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# Case Study of Spatial Pattern Description, Identification and Application Methodology

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**Abstract:** In this case study the authors created and tested a configurable and expandable spatial patterns (SP) description, identification, and application methodology (SPDIAM) and an SP identification algorithm. SPDIAM allows urban planning and design (UPD) practitioners to describe SP in a computerized manner, identify SP automatically and then apply them in the UPD domain. SPDIAM is based on the space syntax (SS) method and normalized spatial and non-spatial measures and can be used with the statistical social, economic, and environmental indicators, which are related to the urban sustainability and spatial capital. The goal of the case study experiment was to proof a concept of SPDIAM and to identify the rules and the values of the measures used for the SP identification. For this City Layout SP was identified in the vector data of 12 European, North American, and African cities. The experiment results confirmed that SPDIAM is appropriate to describe SP and identify them automatically. The use of the normalized measures enables the comparison of different SP and reduces the degree of the subjectivity of the UPD solutions. SPDIAM no longer relies on statistical information but forms SP based on the probabilistic complex modelling of a city, which lets SPDIAM indicate possible directions of SP future transformation. SPDIAM uses the newly offered measures CENTER and URBAN COMPACTNESS INDEX to identify SP automatically and can add quantitative and qualitative improvement to the spatial network analysis tools in Geographic Information Systems.

**Keywords:** Spatial Pattern, Pattern Recognition, Geographic Information System, Space Syntax, ESRI ArcGIS, depthmapX
**Categories:** I.5.1, I.5.2, I.5.4

# 1 Introduction

The methods of describing and identifying spatial patterns (SP) and various measures of shape, form, density, clustering and centrality include the domain-specific SP, such as patterns of towns, clustering of diseases, forms of physical features and shape of economic regions, and the universal SP methods without reference to the subject areas, such as fractals, tessellations, scale, map projections and measures of centrality [Getis and Paelinck 2004]. The most significant benefit of the application of these methods is that SP, such as urban and transportation models, buildings and city blocks (BCB) and land use (LU) patterns, area-class (AC) maps and road networks, can be used to predict, analyze and understand the environmental, social and economic processes using Geographic Information System (GIS).

The main objective of the urban planning and design (UPD) domain is the urban sustainability. Negotiating urban sustainability is a complex challenge, as its dimensions – economy, environment and society – are influenced by economic viability, prosperity, sociocultural cohesion and environmental impacts, but the decisions are made by generally diverse and contradicting interest groups [Hill et al. 2014]. Targeting this problem, the spatial configuration plays an important role in the different dimensions of urban sustainability [Hillier 2009] and adds additional value to the function of the city form, called spatial capital [Marcus 2007]. Space syntax (SS) can be used to analyze cities as networks of space and lets us observe how the networks relate to the functional patterns [Akkelies and Yamu 2018].

The UPD theorists evaluate and classify spatial phenomena differently, so there is no unified system of how to evaluate the UPD decisions for the urban areas. As the existing assessment tools provide an ex-post evaluation but often fail in the process of guiding a holistic approach to decision making, UPD practitioners need SP identification and prediction tools to find the most sustainable UPD solutions and get the recommendations for the UPD activities [Hill et al. 2014].

The authors of this case study created and tested configurable and expandable SP description, identification and application methodology (SPDIAM) together with SP identification algorithm that lets us describe SP in a computerized manner, identify SP automatically, and then to apply SP for the UPD solutions. Later in the text, the UPD practitioner (UPD P in diagrams) means the primary user and further developer of the SPDIAM.

In the background section, the analysis of the existing SP types, properties and analysis methods is presented with the examples of SP application in the UPD domain. In the methodology section, the static and dynamic views of SPDIAM using UML diagrams and spatial data preparation routine are discussed. For this purpose, a basic urban pattern UML class and data model [Germanaite et al. 2018] were extended and a description of the SP identification method was added. SS method was selected to detect SP in spatial data as it provides a set of theories and methods for the analysis of spatial configurations of all kinds and at all scales [Germanaite et al. 2018]. In the experiment section, the City Layout SP is described using the proposed UML class model, SS method and measures, and the value of the City Layout SP is identified in the vector data of 12 European, North American and African cities.

The case study of SPDIAM can be consistently reproduced by using the presented methodology, examples and the results of the practical experiment and the remarks about the spatial data preparation requirements.

## 2 Background of the Case Study

### 2.1 Spatial Pattern Description and Taxonomy

SP depicts a complex physical entity or any kind of structure, spatial distribution, or recurring feature that is represented as lines, areas, or bodies in a 2D or 3D map and can be described by pattern specification [Marshall and Gong 2009; Germanaite et al. 2018]. The identification of SP types, properties and measures can be performed by using urban geometry, topology, morphology and transformation. However, the urban system is a complex system that has powerful interrelationship among its components, therefore, the analysis of the separate components does not give the full picture of the complex system [Bölen and Kaya 2017].

Though SP can be regarded as abstract types that allow generalization and a better understanding of the spatial entities, there is no single correct way of classifying patterns or identifying pattern types [Marshall and Gong 2009; Germanaite et al. 2018]. The primary and the most comprehensive source of SP is Alexander [Alexander 1977] pattern language that describes ~250 patterns of the towns, buildings and structures. The oldest SP are urban models that nowadays can be defined as computer simulation models, combining theory, data, and algorithms, and which are classified into basic models (scale, analogue, conceptual); mathematical models (normative, probabilistic, optimizing) [Torrens 2000]; descriptive and analytical models [Seyed et al. 2015]. Land-use–transportation (LUT) models are used to predict demographic and economic measures of land-based activities; the differentiating factor between descriptive, analytical and LUT models is that the first two offer explanations how various urban phenomena emerge, but they do not analyze questions why those patterns materialize [Torrens 2000].

LU patterns allow us to analyze the form of different LU within the zone and find correlations between LU types and morphological properties of parcels and their spatial arrangement indexes [Seyed et al. 2015]. Point-based patterns identify the configuration of various types of residential and commercial LU. AC maps are referred to as categorical, nominal, data-driven and dasymetric maps, and represent a single phenomenon in a defined area or data-driven patterns [Williams and Wentz 2008].

