Online Spatio-Temporal Risk Assessment for Intelligent Transportation Systems

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***Abstract*—Due to modern pervasive wireless technologies and high-performance monitoring systems, the spatio-temporal information plays an important role in areas such as intelligent transportation systems (ITS), surveillance, scheduling, planning or industrial automation. The security or criminal/terrorist threat prevention in modern ITS, are one of today's most relevant concerns. This paper presents an algorithm for online spatio-temporal risk assessment in urban environments. In its first phase, the algorithm uses online Nearest Neighbor Clustering (NNC) algorithm to identify a set of significant places. In the second phase, a fuzzy inference engine is employed to quantify the level of risk that each significant place poses to the place of interest (e.g. vehicle, person, building or an object of high assets). The contributions of the presented algorithm are as follows: i) recognition and extraction of the set of the most significant places, ii) dynamic adaptation of the solution to time-dependent traffic distributions, iii) parametric control by adjusting geographical proximity threshold, significance threshold and discount factor, and iv) online risk assessment. The performance of the algorithm was demonstrated on a problem of traffic density estimation and risk assessment in virtual urban environment.**

***Index Terms*— Clustering, Fuzzy Control, Traffic Analysis, Pattern Recognition, Risk Assessment**

I. INTRODUCTION

MODERN Intelligent Transportation Systems (ITS) rely heavily on processing spatio-temporal information. This information is then used to predict the future traffic densities and flow [1]-[5], determine road congestion patterns [6], generate evacuation plans [7] or evaluate security risks [8].

Modern pervasive wireless technologies as well as high-performance monitoring systems are capable of collecting the spatio-temporal information. Typically, in case of an ITS the amount of input information is overwhelming. Moreover, previous input data soon become obsolete in dynamic environments. Hence, the online analysis of the obtained dynamic spatio-temporal data constitutes a complex problem.

In general, the traffic distribution can be monitored by three types of sensors: point, space and mobile sensors [2]. The spatio-temporal information from mobile sensors, such as GPS is considered in this paper [9]. For example, GPS devices mounted on 4000 and 100 taxis have been used in Shanghai and in Guanhzhou City, respectively [18], [19]. Similarly, buses equipped with GPS mobile sensors were utilized for data collection in [20]. In these applications the collected data are utilized for traffic status monitoring and for travel time prediction.

Computational intelligence techniques have recently drawn significant attention among ITS researchers [1], [4], [6], [10]-[12]. Accurate models for traffic prediction and modeling can be constructed using machine learning paradigms, such as artificial neural networks, fuzzy inference systems or clustering techniques. For instance, distributed clustering algorithms for data-gathering in mobile sensor network minimizing the energy dissipation were presented in [21]. Grid-based interpolation of data from mobile distributed sensors with objective function minimization was used for nuclear threat detection [23]. The Risk-adjusted Nearest Neighbor Hierarchical clustering (RNNH) [22] adjusts the clustering parameters based on the kernel densities of the baseline factors applied to a grid. When compared to the reviewed work [21]-[23], the algorithm presented in this manuscript combines clustering with Fuzzy Inference System (FIS) into an online hybrid algorithm for ITS risk assessment. Instead of the kernel-based adjustment of RNNH control parameters, the presented algorithm uses fast flat-partition NNC, which is then adjusted by the FIS.

The presented algorithm is based on the previously developed DSTiPE algorithm [13]. It computes an online solution to the problem of pattern extraction from dynamic spatio-temporal input data and its risk assessment. First, the algorithm uses a modified online Nearest Neighbor Clustering (NNC) algorithm to extract the set of significant places. A discount factor is introduced to model the significance decay for continuously aging previous information. In order to maintain computationally tractable solution, a significance threshold is proposed to prune the solution between consecutive iterations. In the second phase, FIS is utilized to quantify the level of risk that each significant place poses to the object of interest.

The presented algorithm is applicable to many areas of ITS. It enhances the input data for traffic prediction and traffic flow modeling algorithms [1]-[5], [8], [10]. Further, the extracted patterns of dangerous places are essential for accurate itinerary planning [14]. The computed risk assessment can be utilized by a traffic flow control system, by a container terminal management or by an evacuation planner [7], [15].

