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The application of artificial intelligence in public administration for forecasting high crime risk transportation areas in urban environment

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Abstract

Public administration has adopted information and communication technology in order to construct new intelligent systems and design new risk prevention strategies in transportation management. The ultimate goal is to improve the quality of the transportation services and also to ensure public transportation safety. In this research, a combination of spatial clustering methods and artificial neural network models was used in order to predict the high crime risk transportation areas. Geographic information systems were used to perform spatial analysis so as to identify the regions with a high concentration of crime incidents. Artificial intelligence was used in this study in order to build artificial neural network predictive models. The neural network predictive models were evaluated by using the Mean Squared Error (MSE) in order to find the optimal forecasting model. The optimal forecasting model was used in order to predict the high crime risk transportation areas. The scaled conjugate gradient algorithm was utilized as the training algorithm for the construction of the feedforward neural network models, since it is considered as one of the fastest learning algorithms compared to several other algorithms such as backpropagation learning algorithms.

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Keywords: Artificial intelligence; Artificial neural networks; Crime prediction; Geographic information systems; Hotspot analysis; Public transportation management; Spatial clustering; Transportation safety; Urban environment.
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1. Introduction

Several researches have studied the transportation risk management strategies that must be adopted by the authorities in order to improve public transportation safety and reduce transportation risk in urban areas (Abkowitz 2002; Liu et al. 2011). Crime violence against citizens in urban environment has a negative impact on people's lives and should be considered as an important factor in public transportation management and planning and in constructing the transportation infrastructure in urban areas. The development of communication and information technologies has led to the development of new technology-based management systems in public administration (Kouziokas 2016) and also to new intelligent systems for transportation management in urban areas which facilitate decision making in choosing the optimal routes in public means of transport (Grant-Muller and Usher 2014).

Furthermore, the development of geographic information systems and geospatial technologies has led to new crime analysis and prediction methods focusing on the spatial dimensions of crime incidents (Leitner 2013; Wolff and Asche

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2009; Li and Radke 2012). Several researches studied the application of artificial intelligence in crime analysis and forecasting in combination with geographic information system based methods and techniques (Lee and Phillips 2008; Liu 2008; Lo et al. 2015; Palocsay et al. 2000).

Several researchers have proposed intelligent systems or techniques to improve public safety of citizens when travelling by public means of transport in urban areas (Di Bella et al. 2014; Hadayeghi et al. 2013; Lord and Persaud 2004; Sham et al. 2013). Sham et al. (2013) proposed a smart tracking security system to improve travel safety against crime occurred on buses, taxis and trains. The aim of the study was to develop an improved GPS- based tracking system for people that travel in urban areas. Hadayeghi et al. (2013) developed prediction models to forecast the number of accidents in planning zones in the urban area of the city of Toronto by using weighted regression method to investigate the spatial variations in the estimated factors. Lord and Persaud (2004) estimated future traffic safety of transportation networks in urban areas by using transportation planning models. The results revealed that it is possible to predict crashes on transportation networks, but the accuracy of the forecasts depends on the precision of the traffic flow estimations.

In this research, crime risk prediction is examined as an important factor that contributes to safer travelling in urban areas in public transportation places where many people are gathered and must be protected efficiently by the police forces from crime committers.

2. Theoretical background

2.1 Geographic Information Systems

Spatial data include the coordinates and the topology in their features and can be processed and analyzed by Geographic Information Systems (GIS). Geographic information systems are considered as an emerging technique for visualizing and analyzing spatial features. Geospatial analysis methods are used to analyze spatial characteristics and produce results regarding the optimal allocation of a place or spatial distribution of geographic features.

2.2 Spatial clustering

Spatial clustering is defined as the process of aggregating a set of spatial objects into groups (clusters) according to their geographical attributes (Wang and Wang 2011). There are several methods of spatial clustering such as hierarchical, density-based (e.g. kernel density estimation), thematic mapping and grid-based (Chainey et al. 2008; Han et al. 2009). Hotspot Analysis is a geospatial analysis method that uses techniques to discover areas with increased concentration of incidents (clusters). The most commonly used spatial analysis methods for hotspot analysis are kernel density estimation (Borruso 2008; Silverman 1986) and Getis-Ord Gi* statistic (Getis and Ord 1992).