Urban DNA study [Bölen and Kaya 2017] highlights that, although local characteristics of settlements differentiate the geometrical properties of urban patterns, universal principles exist in all patterns, and these properties have been analyzed through classifying spatial elements into buildings, building blocks and roads. BCB patterns refer to salient structure perceived individually or as a group in space, which can be at the city block scale divided into areas; in digital cartography, they can be identified as regular geometric shapes; and from the perspective of visual cognition, they can be classified into linear arrangements [Yan et al. 2019]. Road networks are complicated physical entities with numerous complex elements, such as multilane highways or airports with several runways [O'Sullivan 2014], thus SP of road networks play an important role in urban structure analysis [Yang et al. 2010].

Looking through the different SP types shows that although the taxonomy of the SP has been studied extensively, there remains a lack of a clear and unanimous criterion for SP formalization and automatic identification [Yan et al. 2019].

### 2.2 Spatial Pattern Properties

SP properties and analysis techniques depend on the chosen spatial data type and the space model. There are two basic data models for representing spatial data: raster and vector; space can be modelled as set-based, topological, Euclidean, metric and network space; and data inputs can have non-spatial and spatial attributes [Shekhar et al. 2011]. Therefore, SP is a multidimensional concept where each dimension requires a specific measuring rod [Getis and Paelinck 2004].

The description of all Alexander patterns has the same format: example of the pattern, context, problem, solution, connection to other patterns, but they do not share similar abstract properties. Urban models focus on spatial distribution of sites, structures of the city zones, direction and distance of the spatial distribution of urban activities; LUT models represent dynamic functionalities, spatial resolution, visual representation, scaling and zonal geography [Torrens 2000]. BCB patterns are using city blocks as spatial units for morphological properties to be derived [Yoshida and Omae 2005]. For LU patterns the morphological properties of urban features and socio-economic data are analyzed to find the relationships between urban features of different LU and corresponding socio-economic activities [Seyed et al. 2015]. AC maps data are frequently represented as irregular tessellation with categorical attributes or discrete objects. For road networks many different parameters (grid-like index; shape similarity; measures of consistent arrangement) to identify the SP are determined [Yang et al. 2010].

From the analysis of SP properties, the conclusion can be made that SP properties are very diverse and closely related to various statistical indicators that describe economic, social and environmental activities and processes affecting the urban form (statistical indicators). However, spatial properties of SP can be classified into four categories [Bölen and Kaya 2017]: 1) geometrical; 2) topological; 3) visibility and perception; 4) complexity.

### 2.3 Spatial Pattern Identification Techniques

Pattern recognition (PR) is a discipline researching description and classification methods of objects, described by a collection of mathematical, statistical, heuristic and inductive techniques, and executing the tasks on computers, but whether the decision made by the system is right mainly depends on the decision of the human expert [Dutt et al. 2012]. PR techniques depending upon the method used for data analysis and classification can be categorized into statistical and structural techniques, template matching, neural network approach, fuzzy and hybrid model, but a comparative view of the PR models shows that for the various domains different PR models or combination of models can be used [Asht and Dass 2012]. A PR system based on any PR method includes: 1) data pre-processing (feature selection and feature extraction); 2) pattern classification, that utilizes pattern analysis information to accomplish the classification [Dutt et al. 2012]. Structural PR is based on the language, which provides structural description of patterns in terms of pattern primitives and their composition

and the morphological interrelationships present within the data [Asht and Dass 2012; Subba and Eswara 2011].

The urban and transportation analytical models include analysis of form and structure of urban features based on an urban landscape model; physical structure of cities by identifying urban features from geographic data; topology of road networks and the grid-like patterns [Seyed et al. 2015]. The method to derive morphological properties uses urban landscape model and city blocks to derive and interpret morphological properties on a quantitative basis [Yoshida and Omae 2005] or for classifying residential and commercial LU defined through stepwise binary logistic models [Seyed et al. 2015]. Various authors have focused on understanding urban form using spatial metrics: fractal analysis is used to quantify irregularity in landscapes [Williams and Wentz 2008] and to analyze the growth pattern of metropolitan areas with the spatial socioeconomic indicators. In the TOSS method [Williams and Wentz 2008] pattern analysis is performed with a metric that describes the spatial distribution of a non-spatial attribute.

In automatic building pattern identification, the rule-based method is used and it consists of the representation of the spatial neighbor relationship using a mathematical graph; the measurement of the shapes to determine geometric or semantic homogeneities among a building group; the definition of the rules for a specific pattern [Yan et al. 2019]. The cellular automata model replaces the traditional mechanics of urban models with rule-based mechanisms, and the agent-based approach seeks to represent actors in a given system and has been used to simulate urban systems and traffic dynamics [Torrens 2000]. Another strategy for classifying building patterns is based on machine learning algorithms; these methods depend on the training of labelled examples rather than on manual rule definitions for patterns [Yan et al. 2019].

Techniques that examine the spatial distribution of objects are nearest neighbor and quadrat analysis; spatial tessellations and the application of Voronoi diagrams have been used to analyze the distribution pattern of points and spatial intensity [Williams and Wentz 2008]. The postal points methodology used in image pattern recognition is an effective way of integrating GIS data with remote sensing [Mesev 2005]. The graph-convolutional neural network model analyses graph-structured data representing grouped buildings, the pattern features are extracted by training labelled data and classifying building perceptual patterns [Yan et al. 2019]. For AC maps and categorical data join count statistic technique is most commonly used [Williams and Wentz 2008]. The topology analysis method [Yang et al. 2010] is used to recognize the SP of the road networks.

Extracting SP from spatial data sets is more difficult than extracting patterns from traditional numeric and categorical data due to the specific features of geographical data that preclude the use of general-purpose data mining algorithms; the data inputs for SP are also more complex because they include extended objects in vector representation and field data in regular or irregular tessellation [Shekhar et al. 2011]. Some SP such as Alexander patterns currently can be detected only by empirical observation, though they also should be referred as SP. Despite this, there are many qualitative (morphological and morphographic descriptions) and quantitative (network and fractal analysis) methods to identify SP [Marshall and Gong 2009; Germanaite et al. 2018].

