Complex Event Post Processing for Traffic Accidents

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Abstract— **In this paper, we describe a framework for an expert system that tries to predict effects of an accident based on past data using supervised learning employing artificial neural networks. For this purpose, sensory data events are post processed in order to generate a reasonable mapping between input and output parameters in case an event is detected automatically or manually. The framework is intended to be used to take actions for reducing the effects of the accident on traffic congestion and to inform necessary parties to intervene in a timely fashion.**

I. INTRODUCTION

Traffic on motorways is a major component of the daily life, especially in urban areas where millions of people spend hours while they are commuting. Local governments set up systems to monitor the traffic flow in real time in order to inform the public about the traffic and in order to take action against the problems in the flow. Those problems can be categorized into two main groups: Congestion due to the abundance of the vehicles flowing into certain directions (what we call "normal" congestion) and congestion due to an abnormal condition such as an accident or a faulty vehicle hindering the flow. Traffic control and management centers may also implement several kinds of action in order to remove or reduce those congestions. They can be listed as rerouting the traffic, displaying warning signals at digital road sign screens (variable message signal panels), generating congestion maps and alerts on mobile and/or web platforms including social media, and informing other legal bodies: police, ambulance, rescue, fire etc. An expert system is required to complement the information system that is used to store and process the data collected.

Different methods of computational intelligence can be used to monitor vehicle traffic for detection of anomalies such as accidents and congestion on the road: complex event processing (CEP) based on rules implemented in stream processing [1, 2], neural networks [3, 4], and clustering [5] are among the methods in the literature. There are several types of inputs for such a traffic monitoring system that stores huge amount of data collected from diverse groups of sensors located in a large distributed environment. The most influential data are the location of the road (identified as segments) and average speed of traffic flow on the segment. There are environmental inputs such as temperature (of the air and of the road), wind speed, humidity, and weather condition (rain, snow, fog, etc.). Given a fixed topology for the roads of interest and the time stamps (so that we can identify the date, day of the week, time of the day, etc.) for sensory inputs, a CEP system can be used to detect accidents or other anomalies causing congestion as a complex event. There are many articles in the literature that deal with this problem of accident detection where the recent survey in [6] gives a comprehensive list of papers along with a comparison of statistical and neural network methods. Even if there is no such automatic detection system, anomalies are monitored "manually" using camera systems installed at major locations of the road network so that several actions can be triggered as mentioned above. Thus, there is also a record of an event (e.g. accident) associated with a group of sensory data. Besides this, several legal bodies (police department, ambulance service, fire department, rescue teams) keep official records for accidents at which they take a role where the segment of the road and the time are explicitly recorded. Those records also include data related to the severity of the accident: deaths, injuries, case of a fire, need for towing etc. The database of the traffic control center can be extended to include those details related to the accident.

