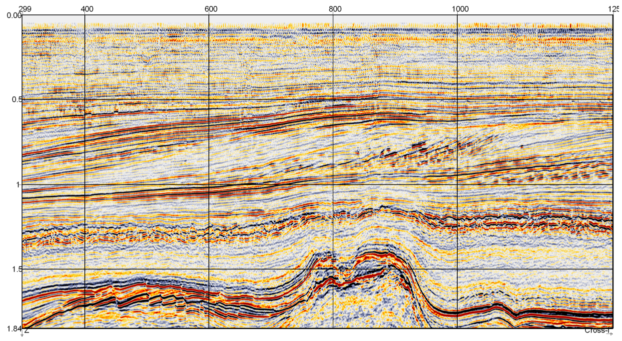
Seismic dataset is a set of spatial-time series. Each spatial-time series has a position in which the geophone or hydrophone is placed. The experiment proposed in this work consists in applying CSA in seismic dataset to support seismic interpretation. As presented in chapter II, an important task in seismic analysis is to identify seismic horizons. They correspond to different layers in subsoil. The large size of a seismic dataset makes visual analysis conducted by seismic specialists hard and time consuming.

A seismic dataset, called F3 Block, was selected to evaluate CSA. The dataset was collected in a region localized in the Dutch sector of the North Sea. Such dataset is a sample that contains the superior part of seismic of that region. In the bottom part, which is not available for public, contains the data regarding oil and gas formations. The dataset available is largely studied by seismic community. Due to that, it was explored by seismic specialists that mapped some relevant information, such as seismic horizons.

Considering the 3D F3 block, we selected a 2D slice from it (inline 401). Inlines refer to the direction in each receiver and increase from west to east. Crossline refers to the direction that is perpendicular to the orientation of receiver and their coordinates increasing from south to north. Figure VI.1a shows the position of inline 401 extracted from the F3 block. Figure VI.1b is a 2D view of Inline 401.



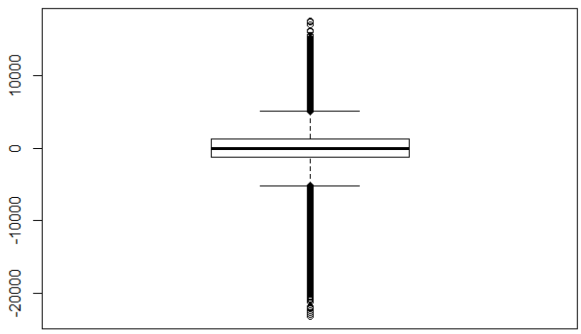
(a) Inline 401 in block data



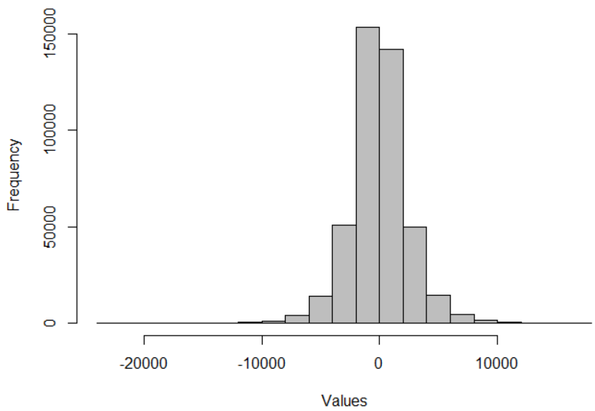
(b) Inline 401 2D view

Figure VI.1: seismic dataset - Inline 401

Inline 401 consists in a table with 462 rows and 951 columns. Columns represent positions of the receivers and lines represent time, which is also related to the depth of soil. The value of observations represent the wave amplitude reflected from the soil in a particular position and depth. Figure VI.2a depicts the boxplot characterizing data distribution. Median is approximate to zero and values generally vary from -10000 to 10000. Considering the histogram (Figure VI.2b), it is possible to observe a frequency distribution with high concentration of values close to the median. From our exploratory analysis, we considered it adequate to be the basis for experimenting the CSA algorithm.