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The rest of the paper is organized as follows. Section II provides review of the NNC algorithm and the FIS. Section III describes the online spatio-temporal extraction of significant places. The fuzzy risk assessment of significant places is discusses in Section IV. Experimental results are reported in Section V and the conclusion is given in Section VI.

II. BACKGROUND

This section gives a brief overview of the Nearest Neighbor Clustering (NNC) algorithm and the Fuzzy Inference System (FIS).

A. Nearest Neighbor Clustering

The NNC algorithm constitutes an unsupervised clustering technique, which does not make any upfront assumptions on the number of clusters. Instead, the clustering process is driven by the established maximum cluster radius parameter. This approach is especially suitable for traffic pattern analysis, where the radius can be set according to the desired spatial resolution of the solution.

The input dataset X composed of N patterns can be denoted as:

$$X = \{\vec{x}_1, \ldots, \vec{x}_N\},\ \vec{x}_i \in \Re^m \tag{1}$$

Here, m denotes the dimensionality of the problem. Hence, vector $\vec{x}_i$ can be written as $\vec{x}_i = \{x_i^1, \ldots, x_i^m\}$.

Each cluster is a prototype of similar instances, subject to a certain similarity measure (e.g. Euclidean distance). Each cluster is defined by its center of gravity (COG) and its weight - $\{\vec{c}, w\}$. The weight w reflects the number of patterns previously assigned to particular cluster. Cluster P_i can be denoted as:

$$P_i = \{\vec{c}_i, w_i\},\ \vec{c}_i \in \Re^m, w_i \in \Re^+ \tag{2}$$

The NNC algorithm is initialized by creating a starting cluster P_1 at the location of the first input pattern $\vec{x}_1$. Next, input patterns from dataset X are sequentially selected and their prototypes are determined. Considering input pattern $\vec{x}_i$, the nearest cluster P_a is determined as follows:

$$dist(\vec{c}_a, \vec{x}_i) = \min_j \sqrt{\left(c_j^1 - x_i^1\right)^2 + \ldots + \left(c_j^m - x_i^m\right)^2},\ j = 1 \ldots C \tag{3}$$

Here, C denotes the number of currently identified clusters. Using the maximum cluster radius parameter - rad, the input pattern $\vec{x}_i$ is assigned to cluster P_a if $dist(\vec{c}_a, \vec{x}_i) \le rad$. Cluster P_a is then updated as:

$$\vec{c}_a = \frac{w_a \vec{c}_a + \vec{x}_i}{w_a + 1},\ w_a = w_a + 1 \tag{4}$$

If $dist(\vec{c}_a, \vec{x}_i) > rad$, a new cluster is created at the location of input pattern $\vec{x}_i$, and its weight is set to 1.

B. Fuzzy Inference System

Fuzzy logic became popular in many engineering areas due to its ability to cope with linguistic uncertainty originating in the imprecise and vague meaning of words. The core of the FIS consists of linguistic fuzzy rules. Hence, two main advantages of FIS can be recognized: i) the ability to incorporate the human operator's experience and knowledge, and ii) the interpretability of the system in a human understandable form.

In general, FIS is composed of four main parts – input fuzzification, fuzzy inference engine, fuzzy rule base and output defuzzification. Here, the Mamdani FIS is considered. This Mamdani type of FIS uses output fuzzy sets for the consequent part of each fuzzy rule. The fuzzy rule base is populated with fuzzy linguistic rules R_k in the implicative form as:

Rule R_k: **IF** x_1 is A_1^k **AND** … **AND** x_n is A_n^k **THEN** y_k is B^k (5)

Here, symbol B^k denotes the output fuzzy set and n is the dimensionality of the input.

Using the multiplication product as the t-norm operator, the degree of fulfillment of the rule R_k can be calculated as:

$$\mu_{R_k}(\vec{x}) = \prod_{i=1}^{n} \mu_{A_i^k}(x_i) \tag{6}$$

The crisp output y is obtained by applying the weighted average defuzzification:

$$y = \frac{\sum_{i=1}^{K} \mu_{R_i}(\vec{x})\, y_i}{\sum_{i=1}^{K} \mu_{R_i}(\vec{x})} \tag{7}$$

Here, symbol K denotes the total number of fuzzy rules in the system and y_i denotes the mean of the output fuzzy set.