2.3 Artificial neural networks

Artificial Neural Networks (ANNs) can be defined as computing systems that simulate the structure of the brain system. A neural network elaborates data from the input parameters. The information traverses via connections to produce an output according to the input values (Basheer and Hajmeer 2000; Svozil et al. 1997). Artificial neural networks are used in this study to forecast values related to crime data in transportation stations since they can model non-linear relationships between input and output. A feedforward multilayer perceptron (MLP) was utilized in this study, as many researchers consider it as one of the most appropriate for time series forecasting problems (Hornik 1991; Koskela et al. 1996). A typical artificial neural network consists of the input and the output layer and the hidden layer or layers. Every layer has a specific number of neurons. In a feedforward neural network, the input signal traverses the neural network in a forward direction from the input layer to the output layer through the hidden layer or layers. A typical feedforward neural network and its structure is illustrated in Figure 1.

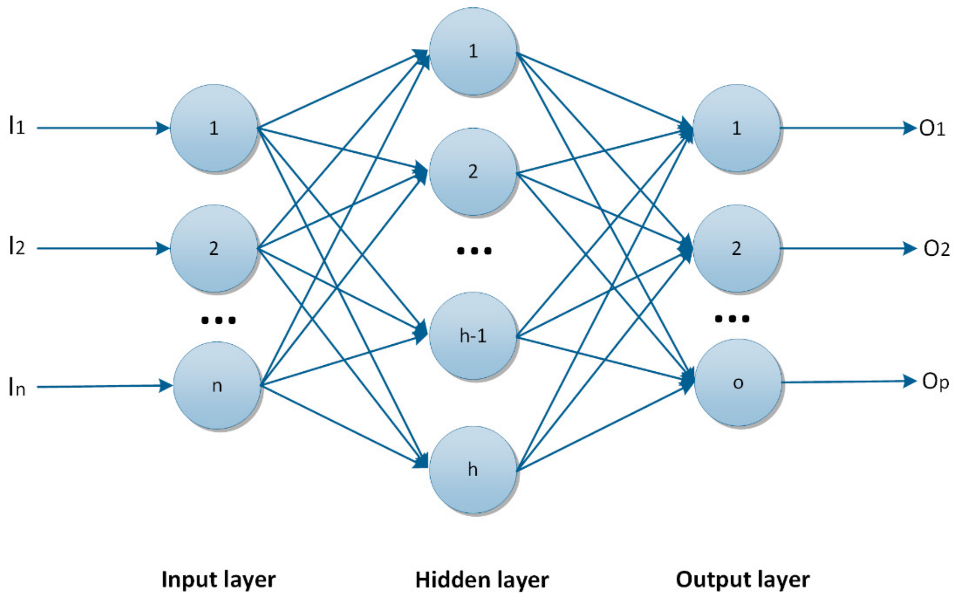

Figure 1. A typical feedforward neural network. I_1, I_2, …,I_n are the input values and O_1, O_2, .., O_n are the output values.

2.4 Scaled conjugate gradient algorithm

The scaled conjugate gradient (SCG) algorithm was proposed by Møller (1993). The scaled conjugate gradient algorithm was selected as a training algorithm for the feedforward neural network, since it is considered as a faster learning algorithm compared to other algorithms such as backpropagation learning algorithms (Møller, 1993). The scaled conjugate gradient algorithm, which is a second order conjugate gradient algorithm, minimizes goal functions of several variables and utilizes a step size scaling method in order to avoid the time consuming line-search per iteration during the training process (Riedmiller, 1994). That method makes SCG faster than other training algorithms and it shows superlinear convergence in most cases since the number of computations in each performed iteration is significantly reduced (Cetişli and Barkana 2010; Møller 1993).