(a) Boxplot Inline 401 data



(b) Histogram Inline 401 data

Figure VI.2: Inline 401 data distribution

This dataset has already been studied by seismic specialists who interpreted some of its characteristics, such as seismic horizons. They aim to identify potential regions for oil and gas reservoirs. Such horizons represent an abrupt change in soil characteristics. They are commonly related to spikes in wave amplitude. Figure VI.3 shows eight mapped horizons represented by colored lines. These mapped horizons are referenced to evaluate the accuracy of CSA.

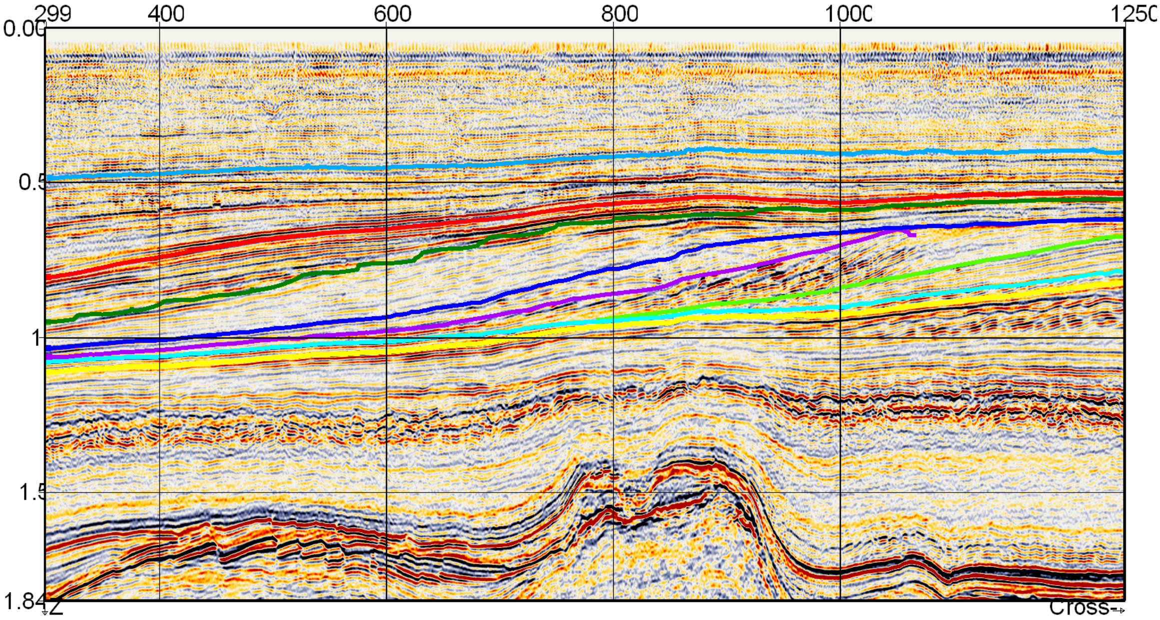


Figure VI.3: Mapped Horizons

A seismic tool (software OpendTect) that is used for mapping seismic horizons, plots seismic shots using color maps. In Figure VI.3, not taking into account the colored mapped horizons, colors are associate to an amplitude range. The scale is based on red color for more negative amplitudes, light colors for amplitudes around zero and dark blue for high positive values.

Mapped horizons were identified based on the dataset and other previously known information of the explored region. Specialists consolidated such information to help them in the seismic survey. They normally map horizons that are relevant for the objective of finding oil and gas reservoirs. This dataset presents some other horizons that were not mapped. However, knowing such information could help to select the best drilling technology.

VI.2 Experiments

This section discusses the actual experimental evaluation aiming to evaluate the accuracy of combined series approach in spatial-time series motif discovery task applied to seismic dataset. Our evaluation was driven by comparing the result of better ranked motifs with the horizons from ground truth identified by seismic specialists. The algorithm to execute the experiments was implemented in R programming language.

The CSA Algorithm, as described in Section V.3, requires parameters $alpha$, $word$, $tslice$, $sslice$, σ, κ, and rf to be specified. These parameters influence both computation ellapsed time and quality of results. The description of these parameters is summarized in Table VI.1.