III. ONLINE EXTRACTION OF SPATIO-TEMPORAL SIGNIFICANT PLACES

The presented algorithm is composed of two phases. In the first phase, a set of significant places is constructed. In the second phase, the significant places are evaluated for the level of risk they are posing to the object of interest.

The previously developed DSTiPE algorithm, determines the set of significant places by clustering the input patterns in the combined spatio-temporal domain [13]. The calculated model was based on a static input data and provided a stationary fixed solution.

However, in many applications an online solution is required to track the dynamic input data. This paper presents an algorithm for tracking such dynamic time-dependent solutions. Unlike the previously published DSTiPE algorithm, the new algorithm does not work in the combined input-output space. Instead, it first discretizes the time domain and then analyzes the spatial data at particular time sample.

A. Spatio-Temporal Calculation of Significant Places

In this section, the concept of spatio-temporal significant place is formalized. Consider dataset X of input patterns $\vec{x}_i$, denoting a spatial location of objects of interest in the 2D Euclidean space. Hence, (1) can be written as:

$$X = \{\vec{x}_1, \ldots, \vec{x}_N\},\ \vec{x}_i \in \Re^2 \tag{8}$$

Upon expanding the computation to the time domain, the input vectors $\vec{x}_i$ as well as their number N can vary over time:

$$X(t) = \{\vec{x}_1(t), \ldots, \vec{x}_{N(t)}(t)\},\ \vec{x}_i(t) \in \Re^2 \tag{9}$$

The significance S of spatial location $\vec{c}_i$ can be defined as the total amount of time spent by the monitored objects at that location:

$$S(\vec{c}_i) = \int_{t \in T} \sum_{j=1}^{N(t)} f\left(\vec{c}_i, \vec{x}_j(t)\right) dt \tag{10}$$

Here, symbol T denotes the considered time interval and function f determines the presence of pattern $\vec{x}_j$ at location $\vec{c}_i$ at time t.

The significance of certain location $\vec{c}_i$ can be extended to a significance of certain cluster P_i. The radius of cluster P_i has to be taken into consideration. In case of the spatio-temporal pattern extraction, the established maximum cluster radius is expressed in form of the geographical proximity threshold δ. Any input pattern within the proximity δ of $\vec{c}_i$ contributes to the overall significance of cluster P_i.

$$S(P_i) = \int_{t \in T} \int_{\vec{p} \in \Omega} \sum_{j=1}^{N(t)} f\left(\vec{p}, \vec{x}_j(t)\right) d\vec{p}\ dt \tag{11}$$

Here symbol Ω denotes the sphere of influence of cluster P_i (defined by its COG $\vec{c}_i$ and the geographical proximity threshold δ) and function f determines the presence of input pattern $\vec{x}_j$ at certain location $\vec{p}$ at time t.

When analyzing the dynamic time-dependent traffic patterns the most recent available data provide the most significant information. In the presented model, the information gain of the input patterns decay as the events become older and do not reflect the current state any more. In (11) all available input patterns have the same influence on the solution; regardless of the time elapsed since they were recorded. This discrepancy is alleviated by introducing a discount factor $\lambda \in [0 \ldots 1]$. Then, the discounted significance S^* of cluster P_i can be determined as follows:

$$S^*(P_i) = \int_{t \in T} \int_{\vec{p} \in \Omega} \sum_{j=1}^{N(t)} f\left(\vec{p}, \vec{x}_j(t)\right) \lambda^{(\tau - t)}\ d\vec{p}\ dt \tag{12}$$

Here, symbol τ denotes the present time. The older the available information, the closer is the exponentiated discount factor λ to zero and the greater is the suppression of the influence of pattern $\vec{x}_j(t)$.

B. Online Spatio-Temporal Clustering Algorithm

This section presents an online spatio-temporal clustering algorithm, which constitutes an iterative solution to the integral form given in (12). It extends the original DSTiPE algorithm and computes a dynamic online solution [13]. Here, the time domain is discretized and the solution is continuously updated. Further, in order to keep the dynamic solution computationally tractable, pruning of insignificant places is introduced.