The general view of the expert system to be used in the traffic information system can be seen in Fig. 1. The system consists of different layers where each layer feeds information to the next layer by processing and refining data. As this is an event based system, the event driven architecture of [1] can be used as a reference. The current literature deals mainly with the problem of sensory signal processing and incident detection [1-5] for real time applications where there is no work on an expert system for action planning in real time. The expert system will be triggered by the incidents detected. On the other hand, the expert system should be "trained" based on the history data where the events of sensors and other information derived from external sources should be used. This training can be carried out by different methodologies such as decision trees, hierarchical clustering, neural networks, and fuzzy systems. An ideal expert system would employ a collection of those and the results would be merged to a final conclusion. The expert system is not necessarily triggered by the incident detector but it can also be triggered by a manual accident event. The expert system is supposed to use data related to the accidents in the history for training and the short term past data for operation as will be explained in the next section.
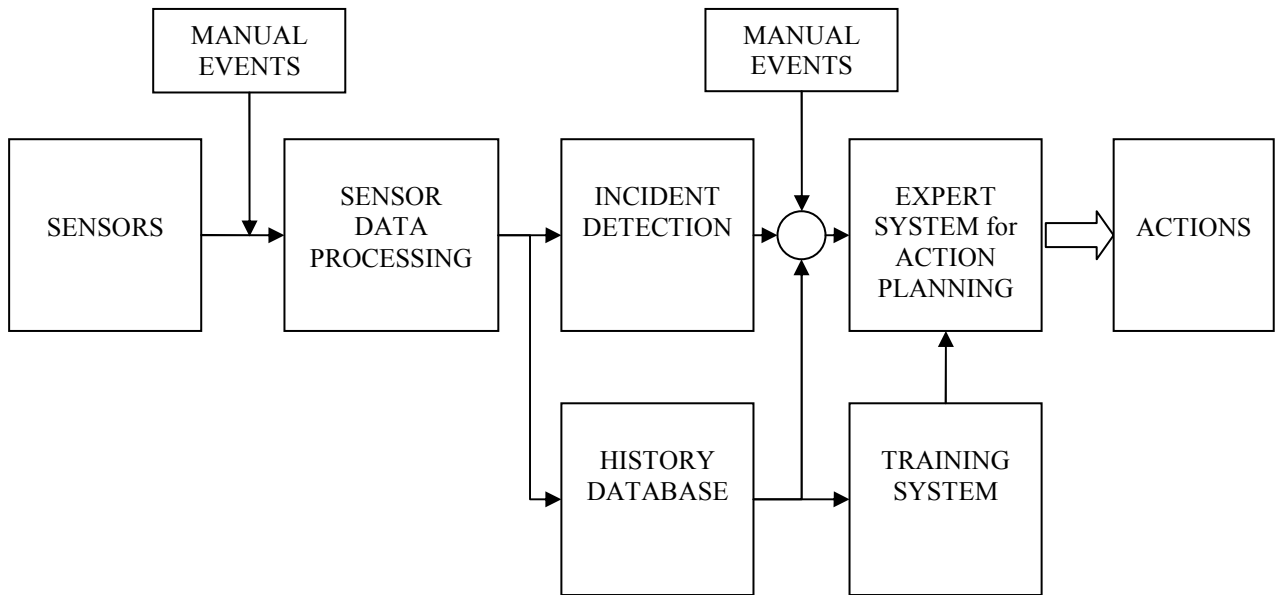
Figure 1. Event driven architecture of an expert traffic information system

There are also numerous works on the analysis of the severities of the accidents. Most of the research tries to figure out a relationship between the severity of the accident and the factors related to the vehicles, drivers, and the environment [7-11]. Statistical as well as different neural network methods are employed in determining the correlation between those abovementioned factors where none of them is utilizing the dynamic data supplied by the sensors. The research is limited to use stored or reported data about the position on the road, weather and vehicle conditions. Hence, they cannot be used for a real time action planning expert system effectively.

The aim of this research is to predict outcomes (effects) of an accident based on past data using supervised learning employing artificial neural networks. For this purpose, a framework has been developed where the following accident data are used as inputs to the multilayer neural network: segment of the road, average speed before the accident, temperature (of the air and of the road), wind speed, humidity, weather condition (rain, snow, fog, etc.), and the time stamp of the accident. The following data are used as the outputs of the system: time spent to reach the average speed before the accident again (this is a measure for the intensity of the congestion caused by the accident), severity of the accident (may take one of the following values: death, injuries, material damage only), need for interaction of third parties (police, ambulance, rescue, fire, and towing truck). The work includes normalization of data, selection of optimal neural network architecture, training and validation over synthetically produced data sets.

This work combines the inputs from sensors in case of the occurrence of accidents as events in order to predict the likely consequences of the accident so that several important actions can be triggered automatically: informing necessary parties for help, informing the public (including drivers on the road) about speed reduction and rerouting. The automatic event detection mechanism of the CEP system or a manual interrupt may mark the existence of an accident, and our system will be triggered to predict the consequences of the accident. The system can also be used to carry out "what-if" scenarios in order to proactively tune the traffic flow using measures that would decrease the probability of an accident. In this sense, this framework can be extended to cover more functions in traffic monitoring and control systems. The rest of the paper is organized as follows: Section II will define the problem in detail where Section III will introduce the framework of neural network based expert system to predict accident severity. Numerical experiments are given in Section IV, and Section V will conclude the paper.