### 2.4 Spatial Network Analysis and Space Syntax

The road network PR has a good potential to identify urban structure [Seyed et al. 2015], as the topology analysis method performs very well in detecting and classifying road networks, as it presents road networks by node-edge topology in GIS [Yang et al. 2010]. SS is a spatial network analysis (SNA) method that incorporates the urban morphology and offers not only the main variables of urban form (accessibility, density and diversity) [Marcus 2007] but is also related to the user preference and perception of open space [Bölen and Kaya 2017] and spatial capital. SS can operate the axial, convex or visibility graph analysis maps and provide a range of spatial property parameters derived from the connectivity graph (connectivity, control, integration and many others). SS analysis based on different centrality measures allows us to find scale-free properties using the normalized measures [Hillier et al. 2012]. SS angular segment analysis method adds improvement to the various integration analyses [Akkelies and Yamu 2018], as it is not affected by the 'segment' problem; also varying the metric radius tends to identify more intricate local structures than was possible with the axial analysis [Hillier 2009]. In 2018 SS OpenMapping project [Space Syntax Limited 2018] was released as spatial layout model of Great Britain, and it is an open resource for urban planning, real estate analysis and research, SS was already integrated into applications [Akkelies and Yamu 2018; Jiang 2015; Varoudis 2014].

### 2.5 Spatial Pattern Application

The general object of SP application in the UPD domain is the urban development that covers the planning and design subjects of various structures in different environments. More detailed cases of SP application can be defined as: 1) the evaluation of the possible impact on different urban sustainability dimensions; 2) the capture of the use-value and exchange-value of the spatial capital; 3) the measurement of urbanity, that represents urban form and generates variations in spatial accessibility and diversity [Marcus 2007].

There is no one sustainable UPD solution for the urban area because a perfect solution for the economic dimension will likely impact the environment or social dimensions, so these SP application tasks require a series of layers of information that could allow both a meta-level discussion or a description of specific issues [Hill et al. 2014]. For this reason, the indicator-based assessment model can be used to compare the urban sustainability or spatial capital levels of cities and regions, visualize the phenomena and highlight trends and indicators [Yigitcanlar and Dur 2010]. The exemplary statistical indicators that can be used to detect the level of urban sustainability or spatial capital values can be grouped into social (such as crime rate), economic (such as unemployment) and environment (such as energy use).

## 3 The Methodology of Case Study

### 3.1 SPDIAM Requirements

The background analysis of the case study indicated the fundamental SPDIAM requirements and highlighted the features that should be incorporated into the methodology while trying to add additional value to the existing SNA tools. SPDIAM has to:

- provide the structural and hierarchical description of SP using spatial (geometrical, topological, visibility and perception, complexity) and non-spatial properties and let the user describe new SP, SP identification methods and measures;
- use the automatic SP identification method based on the user-defined rules and measures;
- use the complex and normalized measures based on the whole spatial network information for comparing the spatial entities of different sizes;
- use the statistical indicators;
- analyze: 1) the structure of the spatial entity at the macro and micro level; 2) the weighing available options and the relevance of the proposed UPD solutions; 3) the possible impact on different urban sustainability dimensions and spatial capital;
- analyze several SP for one spatial entity data set and comparing SP visually;
- identify SP not only for the present spatial entity structure but also to predict how the spatial entity structure will transform in the future, using the same spatial entity data set;
- be configurable and expandable.

### 3.2 SPDIAM Static View

The gathering of SPDIAM requirements indicated that SPDIAM should be a structural, ruled-based PR method that provides SP structural description using spatial metapatterns and morphological relationships and uses SS topology and visibility analysis to identify SP of road network using GIS.

The static view of SPADIAM is defined by the UML class diagram (see Figure 1), that contains two principal SPDIAM concepts: the Pattern Identification Method class, which defines the specific Pattern class identification methods, and the Spatial Entity Analysis class, which defines user-created spatial entity analysis. SP identification algorithm is based on two main classes – the Form (defines different SP forms emerging in SP identification process) and the Structure (defines spatial structures of the Form class and is based on the spatial entity spatial data). The measures that will be used to estimate properties of SP form, structure and its elements are defined by the Form Measure class. The instances of the Form and the Structure class can be reused for other SP, using the same method, so it makes the SP description process simpler in the future.

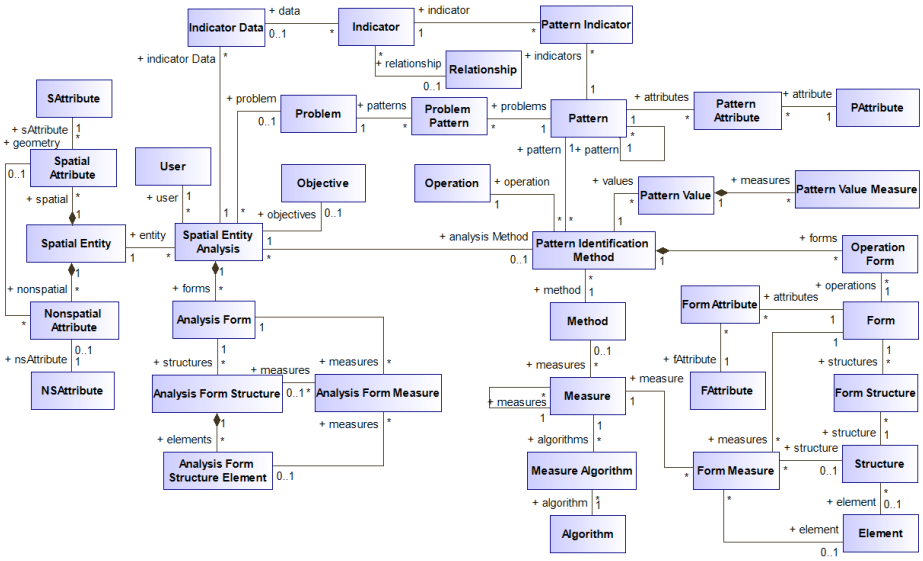


*Figure 1: Static view of SPDIAM*

### 3.3 SPDIAM Dynamic View

SPDIAM consists of 6 phases dedicated to defining the problem and describing, identifying, presenting, evaluating and applying SP (see Figure 2). In these phases, the elements from SPDIAM UML class diagram (see Figure 1) are used. It should be noted that the result of the SP evaluation in the Evaluation phase depends on UPD practitioner that uses SPDIAM, but the identified SP value is based on the quantifiable SS measures, so that it can be compared to the alternative UPD solutions.