Consider an environment with freely moving objects. The behavior of these objects is studied during time interval T. Using time step Δt, the time domain can be discretized as:

$$T = \{t_0, t_1, \ldots t_\tau\},\ \ t_i = t_{i-1} + \Delta t \tag{13}$$

Observing the environment at time t_i yields a set of input patterns:

$$X(t_i) = \{\vec{x}_1(t_i), \ldots, \vec{x}_{N(t_i)}(t_i)\} \tag{14}$$

The algorithm maintains a set of significant places Q. Each significant place is denoted by a cluster P_i with its COG $\vec{c}_i$ and weight w_i. Three beforehand specified input parameters control the iterative computation: geographical proximity threshold δ, discount factor λ and significance threshold α.

The online spatio-temporal clustering algorithm utilizes the NNC algorithm and can be described as follows:

Initial Step: Start with an empty initial solution $Q(t_0) = \{\emptyset\}$.

Step 1: At time t_i record set $X(t_i)$ of $N(t_i)$ input patterns.

Step 2: Initialize the NNC algorithm with the set of clusters from the previous iteration $Q(t_{i-1})$. Apply the algorithm to the input dataset $X(t_i)$. Use the geographical proximity threshold δ as the maximum cluster radius.

Step 3: Prune the obtained solution $Q(t_i)$ by discarding insignificant clusters, subject to the significance threshold α:

$$Q(t_i) = \begin{cases} Q(t_i) \setminus P_j & \text{if } w_j < \alpha \\ Q(t_i) & \text{if } w_j \geq \alpha \end{cases},\ j = 1, \ldots, C(t_i) \tag{15}$$

Here $C(t_i)$ denotes the number of clusters at time t_i.

Step 4: Apply the discount factor λ to the weight of every cluster in the pruned solution $Q(t_i)$:

$$w_j = \lambda w_j\,,\ \ i = 1,\ldots,C(t_i) \qquad (16)$$

Step 5: Proceed to next time sample t_{i+1} and go to Step 1.

The solution of the integral equation (12) was decomposed into three parts. First, the spatial integration over cluster P_i is encoded directly in the NNC algorithm. Every input pattern that is within the geographical proximity δ of cluster P_i increases its weight and contributes to its significance. Second, the integration over time interval T is approximated by the iterative solution using the discretized time domain. Finally, the exponentiated discount factor λ is also handled by the iterative solution. Here, the weights of the clusters from the previous iterations are repeatedly multiplied by factor λ, thus leading to a continuous decay of the information weight.

The geographical proximity threshold δ should be set to the diameter of the areas of interest. The discount factor λ determines the rate at which old information is removed from the system. Values close to 1 should be used when older information is to be maintained in the solution. Lower values of λ result in fast adaptability of the solution and fast removal of the obsolete past information. Finally, the significance threshold α prunes the extracted clusters between the iterations and should be set according to the level of significance that is desirable in the solution. The actual values depend on the accumulated significance of clusters, which is