Table VI.1: Input Parameters

Parameter	Description
$alpha$	Size of alphabet for SAX indexing
$word$	Length of motif word
$tslice$	Number of rows in the block (subsequence size)
$sslice$	Number of columns in the block (number of spatial time series)
σ	Support for Global Occurrence (GO)
κ	Support of Spatial Occurrence (SO)
rf	Ranking function (see Appendix I)

Since CSA has a few parameters, we have conducted parameter exploration in two stages. In the first stage of evaluation, we studied the influence of block orientation by varying both $tslice$ and $sslice$. In this stage, we fixed all other parameters. For this first evaluation, parameters were set as indicated in Table VI.2. The SAX indexing considered $alpha = 4$ with a symbolic frequence distribution according to Figure VI.4.

Table VI.2: Block

Block orientation	$alpha$	$word$	$tslice$	$sslice$	σ	κ
Vertical	4	4	90	10	300	300
Square	4	4	30	30	300	300
Horizontal	4	4	10	90	300	300

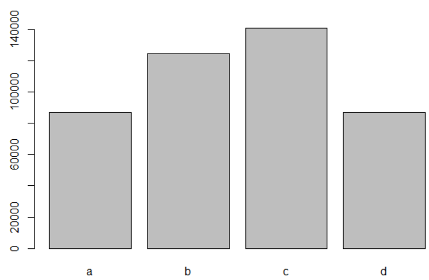


Figure VI.4: SAX with $alpha$ = 4

In order to evaluate the best block orientation, we have set three orientations: vertical rectangle ($tslice$ = 90; $sslice$ = 10), square ($tslice$ = 30; $sslice$ = 30) and horizontal rectangle ($tslice$ = 10; $sslice$ = 90). For fair comparison, all of them contains the same amount of observations. Table VI.3 presents the summary of identified motifs with respect to different orientations. It presents the number of identified motifs, computation time (in hours), and the average ranking function[1] for all

[1]The ranking function is described in Equation I.1

identified motifs. It is possible to observe that horizontal block presented the lowest average rank and computation time.

Table VI.3: Summary of Identified Spatial-Time Motifs

Block orientation	Number of Motifs	Time (hours)	Average Rank
Vertical	314	14.59	0.2463
Square	327	17.23	0.2375
Horizontal	**317**	**13.36**	**0.1954**

The best ranked motif in the block orientation is the one with the lowest ranking function value computed by Equation I.1. In order to measure the quality of the ranking function, Equation VI.1 computes the ground-truth error, *i.e.*, RMSE of all observations with respect to the closest seismic horizons indicated in the ground-truth. Table VI.4 presents the best ranked motif, its ranking function and ground-truth error for each block orientation. It is possible to observe that better ranked motif in the horizontal block led to lowest ground-truth error.

$$rank_{motifvalidation} = \frac{\sum \frac{RMSE_{cluster(horizon)}}{(IG+1)*\frac{SO^2}{GO}}}{ncluster} \tag{VI.1}$$

Table VI.4: Best ranked Spatial-time motif

Block orientation	stmotif	Ranking Function	Ground-truth Error
Vertical	ddaa	0.0403	0.0866
Square	aadd	0.0325	0.0914
Horizontal	**aadd**	**0.0468**	**0.0821**

In stage two, with the best block orientation defined, it possible to evaluate the accuracy of CSA by varying other parameters. In this stage, we explored varying both $alpha$ and $word$ parameters from 4 to 8. Table VI.5 presents the ranking function for the best rank motif identified.