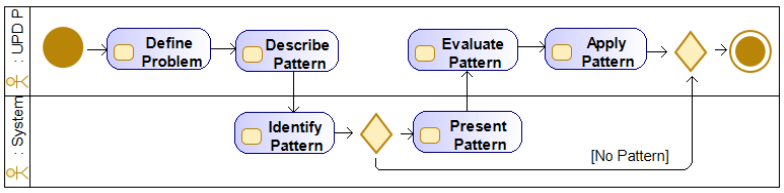


*Figure 2: Dynamic view of SPDIAM*

In the Definition phase (see Figure 3), the UPD practitioner describes the problem that will be linked to SP which can be used to resolve or to get recommendations about the problem. In the Description phase (see Figure 3), UPD practitioner creates an instance of the Pattern class and chooses the method that will be used for SP identification in the Identification phase. Then the operation for the method should be selected: The Pattern Identification operation identifies present SP of a spatial entity and the Pattern Transformation operation identifies the future changes of SP of a spatial entity. For each SP, method and operation the set of the Form class instances with the corresponding instances of the Structure and the Form Measure classes should be

created. The Description phase is ended by creating instances of the Pattern Value class which presents the values SP can acquire and, adding values to the instances of the Pattern Value Measure class that will be used to identify the real SP value.

In the Identification phase (see Figure 4) the instance of the Spatial Entity class is created based on the spatial entity spatial data with both spatial and non-spatial attributes. UPD practitioner can select the problem, SP to solve this problem (or leave it to all possible SP to be detected in the spatial entity data), the method that will be used to detect that SP (or use default method for each SP) and the operation. After this step, SP identification begins, and it depends on the selected method. The SS method workflow to identify the City Layout SP consists of creating different instances of the Analysis Form Structure class (segment graph, grid, and convex graph) and calculating the values for the instances of the Analysis Form Measure class. The last instance of the Analysis Form class, defined as the Operation Form, contains the Form Measure variable, which value can be compared to the variable of an instance of the Pattern Value Measure class, which instance values were set in the previous Description phase (for the SP identification algorithm see Figure 4). In the Presentation phase, if SP were identified, the system draws SP and present them to UPD practitioner in the form that later can be discussed with other users.

In the Evaluation and Application phases (see Figure 5), UPD practitioner can visually evaluate identified SP and select the statistical indicators (briefly described in section 2.5) to intersect with SP, at least at the visual level, though it is possible to add deeper and more complicated analysis in the future. In the Application phase, UPD practitioner can make the observations and set objectives that address the problem, described in the Definition phase, to memorize the results of SP analysis or to use them in future works.

### 3.4 SPDIAM Spatial Data Preparation Routine

SPDIAM spatial data preparation (SDP) routine depends on the method that is selected for SP analysis. SS method requires a vector data model, as the spatial network is formed of the road network layer. The various input spatial data sets can be gathered from the publicly available sources that make SPDIAM easy to customize for personal data needs. Some well-known examples of geodata sources include OpenStreetMap data sets [Geofabrik 2019], official government data sets [Geoportal LT 2019; Geoportal PL 2019] and free data sets [DIVA-GIS 2019]. In some cases, SP identification requires the administrative, geographic, or urban boundaries that will be used for the definition of the spatial entity area.

SDP routine consists of two steps: 1) preparation of the vector map, that later will be transformed to the segment graph, that will be operated by the SS method; 2) verification and correction of the vector map geometrical errors. These steps can be executed using the existing features of ESRI ArcGIS, QGIS or other GIS software. The automation of the repetitive tasks of SDP routine can be performed by ESRI ModelBuilder as it addresses a fundamental problem of GIS: the vast number of possible transformations and operations that can be performed on geographic data and the complexity in practice of many analysis sequences [Goodchild 2015]; and it enables users to develop custom processing models for the workflow and to include scripts within the models [Mihai and Marian 2016]. The repetitive tasks include: 1) clipping spatial entity area from the road network layer using appropriate boundaries; 2)

simplifying road lines and rationally reducing the total count of nodes in the graph to avoid the distortion in calculations due to an excessive number of nodes; 3) dissolving road lines; 4) splitting road intersections into individual segments and delete coincident line segments; 5) checking geometrical connectivity of the road network and correcting errors. For the error verification the in-build GIS features, GIS extensions or stand-alone applications can be used [Jiang 2015, ESRI 2019a; Gil et al 2015].