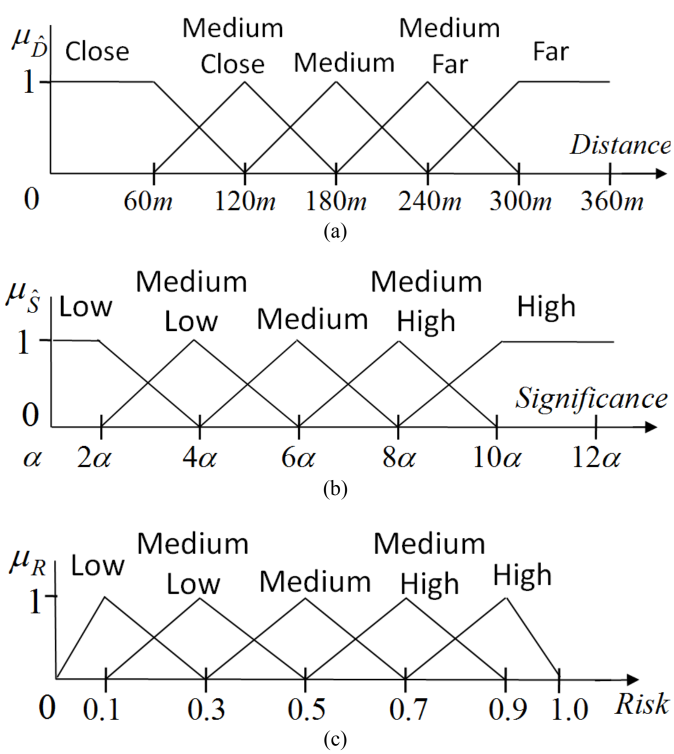


Fig. 1 Input fuzzy sets of concepts Distance (a) and Significance (b) and output fuzzy sets for the concept of Risk (c).

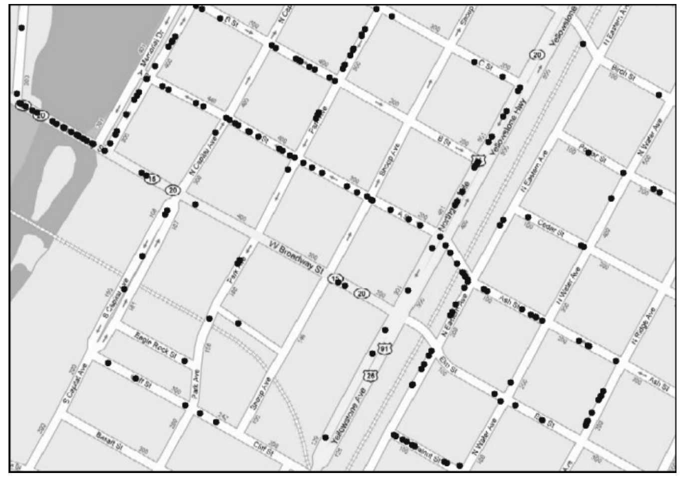


Fig. 2 Traffic simulation environment of downtown area of Idaho Falls, Idaho.

mainly governed by the amount of objects being monitored and their velocities with respect to the sampling rate of the environment.

It should be pointed out that the proposed solution to the online spatio-temporal clustering problem constitutes a flat partitioning approach. Hence, the algorithm does not directly provide the multi-resolution view of the problem available for hierarchical clustering methods. However, this flat partition approach was chosen because of the desire to design a dynamic algorithm capable of fast adaptability to time-dependent data. The flat partition was favored, because clusters need to be easily updated, inserted or removed, which is substantially more difficult with the hierarchical approach.

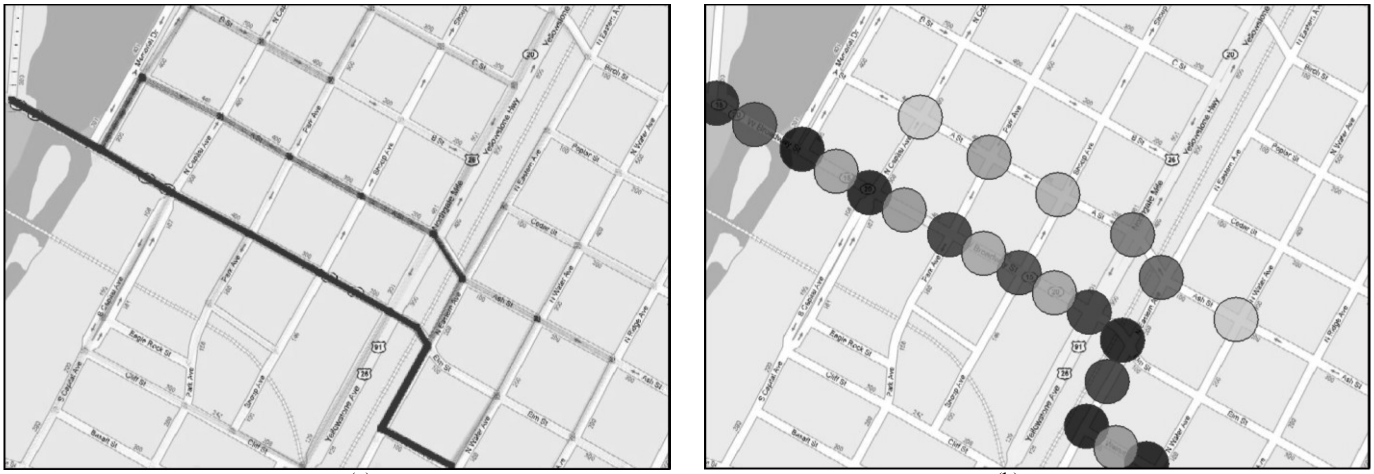
IV. Fuzzy Spatio-Temporal Risk Assessment