Table VI.5: Ranking Result

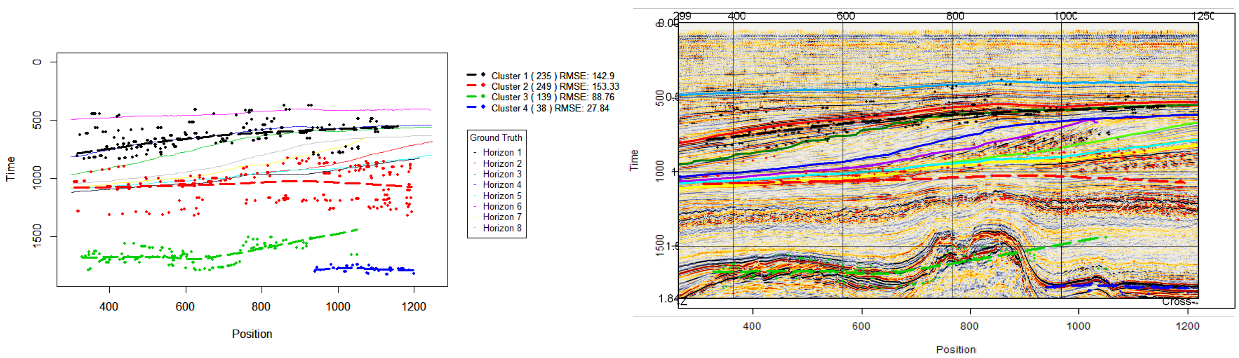
	$alpha$				
$word$	4	5	6	7	8
4	0.0468	**0.0407**	0.1396	0.2646	0.8172
5	0.0838	0.1998	1.0202	1.6679	3.5129
6	0.1654	0.8081	1.5713	3.5870	-
7	-	2.2909	-	-	-
8	-	-	-	-	-

Considering the results presented in Table VI.5, the best configuration observed is $word$ =

4 and $alpha$ = 5. According to Table VI.5, as we increase the $word$ and $alpha$ parameters, the computed rank also increases. When these parameters imposes more restrictive constraints, the algorithm may even not find any motif.

We were expecting that with the increase of $alpha$ value, the precision of the results would have increased. From our observations, it occurred the opposite behavior. We have analyzed that such behavior was due to the way in which we have configured random projection algorithm. We have set it to not explore overlapping sliding windows. In other words, all subsequences were completely independent. This decreased the chances of finding candidate motifs.

The graphical representation of the best ranked motif is presented in the Figure VI.5a. In such Figure, the colored points represents the motif with its observations clustered in four groups. The colored dashed lines are the polynomial regression of each cluster. The continuous colored lines are the ground truth horizons which are used to evaluate the accuracy of CSA. Analyzing the results, the black dashed line is very close to horizon with blue line. Half of dashed line also identified a horizon represented by black line. The green and blue dashed lines are not close to the ground truth mapped horizons, but according to a seismic specialist, they also correspond to seismic horizons. This becomes more clear in Figure VI.5b, as it superpose the identified motifs over the seismic shot. Additionally, both lines does not cover the entire space. This can bring a deeper discussion regarding to the presence of seismic faults.



(a) Result - Best ranked motif

(b) Result over seismic picture

Figure VI.5: Combined series experiment result

Finally, the presented results obtained by CSA are satisfactory specially considering the graphical analysis of the best ranked identified motif. It was able to identify some seismic horizons and also show other potential horizons not previously mapped in the ground-truth survey.

Chapter VII Conclusion

The main contribution of this dissertation is to present an approach for motif identification in spatial-time series, named Combined Series Approach (CSA). The motif concept, initially created in bio-medicine, has been extended to other areas such as time series analysis. Due to the potential of the technique applied to time series, it became a very interesting theme with large possibilities for real-world applications. Evaluating the literature, we observe a gap in motif discovery techniques for handling spatial-time series, which is the focus of this work.

The basic concepts and definitions regarding time series, spatial-time series, and motif discovery in time series were described as background for CSA. Additionally, since the experimental evaluation is done using seismic dataset, a brief introduction on seismic analysis was presented, including a discussion on important information to be extract in seismic surveys, such as identification of horizons, faults, and reservoirs.

In the literature, many works proposed different approaches for motif discovery in time series analysis. They are based on similar concepts and techniques. In data preparation some techniques include normalization and Symbolic Aggregation Approximation (SAX). Due to that, for spatial-time series motifs discovery, CSA was proposed on top of Random Projections.

However, some adaptations were applied to handle with spatial-time series. In fact, CSA is a data mining process that: prepares spatial-time series; partition and combine them into blocks; run a motif discovery algorithm in each block; aggregate candidate motifs; evaluate spatial-time constraints and apply a ranking technique. The constraints aim at evaluating whether a sequence can be considered a spatial-time motifs, and the rank technique considers the word representation and the sequence occurrences in spatial-time series.