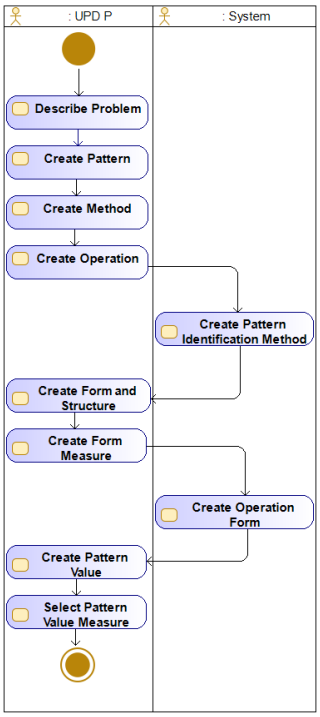


*Figure 3: Definition and Description phases*

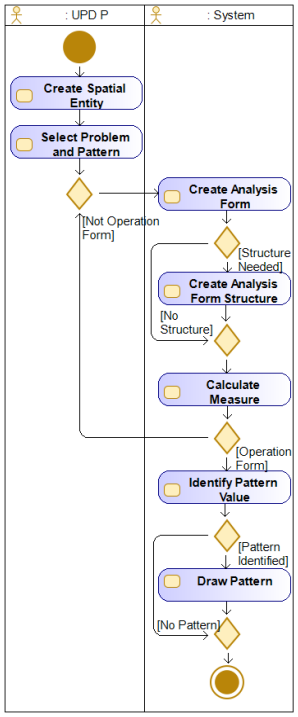


*Figure 4: Identification and Presentation phases*

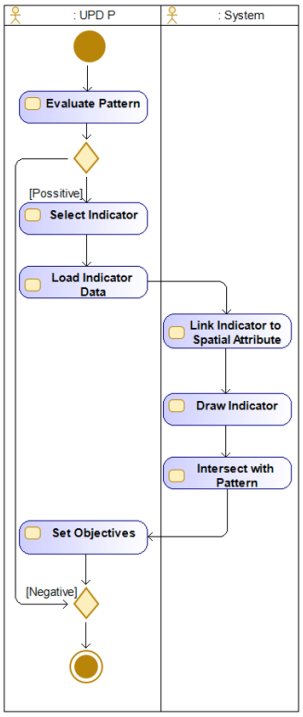


*Figure 5: Evaluation and Application phases*

## 4 The Experiment of Case Study

### 4.1 SPDIAM Spatial Data Preparation Experiment

For the SDP routine experiment 12 North American, European and African cities were selected by different scale, continents, layouts and historical circumstances reflecting the potential diversity of SP: Baltimore (USA), Chicago (USA), Gdansk (Poland), Helsinki (Finland), Ibadan (Nigeria), Kaunas (Lithuania), Klaipeda (Lithuania), Nice (France), Vilnius (Lithuania), Stockholm (Sweden), Bucharest (Romania), Ottawa (Canada). Also, two different types of spatial data sets were chosen: the government

provided spatial data sets [Geoportal LT 2019] and the OpenStreetMaps data sets [Geofabrik 2019]. ESRI ModelBuilder GIS model was created to test described SDP routine and to prepare spatial data for the SP identification. The GIS model was build using standard features of ESRI ArcMap (Clip (Analysis); Simplify Line (Cartography) using Simplification Tolerance 3 – 5 m; Dissolve (Data Management); Feature To Line (Data Management) with YX Tolerance 1 m; Export to CAD (Conversion)). GIS model was executed on the road networks of the selected cities and spatial data was prepared for the transformation to the segment graph. The prepared road networks geometrical correctness was tested using ESRI ArcGIS Data Reviewer, SS Kit for QGIS, and AxWoman [Jiang 2015].

The spatial data used for the experiment contained only roads data, e.g. bike and pedestrian paths (but not pedestrian streets) were removed from the data. The local coordinate system of the spatial entity was used to avoid data distortions [Projest 2017].

### 4.2 SPDIAM Definition and Description Phases Experiment

The UPD discipline usually solves the use cases of the urban development, so the urban development was selected as a general problem to proof the concept of SPDIAM and to illustrate the idea of SP. When looking for SP that would help to solve this problem, the classic concepts known as concentric-zone, sector, multiple-nuclei and linear urban development forms are often mentioned [Major 2018]. Based on them SP named City Layout was created together with the values it can acquire: Concentric-zone, Linear, Sector and Multi-nuclei. The instances of UML classes and explanatory attributes used to describe the City Layout SP and its values are presented in Table 1. The Pattern Configuration attribute contains information on what metapatterns and patterns the City Layout SP consist of, and later it can be used to build new SP based on the previously defined metapatterns and patterns.

For the City Layout SP identification, the SS method was defined by the Method class and SS measures used were defined by the Measure class as presented in Table 2. Apart the standard SS measures two new measures based on SS theory CENTER and URBAN COMPACTNESS INDEX (UCI) (see Table 2 and Table 3) were suggested and tested in the SPDIAM experiment, also standard SS measures NAIN and NACH measures (see Table 2) were suggested to be used in a new way to detect the probable transformation of the identified City Layout SP value in the future.

| **Instance_name : Class_name** | | | | | | |
|---|---|---|---|---|---|---|
| Instance_name : Pattern | Instance_name: Pattern Value | | Pattern Type : Pattern Attribute | Pattern Configuration : Pattern Attribute | Pattern Context : Pattern Attribute | Pattern Dimension : Pattern Attribute |
| **Attribute_name** | | | | | | |
| Name | Name | Image | Value | Value | Value | Value |
| **Attribute_value** | | | | | | |
| 'Center' | 'Center' |  | 'Metapattern' | NULL | NULL | NULL |
| 'Core–periphery' | 'Core–periphery' |  | 'Pattern' | 'Center, Periphery' | NULL | NULL |
| 'City Layout' | 'Concentric-zone' |  | 'Pattern' | 'Center, Core–periphery' | 'City, Regional, District' | 'Economic, Social' |
| | 'Linear' |  | | | | |
| | 'Sector' |  | | | | |
| | 'Multi-nuclei' |  | | | | |

*Table 1: Description of City Layout SP*

For the City Layout SP identification, the SS method was defined by the Method class and SS measures used were defined by the Measure class as presented in Table 2. Apart the standard SS measures two new measures based on SS theory CENTER and URBAN COMPACTNESS INDEX (UCI) (see Table 2 and Table 3) were suggested and tested in the SPDIAM experiment, also standard SS measures NAIN and NACH measures (see Table 2) were suggested to be used in a new way to detect the probable transformation of the identified City Layout SP value in the future.