In the second phase of the presented algorithm, the risk level of individual significant places is evaluated.

The output of the first phase of the algorithm is a set of significant places. The potential risk of each significant place depends on the given problem. In the proposed algorithm, the risk of each significant place is assessed with respect to a certain object of interest (e.g. important building, secured location, crossroad, or a vehicle).

The presented algorithm uses FIS for a risk assessment of each significant place. The FIS was chosen for its implementation simplicity, computational inexpensiveness and ability to model non-linear multidimensional functions. Furthermore, unlike classic mathematical modeling techniques, the FIS can be conveniently designed using available expert's knowledge.

Two inputs were selected for the implemented FIS: 1) distance between the significant place and the object of interest 2) the significance of the place itself. The shorter the distance between the significant place and the object of interest, the more danger/risk is imposed on the object. The greater the significance of the significant place, the more risk it poses to the object of interest. Alternatively, other inputs can be used to fit the specific application. For instance, if the average traffic densities are available for the given



(a) (b)

Fig. 3 Histograms of traffic densities (a) and the set of extracted significant places (b).

(a) (b) (c)

Fig. 4 Set of extracted significant places for geographical proximity threshold 20 *meters* (a), 40 *meters* (b) and 60 *meters* (c).

environment, they could be used as an additional input for the FIS, reflecting the baseline traffic. This constitutes one of the main advantages of the implemented FIS, which can be easily extended to incorporate additional inputs.

Five evenly spaced triangular fuzzy sets were used to model the linguistic variable distance $\hat{D}$ (Close, Medium Close, Medium, Medium Far, Far) as well as the linguistic variable significance $\hat{S}$ (Low, Medium Low, Medium, Medium High, High). The output fuzzy sets were evenly spaced in the output domain *[0, 1]*. They are depicted in Fig. 1

The range of values of distance $\hat{D}$ is set according to the dimensions of the monitored environment. The range of values of significance $\hat{S}$ depends on the sampling rate of the environment. For the simplicity sake, $\hat{S}$ is denoted as a multiple of the significance threshold α , as in Fig. 1(b).

V. Experimental Results

Three test cases will be presented in this section to demonstrate the performance of the online dynamic solution as well as the parametric control of the algorithm.

A virtual model of the downtown of the city of Idaho Falls, Idaho was implemented as a testing environment for the presented algorithm. The application displays the urban environment based on the aerial map. Set of vehicles is freely moving through the streets. Each vehicle randomly chooses its destination from the set of accessible nodes using probability distribution defined by the user. The environment is sampled at equidistant time intervals, yielding a set of input patterns (each input pattern denotes the position of certain vehicle at the given time).

The presented online spatio-temporal clustering algorithm is used to extract the set of significant places and to maintain this set throughout the following iterations. An example of the virtual model of the urban environment with the simulated vehicles is shown in Fig. 2.

A. Significant Places Extraction

Fig. 3(a) shows an aerial view of the implemented urban environment. The actual traffic density is visualized by a grey scale histogram. The grey tone of the road symbolizes the density of the traffic. The darker the tone, the greater the density is. The main roads and crossroads with the most congested traffic are clearly visible.

Fig. 5 Dependency of the number of clusters on the values of the significance threshold and the discount factor.