The experimental evaluation was conducted using a seismic dataset from the Netherlands offshore, named F3 Block. Such dataset is widely used by researches to evaluate tools and studies in the seismic interpreting area. The analysis was divided into three stages.

The first stage aims at defining the best shape of the block configuration, established by combining $tslice$ and $sslide$, to explore seismic dataset. The evaluation measured the accuracy of each shape when compared both the ranking function and to the ground truth.

In the second stage, $alpha$ and $word$ parameters were tested keeping fixed the remaining parameters. The best ranked configuration was obtained using $word = 4$ and $alpha = 5$. The top ranked motif discovered four shapes. Two of these shapes characterized two seismic horizons, whereas the other two were not present in the ground-truth, but also corresponded to seismic horizons, according to a seismic specialist that we have contacted.

Finally, the main contribution of this work was the presentation of a novel approach to identify motifs in spatial-time series in seismic dataset. CSA was able to identify seismic horizons. The results of the experimental evaluation indicates a good accuracy when comparing against the ground truth. Additionally, the discovered motifs were ranked according to their relevance in finding seismic horizons.

As future works, it is possible to indicate some complementary analysis regarding the variations of parameters such σ and κ, evaluating the sensibility analysis. Another relevant parameter whose variation may be interesting to consider is the number of clusters. It can influence directly in the final ranking analysis. Different motif discovery algorithms, instead of Random Projection, can be analyzed as well. Moreover, it is also possible to explore different ranking functions that explore different shapes. Finally, an evaluation regarding overlapping sliding window could be investigated.

Appendix I Ranking Function for Seismic Dataset

This appendices contains a clustering background explaining the main methods for partitioning data in literature. It also describes the ranking function used to rank the spatial-time motifs. Such information are important to support the CSA algorithm and experiement analysis.

I.1 Clustering Background

Clustering is an important area in data mining and consists basically in partitioning a set of data in meaningful groups. It is defined as an unsupervised process since we do not need a previous labeled data to create the groups [Berkhin, 2006]. The clustering is done according to a criterion, property or model that can be observed in the data. Fahad et al. [2014] indicates five categories of clustering methods: (i) partitioning-based, (ii) hierarchical-based, (iii)density-based, (iv) grid-based, and (v) model-based.

Partitioning-based clustering divides data points into a number k of partitions and each partition is a cluster. This method has as requirements that each cluster shall have at least one observation and such observation cannot be in more than one cluster. The most common algorithm is the k-means [Berkhin, 2006]. Hierarchical-based where data are organized hierarchically according to the proximity obtained by intermediate nodes. An agglomerative approach, for example, may build clusterings starting with one observation for each cluster and continuously joining the most similar ones [Karypis et al., 1999].

Given a set of points in some space, it groups together points that are closely packed together (points with many nearby neighbors), marking as outliers points that lie alone in low-density regions (whose nearest neighbors are too far away)

Density-based clustering, such as DBSCAN, groups together points that are closely placed together (points with many nearby neighbors). A Density-based cluster is usually used when data is irregular, marking as outliers points that lie alone in low-density regions [Ester et al., 1996] .

The grid-based clustering approach uses a multi-resolution grid data structure. It partitions the object space into a finite number of cells that form a grid structure on which clustering are performed. Since it does not dependent on the number of data objects, it presents a fast processing time. However, it depends on the number of cells in each dimension where space is partitioned

[Hinneburg and Keim, 1999].

Model-based clustering, such as MCLUST, consists in optimizing the match between data and a specific shape model, which assumes that data has a probability distributions [Fraley and Raftery, 2002]. The main parameters in MCLUST are: number of clusters, distribution type (univariate, spherical, diagonal or ellipsoidal), volume (equal or variable), shape (equal or variable), and orientation (coordinate axis, equal or variable). The different combinations of such parameters results in different organizations and formats of clusters [Fraley and Raftery, 2002].