| **Instance_name : Class_name** | | | |
|---|---|---|---|
| Instance_name : Measure | | | |
| **Attribute_name** | | | |
| Name | Formula | Component | Description |
| **Attribute_value** | | | |
| 'r'; 'k'; 'm' | 'INPUT' | NULL | 'Radius in meters'; 'Radius-from in meters'; 'Radius-to in meters' |
| 'c'; '$n_y$'; '$cn_y$' | 'MAP VARIABLE' | NULL; 'r x'; 'c, x' | 'Grid cell'; 'Segment in radius r from node x'; 'Segment in grid cell x' |
| '$d_{xy}$'; '$\Sigma_y$'; '$\Sigma_{yz}$' '$\Sigma_{zy}$'; '$g_{yz}$' | 'MAP VARIABLE' | 'x, y'; 'x, y'; 'x, y, z'; 'x, y, z'; 'x, y, z' | 'Distance from node x to node y'; 'Sum of the distances from x to y'; 'Sum of all shortest trips from y to z through x'; 'Sum of all shortest trips from z to y through x'; 'Count of shortest trips between y and z through x' |
| 'NC' | '$\Sigma_r$ $n_y$' | 'r, $n_y$' | Node Count at radius r' |
| 'Cell NC' | '$\Sigma_c$ $cn_y$' | 'c, $cn_y$' | Node Count in grid cell c' |
| 'MR r' | '$\Sigma_r$ $d_{xy}$' | 'r, $d_{xy}$' | 'Length of the reachable street length within radius' |
| 'ATD' | '$\Sigma_y$ MIN $d_{xy}$' | 'MIN $d_{xy}$' | 'Angular Total Depth of node x' |
| 'AIN' | 'NC^2 / ATD' | 'NC, ATD' | 'Angular Integration' |
| 'CENTER' | 'AIN * MR 1500' | 'AIN, MR 1500' | 'Center positioning' |
| 'MEAN CENTER GRID CELL' | '$\Sigma_c$ MEAN CENTER / Cell NC' | 'c, MEAN CENTER, Cell NC' | 'Mean CENTER value of the segments in grid cell' |
| 'ACH' | '$\Sigma_y$ $\Sigma_z$ $g_{yz}$' | 'y, z, $g_{yz}$' | 'Angular Choice' |
| 'NAIN' | 'NC^1.2/ ATD' | 'NC' | 'Normalized Angular Integration' |
| 'NACH' | 'log (ACH + 1) / log (ATD + 3) ' | 'ACH, ATD' | 'Normalized Angular Choice' |
| 'UCI' | 'MIN ATD Line – MIN ATD Circle / MIN ATD Line – MIN ATD Structure' | 'MIN ATD Line, MIN ATD Structure, MIN ATD Circle' | 'Urban Compactness Index' |

*Table 2: SS measures for the City Layout SP identification and transformation*

In Table 3 the instances of the Form and the Structure class with corresponding instances of the Form Measure class are presented together with the instances of the Operation class. SPDIAM reuses the same Form, Structure and Measure instances for the different SP identification operations.

| Instance_name : Class_name | | | | |
|---|---|---|---|---|
| *Instance_name* : Form | *Instance_name* : Structure | | *Instance_name* : Form Measure | *Instance_name* :Operation |
| Attribute_name | | | | |
| Name | Type | Variant | Name | Type |
| Attribute_value | | | | |
| 'Spatial Network' | 'Spatial Network' | 'Structure' | NULL | 'Pattern Identification', 'Pattern Transformation' |
| 'Segment Network' | 'Segment Graph' | 'Structure' | 'CENTER' | |
| 'Area' | 'Grid' | 'Structure' | 'MEAN CENTER GRID CELL' | 'Pattern Identification' |
| 'Zone' | ‘Grid' | 'Structure' | 'ZONE COUNT', 'ELEMENT ZONE' | |
| 'Center Zone' | 'Grid' | 'Structure' | 'ELEMENT ZONE' | |
| 'Center Configuration' | 'Convex Graph' | 'Structure' 'Line', 'Circle' | 'PART COUNT', 'PART SIZE', 'MIN ATD' | |
| 'Center Layout' | 'Grid' | 'Structure' | 'UCI' | |
| 'Future Center Layout' | 'Segment Graph' | 'Structure' | 'NAIN', 'NACH' | 'Pattern Transformation' |

*Table 3: Forms and structures for the City Layout SP*

### 4.3 SPDIAM Identification and Presentation Phases Experiment

The goal of the City Layout SP identification experiment was to identify the rules and the values of the measures used for the SP identification. The experiment was conducted on the 12 cities road network data using ESRI ArcMap (10.3) and depthmapX (0.6.0.). The road network was converted to the segment graph and CENTER measure was calculated using depthmapX. Then graph map was imported to ESRI ArcMap, the grid was created and MEAN CENTER GRID CELL measure was calculated. Based on the MEAN CENTER GRID CELL values the area of a spatial entity was classified into zones by Jenks' Natural Breaks algorithm. The grid zone with the highest centre values was chosen as the presentation of the City Layout SP and imported back to depthmapX. Here the convex graph was created, and its segments were linked with the closest accessible neighborhood nodes, then ATD measure was calculated for the three variants of Structure class instance: the real, the most compact and the least compact structures of a spatial entity. Then UCI measure was calculated and based on its value Pattern Value for the City Layout SP was identified. The calculated SS measures were displayed on the map using ESRI ArcMap to present the instances of the Analysis Form Structure class. In Figure 6 five instances of the Analyses Form Structure class together with the set of raw data of Kaunas city are presented to illustrate, how the spatial entity’s form and structure (listed in Table 3) evolves through the City Layout SP identification experiment.

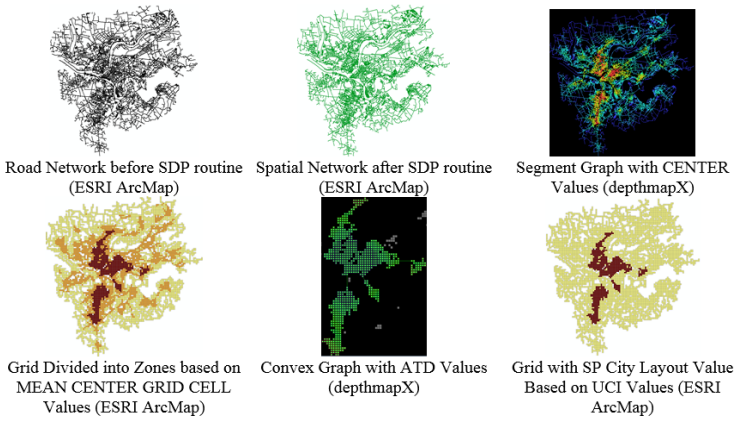


*Figure 6: Instances of the Analysis Form Structure class of Kaunas*

The visual representation of the City Layout SP in USA, Europe and Africa cities are presented in Figure 7 and the numerical results of SPDIAM experiment are explained in Table 4.