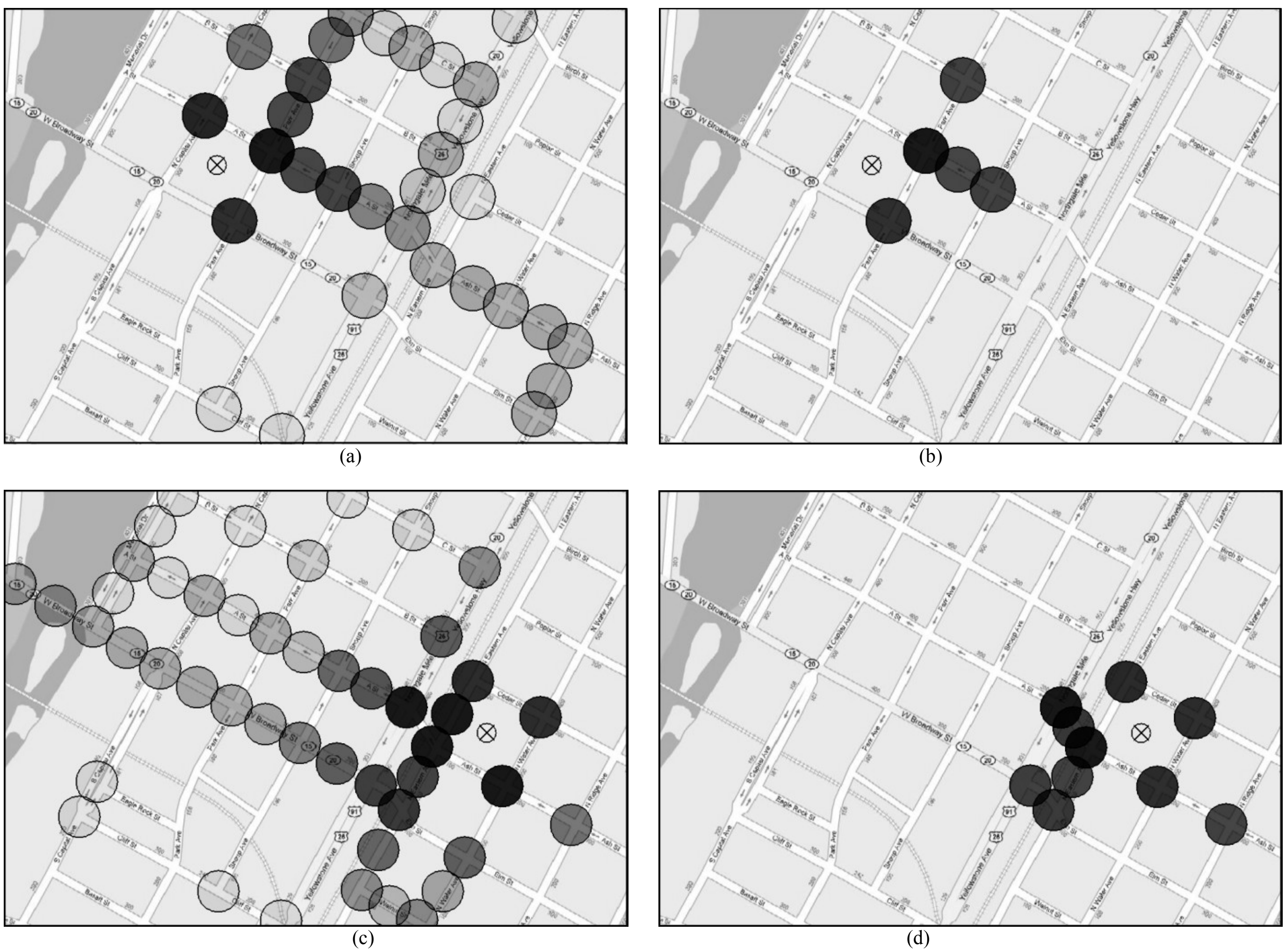


Fig. 6 Histograms of traffic densities (a), (c) and the extracted significant places (b), (d).

The online spatio-temporal clustering algorithm was applied to this experimental data. The resulting set of extracted significant places is presented in Fig. 3(b). Each significant place is displayed as a circle, with its radius equal to the specified geographical proximity threshold δ. The center of the sphere is located at the COG of particular cluster. The significance of each cluster is denoted by its grey tone. The darker the grey, the more significant the cluster is. Similarly, near white grey tones denote relatively insignificant clusters.