3. Research Methodology

The followed research methodology includes five stages: data collection and preparation, spatial clustering, neural network forecasting models creation, testing the optimum neural network model and high crime risk transportation areas prediction. Firstly, crime and transportation data were gathered and prepared. Only crimes related to street, sidewalk, bus stop, and rail station locations were extracted. Spatial layers of bus stops, rail stations and district boundaries were collected for visualizing and analyzing spatial data. In the second stage, spatial analysis of crime data was performed in order to find regions with increased concentration of crime incidents (clusters). In the next stage, artificial intelligence was used in order to build and compare neural network forecasting models so as to find the optimum neural network model. In the next stage, the optimal neural network model was applied to predict the most dangerous transportation stations related to crime risk assessment. In the last stage, the predicted crime hot spots are intersected with the transportation stations spatial features in order to predict the high crime risk transportation areas. An overview of the followed research methodology is illustrated in Figure 2.

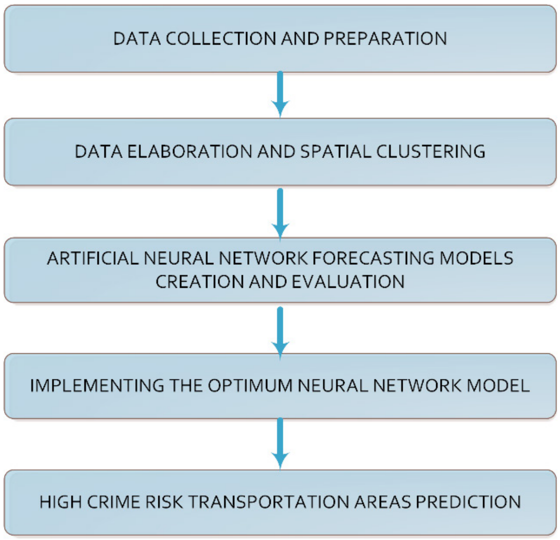

Figure 2. Overview of the followed research methodology.

4. Results

4.1 Data collection and preparation

Crime data, spatial data and transportation data were retrieved from the City of Chicago Data Portal for the January of 2013, derived from the CLEAR (Citizen Law Enforcement Analysis and Reporting) system of the Chicago Police Department. 10,778 incident crime data were collected. The crime types that were selected to be analyzed are: homicides, kidnapping, narcotics, theft, robbery, sex offense, assault and weapons violation. The collected crime data were prepared and checked for duplicates, gaps, or other incoherencies.

4.2 Spatial clustering and analysis

The spatial database was constructed by the collected spatial data. The visualized spatial data were processed and analyzed in ArcGIS software in order to find the areas with increased concertation of the crime incidents. Hotspot analysis was used as a spatial clustering technique in order to find the most statistical significant areas with increased number of crime incidents and also proximity analysis was utilized to locate the nearest most dangerous bus stops and rail stations in the urban study area.

4.3 Artificial neural network forecasting models

Predictive artificial neural network models were built by using the derived data from geospatial analysis as input data. The scaled conjugate gradient algorithm was selected as a supervised training algorithm method, since it is considered as a faster learning algorithm compared to other algorithms such as backpropagation algorithm (Møller, 1993). The data was divided into three different parts. 60% of the data was used as the training set, 20% of the data was used as the validation set and 20% of the data for the test set. The training set was used to train the network with historical data and the validation set was utilized to evaluate the neural network performance. The topology of the feedforward neural network was defined according to the performance of every tested neural network (Wang, 1994). Mean Squared Error (MSE) was used as a measure to calculate the prediction error and evaluate the performance of the constructed neural network models so as to choose the optimum model during the validation process. The function for calculating MSE is given by the following equation:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \widehat{y_i})^2 \qquad (1)$$

Where y_i is the real value and $\widehat{y_i}$ is the predicted value and N is the number of output values. After testing different topologies, the best topology was found to be the one with 24 neurons in the hidden layer. The optimum model had the minimum MSE compared to all other neural network models. The Mean Squared Error (MSE) of the optimum model was found to be 0.00013833 at epoch 153. The neural network training performance of the optimum model according to Mean Squared Error (MSE) is illustrated in Figure 3.