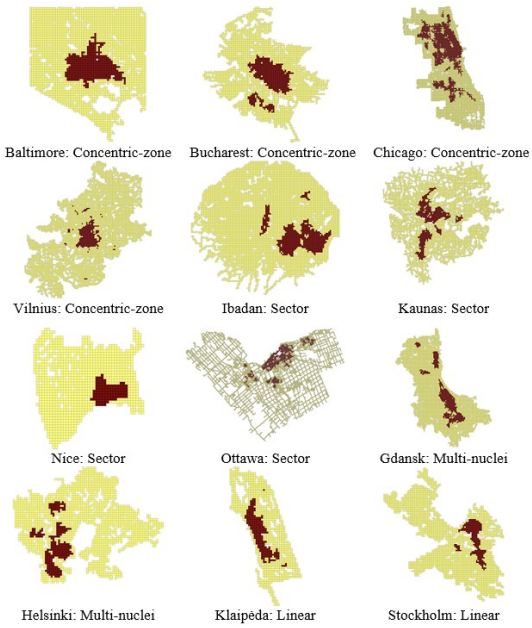


*Figure 7: The City Layout SP in USA, Europe and Africa cities*

The Pattern Value class measures UCI and PART COUNT are defined by UPD practitioner and used to identify SP Pattern Value: 1) if 0.9 >= UCI <= 0.95 (maximum scattered form of the center) and PART COUNT >= 1, then Pattern Value = Linear (Klaipeda); 2) if 0.9 >= UCI <= 0.95 and PART COUNT >= 2 (parts are similar in size, spaced apart), then Pattern Value = Multi-nuclei (Gdansk, Helsinki); 3) if 0.951 >= UCI <= 0.979 and PART COUNT >= 0 (one part is non-compact (Nice) or one part of several is significantly dominant (Ibadan, Kaunas, Ottawa)), then Pattern Value = Sector; 4) if 0.98 >= UCI <= 1.0 and PART COUNT >= 0 (one part is compact (Baltimore, Vilnius) or dominant or several satellite parts are small and non-competing (Chicago)), then Pattern Value = Concentric-zone.

| **Instance_name : Class_name** | | | | | |
|---|---|---|---|---|---|
| *Instance_name* : Pattern Value | *Instance_name* : Measure | *Instance_name* : Patern Value Measure | | *Instance_name* : Spatial Entity | *Instance_name* : Analysis Form Measure |
| **Attribute_name** | | | | | |
| Name | Name | Value Range Bottom | Value Range Top | Name | Measure Value |
| **Attribute_value** | | | | | |
| 'Concentric-zone' | 'UCI' | 0,98 | 1 | 'Baltimore' | 0.995036 |
| | | | | 'Bucharest' | 0.986749 |
| | | | | 'Vilnius' | 0.98435 |
| | | | | 'Chicago' | 0.981303 |
| | 'PART COUNT' | NULL | NULL | 'Baltimore' | 0 |
| | | | | 'Bucharest' | 2 |
| | | | | 'Vilnius' | 0 |
| | | | | 'Chicago' | 5 |
| 'Sector' | 'UCI' | 0,951 | 0,979 | 'Ibadan' | 0.976406 |
| | | | | 'Nice' | 0.974596 |
| | | | | 'Ottawa' | 0.966274 |
| | | | | 'Kaunas' | 0.959669 |
| | 'PART COUNT' | NULL | NULL | 'Ibadan' | 2 |
| | | | | 'Nice' | 0 |
| | | | | 'Ottawa' | 8 |
| | | | | 'Kaunas' | 3 |
| 'Multi-nuclei' | 'UCI' | 0,9 | 0,95 | 'Gdansk' | 0.923935 |
| | | | | 'Helsinki' | 0.920774 |
| | PART COUNT | 2 | NULL | 'Gdansk' | 2 |
| | | | | 'Helsinki' | 2 |
| 'Linear' | 'UCI' | 0,9 | 0,95 | 'Klaipeda' | 0.904954 |
| | | | | 'Stockholm' | 0.904458 |
| | PART COUNT | 0 | 1 | 'Klaipeda' | 0 |
| | | | | 'Stockholm' | 1 |

*Table 4: Ranges of the City Layout SP measures and experimentally obtained values*

### 4.4 SPDIAM Evaluation and Application Phases Experiment

In the Evaluation phase, the obtained City Layout SP values of the 12 cities were visually evaluated by UPD practitioner. The first insight was, that SPDIAM can be used for the automatic SP identification as the detected City Layout SP values match the empirically observed urban models, for example, Chicago is known as a Concentric Zones city, Gdansk is a Linear city and etc. Second, the improvement to the City Layout SP can be done by detailing the difference between the values of the measures that would help to highlight trends in the city layouts. Third, it is possible to transform the UCI measure scale and meaningfully use all values from 0 to 1.

In the Application phase, the identified City Layout SP was used for the setting of the objectives that can help to solve the previously defined *urban development* problem. The Sector City Layout SP and ATD measure values were intersected with the Kaunas street network and statistical data of the commercial entities (see Figures 8 and 9). It shows the definite correlation: 67 % of all Kaunas commercial entities are distributed in the area of the identified City Layout SP which covers 37 % of whole Kaunas territory. That presence of the commercial entities is related to the most active and economically important parts of the city. It should be noted when planning the new infrastructure or defining the existing economic and social attraction of the city centre areas together with their desired expanding directions. As the Spatial Layout SP value for Kaunas is Sector, the objectives for Kaunas urban development should be directed towards increasing the accessibility and integration of city spaces, and the City Layout SP can help to emphasize it. The experiment of SP Application phase proved that statistical indicators can be used not only to get insights about the UPD domain, but also to verify the identified SP. For the best precision, the same type of the spatial data should be used for the spatial entity and the statistical indicators.