By observing Fig 3(a) and 3(b), it can be seen that the set of extracted significant places correctly reflects the underlying traffic density distribution.

It is important to note that the algorithm dynamically adapts to the changing traffic patterns. In this manner only the most recent and valid view of the solution is presented to the user.

This constitutes one of the main contributions of the presented algorithm when compared to the original DSTiPE algorithm [13]. The DSTiPE algorithm only provided a static solution based on the available data, but lacked the adaptability to time-dependent problems.

B. Parametric Control

The three main control parameters play an essential role in controlling the computed solution. The geographical proximity threshold δ, the discount factor λ and the significance threshold α can be modified "on the fly" and the solution will adjust accordingly. The following two test scenarios demonstrate the influence of particular parameters.

First, the geographical proximity threshold δ was modified online. Starting from relatively low value of 20 *meters*, the threshold was continually increased up to 60 *meters*. The effect of such parameter modulation is displayed in Fig. 4(a)-(c).

Fig. 4(a) shows the set of extracted significant places for $\delta = 20\,meters$. Because this value is used as the maximum cluster radius for the NNC algorithm, it results in a high number of clusters with smaller diameters. Fig. 4(b) shows the updated solution for $\delta = 40\,meters$. Fig. 4(c) shows the solution for the maximum tested value of $\delta = 60\,meters$. Here only few clusters were generated covering large areas of the environment.

It can be noted that the granularity of the solution is inversely proportional to the value of the geographical proximity threshold δ. Generated clusters need to maintain certain level of significance in order to survive into the next iteration (specified by the significance threshold α). When their radius is increased, neighboring clusters start competing for input patters, which results in natural elimination of the number of extracted significant places.

Next, the dependency of the number of clusters on the significance threshold α and on the discount factor λ was demonstrated in Fig. 5. It can be observed that lower values of α and greater values of λ lead to generation of more clusters.

Further, the time complexity of the presented algorithm is linearly dependent on the number of clusters. Hence, it can be seen that the discount factor and the significance threshold can be used for maintaining computational tractability of the solution. The appropriate values of these parameters mainly depend on the sampling rate of the data, the hardware parameters of the computer and on the required response latency of the system.

C. Fuzzy Spatio-Temporal Risk Assessment

Two scenarios of the computation of the risk of individual significant places with regards to the object of interest are demonstrated in Fig. 6(a), (c) and Fig. 6(b), (d). Symbol $\otimes$ denotes the selected building of interest (e.g. nuclear plant, bank, embassy, airport, etc.). The implemented fuzzy inference engine evaluates the level of risk (potential danger) of each identified significant place towards this object of interests based on their mutual distance and significance. The obtained risk is denoted by the grey tone of the visualized clusters. The darker the tone, the greater is the risk of particular significant places.

The evaluation of all the extracted significant places is displayed in Fig. 6(a) and Fig. (c). It can be seen that both distance and significance influence the risk assessment of each cluster. Fig. 6(b) and Fig. 6(d) show the reduced set of significant places. Here, a relevance threshold enables the identification of only the most significant places.

VI. Conclusion

This paper presented an algorithm for online spatio-temporal risk assessment for ITS. In the first phase, the algorithm extracted a set of spatio-temporal significant places. In the second phase, the fuzzy inference engine was implemented for calculation of the risk level that each significant place imposes on the object of interest.

The algorithm was applied to traffic density estimation and risk assessment in a virtual traffic urban environment of the city of Idaho Falls, Idaho. It was demonstrated that the algorithm correctly recognized and extracted spatial areas with the highest traffic density. Using a specified object of interest, the fuzzy inference engine evaluated the level of risk of each significant place. Furthermore, the algorithm allows "on the fly" adjustments of control parameters.

The future work directions will include the following. Consideration of using additional FIS inputs (e.g. baseline traffic densities) and incorporating hierarchical clustering.

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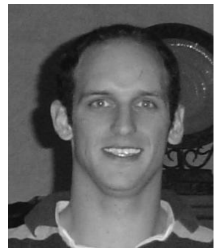

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