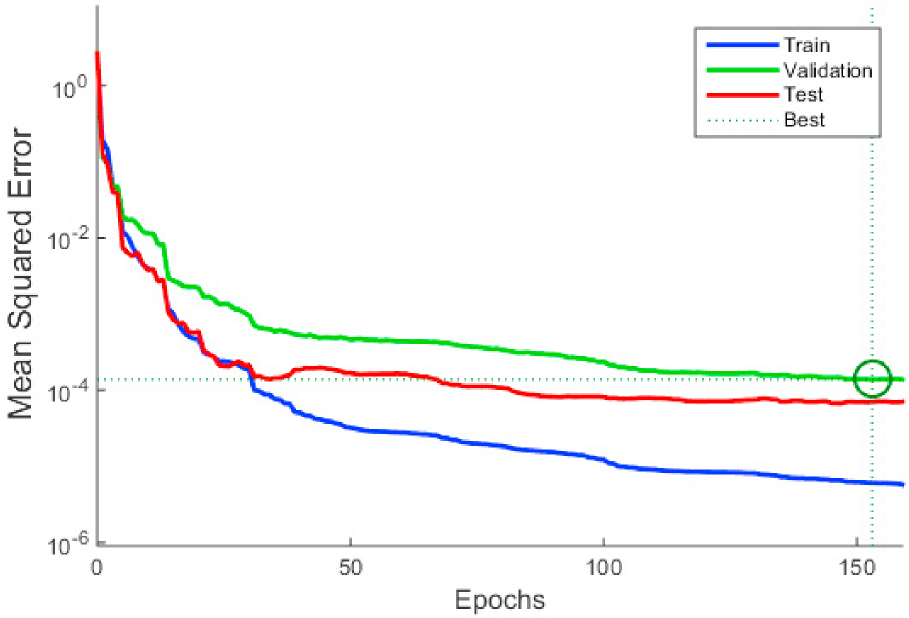

Figure 3. Neural network training performance of the optimum model according to Mean Squared Error (MSE).

4.4 Optimum neural network model predictions

High crime risk transportation stations were predicted by using the optimum neural network prediction model. Firstly, the constructed model was tested by using the test data of the dataset for the last week of January 2013 in Chicago city. The results showed very precise prediction accuracy. The Mean Squared Error (MSE) of the test set was found to be 0.00006996 and the Root Mean Squared Error (RMSE) of the test set was 0.0084.

Regression analysis was used in order to estimate the prediction accuracy. Regression analysis is a statistical method for analyzing and studying the relationships between variables (Montgomery et al. 2015). R linear correlation coefficient, which expresses the degree of the linear dependence, was found to be 0.99979. The predicted crime hotspot areas where intersected with the transportation spatial layers regarding features about bus stops and rail stations. The final results showed the predicted transportation stations with high crime risk.

5. Conclusions and discussion

The applicability of artificial intelligence in transportation safety management is examined in this paper by using also spatial clustering methods. Adopting artificial intelligence techniques and geographic information systems in public management and transportation can be very fruitful and valuable. An application example is this research, which applies geospatial technologies and artificial neural networks in order to predict efficiently the most dangerous public transportation stations in daily basis. High crime risk transportation stations were located by using spatial analysis methodologies in order to analyze the historical data of crime incidents of specific offenses which were negatively correlated to the transportation safety. Artificial intelligence as an emerging forecasting technique was implemented in order to build the optimum neural network predictive model by investigating the most adequate network topologies and training parameters. The results showed a very good prediction accuracy of the transportation stations with high crime risk. That is very promising and can promote safer transportation management policies, especially in the cities where crime rates are very high.

Considering the number of people that are using the public means of transport, high risk stations predictions will help public administration to adopt planning and intervention strategies to ensure public safety. Obtaining spatial information about the crime distribution in transportation facilities, and especially predicting the crime occurrence – based high risk transportation stations can be very valuable for public management, urban planning and transportation management, and also in designing and planning proactive policies and strategies in order to protect people that are commuting with public means of transport and also to preserve human lives from criminal acts.

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