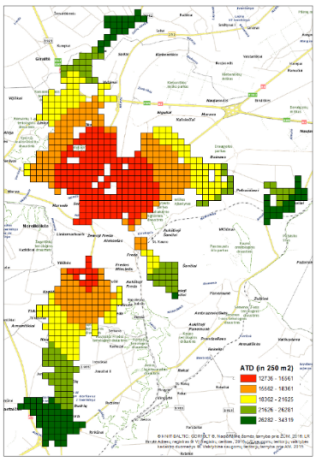


*Figure 8: City Layout SP of Kaunas with ATD values*

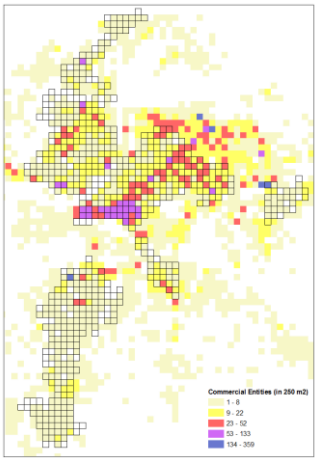


*Figure 9: City Layout SP of Kaunas with commercial entities data*

### 4.5 Other Methods and Tools Comparison

For now, there is no one formalized SP identification method, thus UPD practitioners tend to identify SP visually, based on observations or statistical data, and only some of the SP identification methods are using the bottom-up modelling principle. In this section, the features of the most common SP identification methods are compared, from which the conclusion can be made that SPDIAM is making a step forward from the previously known SP identification methods.

Alexander patterns can be used to describe the variety of SP, but they are based on the observation and comparison of the city and its processes; that leads to the subjective determination of SP, and only a few Alexander patterns cover the whole city; most of them are dedicated to the individual spaces.

Geographer models can cover the whole city and they are based on the detailed statistical information of the certain functional objects. Geographer models can define the territories with the different characteristics and use the configuration of the territory to define SP, which explains the functional features of the city. On the other hand, geographer models lack details and can be used for modelling only the generalized, explanatory SP and they are also based on the top-down modelling principle.

Fractal analysis is based on the examination of the urban morphology aspects, that can be associated with the functional features of the city. Also, it uses multi-hierarchy to define the urban morphology aspects related to the functional properties and the potential of the city. However, this method completely elucidates the Euclidean form and it is difficult to associate with Alexander patterns and geographer models.

The main advantage of cellular automata, agent-based modelling and SS methods is that they are all based on the bottom-up modelling principle, that conforms to the complex nature of the city. These methods are probabilistic and can be used to model and predict self-organizing SP. Additionally, SS also can cover the whole city due to the links that are modelled between the road segments. On the other hand, it is difficult to associate the cellular automata, agent-based and SS models with Alexander patterns or geographer models.

SPDIAM method shares all advantages of the methods described above and can be used to compare different SP using the normalized SS values further reducing the subjectivity of the method. SPDIAM no longer relies on the statistical information and forms SP based on the probabilistic complex model of the city. SPDIAM can be used to associate the shape of the territory with the geographer models using the bottom-up modelling principle. SPDIAM indicates a possible direction of SP transformation, which is consistent with the probabilistic nature of the SS model. The disadvantage of this method is that SPDIAM requires practical experiments to acquire the values of SP for SP identification.

The analysis of SNA tools [Cardiff University 2019; City Form Lab 2016; ESRI 2019b; Gerlt 2018; Space Syntax Laboratory 2019; Urban Design Studies Unit 2012; Varoudis 2014] by comparing features, provided measures and techniques of network vertices mapping reveals that SPDIAM also offers the improvements to the quantitative and qualitative characteristics of existing SNA tools. Analyzed SNA tools operate with the basic measures of centrality, thus the aggregated and complex measures that would allow us to combine basic measures and to define new ones would improve the characteristics of SNA tools. Though QGIS Space Syntax Toolkit (using depthmapX) already works with normalized measures, it is not yet widely used; the method that

would use normalized measures in SNA calculations would enable the comparison of the spatial entities of different sizes(?) and between their elements. ESRI ArcGIS Network analyst focuses on the analysis of the individual networks vertices rather than the whole network; most SNA tools use the whole network information, but do not use the normalized measures; the method that could offer both will also improve the characteristics of the existing SNA tools. Analyzed SNA tools do not offer capabilities for the user to describe SP, SP identification methods and measures; this can be seen as the main quantitative and qualitative improvement to SNA tools family.

## 5 Conclusions

SP are simplified spatial models that associate the spatial configuration with the functional features of the city and can be used to solve the urban development and sustainability problems or to evaluate the spatial capital of the city areas. In this case study, the authors created and tested the configurable and expandable SPDIAM, which can be defined as a structural, ruled-based PR method, and the SP identification algorithm based on the SS topology and visibility analysis. SPDIAM allows UPD practitioners to describe SP in a computerized manner, identify SP automatically and then apply SP for the UPD solutions. SPDIAM is based on the proposed normalized spatial and non-spatial measures and can be used with the statistical indicators, which are related to the complex urban concepts. SPDIAM can be used at the macro level to evaluate the impact of the UPD decisions on the sustainable development and at the micro-level to find the synergy or competition of the functional areas or the model's preference for the multifunctionality or specialization.

In the experiment section, the City Layout SP was described using the proposed UML class model, SS method and measures and then identified in the spatial vector data of 12 European, North American and African cities. The experiment results confirm that SPDIAM is appropriate to describe SP and identify them automatically; the use of the normalized measures enables SP comparison with each other and reduces the degree of subjectivity; SPDIAM no longer relies on the statistical information, but forms SP by the probabilistic complex modelling of a city and then associates territories with SP; SPDIAM indicates a possible direction of the future SP transformation, which is consistent with the probabilistic nature of the SS model and can be used for the evaluation of UPD plans of urban areas.

The difference with the similar methods and researches is that they are often limited to analyzing the local spatial relationships as a basis but do not seek synergies with the models at the higher hierarchical levels. SPDIAM assesses the city at many scales and levels, that are inseparable and interrelated, and can be modelled from the bottom-up to the higher hierarchical level by associating it with Alexander patterns or geographical models, and thus giving these known SP a complex basis and accessing the top-down models from the bottom-up side. SPDIAM displays the scientific novelty as it uses the newly offered measures CENTER and URBAN COMPACTNESS INDEX to identify SP automatically and, in summary, can add the quantitative and qualitative improvement to SNA tools family.

## 6 Future Work

In the future, SPDIAM can be improved by detailing the difference between SP values that would help to highlight trends in SP layouts. The statistical indicators can be used to verify the identified SP, as the correlation between the two can be observed. SPDIAM can be expanded from SS towards other spatial analysis methods like fractal analysis. The statistical indicators for the future spatial entity settlements can be applied by using the assigned urban data models.

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