After validating the candidate motifs as spatial-time motifs, we can still have many of them. Commonly, it is important to present the top-k most relevant motifs found. In this way, we evaluate the dispersion of motif occurrences by applying a clustering method proposed in Fraley and Raftery [2006]. It is based on finite normal mixture modeling. It includes functions that combine model-based hierarchical clustering, EM for mixture estimation, and Bayesian Information Criterion (BIC) strategies for clustering, density estimation and discriminant analysis. Since we are interested in looking for motifs that have both spatial and time constraints, we choose a model that best fit an ellipsoidal shape, with variable volume, equal shape, and a horizontal orientation (VEE).

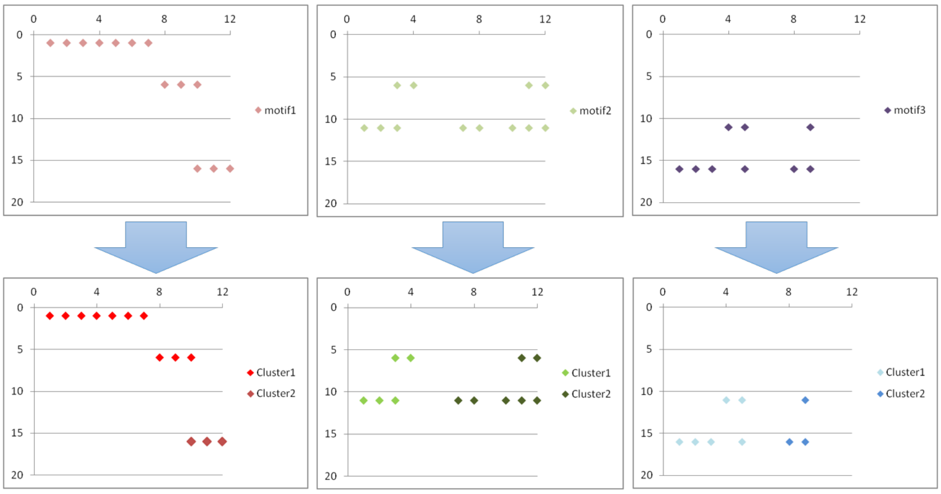


Figure I.1: Clustering

Figure I.1 presents the clustering result for motifs identified in our toy dataset. In the upper portion of Figure I.1, there are three motifs represented as a point in the initial position of occurrence. In each one, we apply the clustering method as described, considering the number of clusters fixed as 2. The clustering process divide each motif into 2 groups each one respecting the model characteristic according to equal orientation and shape but variable volume.

I.2 Ranking Function

After clustering step, we have now to rank the clusters. This step is important to drive the analysis to the most significant motif. For ranking, a function that considers the Global Occurrences

(GO), Spatial Occurrences (SO), Information Gain (IG) of the motif, and the root mean squared error (RMSE) for the elements inside clusters with respect to it mean value is applied. Equation I.1 presents the ranking function proposed.

$$rank_{motif} = \frac{\sum \frac{RMSE_{cluster(average)}}{(IG+1)*\frac{SO^2}{GO}}}{ncluster} \tag{I.1}$$

The rank sorts motifs by ascending value, put the ones with lowest rank values first. The objective of ranking function is to prioritize the lowest dispersion with wide spatial range data also considering the information gain. The GO and SO are parameters returned in motif discovering. The Information Gain is a classification for motif word according to the variability of data. For each letter of the alphabet considered in the analysis an associated an unitary incremented vector of values starting from zero.

For example, in the alphabet considered in the example [a,b,c,d,e] we consider the respective values [0,1,2,3,4]. In the motif word, the value of Information Gain is computed by making the absolute difference between each pair of letters combined. Consider motif1 (beeeb) as example. IG is computed by as $IG = |b-e|+|b-e|+|b-e|+|b-b|+|e-e|+|e-e|+|e-b|+|e-e|+|e-b|$. Converting the word to a correspondent value vector, we obtain [1,4,4,4,1] then: $IG = |1-4| + |1-4| + |1-4| + |1-1| + |4-4| + |4-4| + |4-1| + |4-4| + |4-1| = 12$.

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