II. PROBLEM DEFINITION

The essential problem is to find a mapping between the observed input sets and the output sets that are recorded in events categorized as accidents on motorways. The inputs and outputs are listed in Table 1. All of the inputs can either be collected by the sensors located on the roads, or they can be calculated based on sensor data. On the other hand the binary values related to the severity of the accident have to be supplied manually based on the accident reports and camera captions if available. It is clear that some of the inputs are analog and some of them are discrete values. On the other hand, most of the outputs are binary values. Hence, the desired system should be able to cope with such a mixed nature. As this problem is nonlinear by its nature, the solution to this problem cannot be a simple regression. It should also be noted that in real life situations, many inputs and or outputs may have missing or, worse than this, misleading values in case of accidents. Thus, a thorough pre-cleansing of data may be necessary in order to develop a reliable expert system for accurate predictions. The review work in [6] suggests that statistical methods can be employed in transportation

related research best when there exists a priori information on functional relationships of the variables in the problem. On the other hand, the literature review suggests efficient use of neural networks when the true data generating process is unknown and hard to identify, and when idealized assumptions are not valid [6]. Hence the choice of supervised learning using neural networks seems to be reasonable for a starting point.

TABLE 1.
INPUTS AND OUTPUTS OF THE EXPERT SYSTEM

INPUT	OUTPUT
Segment of the road	Time spent to reach the average speed before accident
Average speed before event	Severity (death, injury, material damage only)
Average speed after event	Need for police
Air temperature	Need for ambulance
Road temperature	Need for rescue
Wind speed	Need for fire
Humidity	Need for towing
Weather condition (rain, snow, fog)	
Month of event	
Day of the week	
Holiday indicator	
Hour of the event	

III. NEURAL NETWORK BASED FRAMEWORK FOR ACTION PLANNING

As neural networks have been used successfully in many real life applications for supervised learning, neural networks look as a good candidate to solve the problem of predicting necessary actions in case of an accident based on previous data. In this work, MLP (Multilayer Perceptron) neural networks have been used employing back propagation algorithm in learning. The basic structure of a MLP neural network with two hidden layers is shown in Fig. 2 where each node (N) represents a neuron with nonlinear processing.
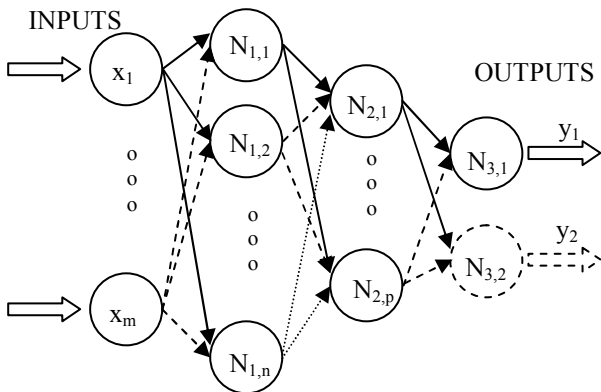

Figure 2. Structure of MLP neural network

Each input ($x_i=N_{0,i}$) is connected to every neuron ($N_{1,j}$) in the first hidden layer with n neurons where each connection has an associated weight ($w_{1,i,j}$). Similarly, each neuron output of the first hidden layer is connected to every neuron ($N_{2,k}$) in the second hidden layer with weight ($w_{2,j,k}$). Finally, outputs of neurons $N_{2,l}$ are connected to the output nodes N_3 with weights ($w_{3,k,l}$). The massively connected neurons have an output that is a weighted sum of their inputs, filtered through a nonlinear function Φ. Equation (1) displays the relationship between neuron inputs and output where θ is the so called bias weight associated with each neuron.

$$N_{s,t} = \Phi\left(\left(\sum_{u=1}^{u_s} w_{s,u,t} N_{s-1,u}\right) - \theta_{s,t}\right) \quad (1)$$

The linear summation of weights and inputs will be filtered using the so called activation function Φ which is usually a nonlinear function bounded between two values. In this work, we have used the sigmoid function as given in (2).

$$\Phi(a) = \frac{1}{1+e^{-a}} \quad (2)$$

Hence the outputs of neurons are bounded between 0 and 1. In supervised learning, inputs and their corresponding desired outputs are known. Given a training set T={x_i^t, y^t} where y^t is the desired output for the input vector x_i^t, in one epoch, each input vector is supplied to the MLP with randomly initialized weights giving the output Y^t. The sum of squared error (SSE) for the training set for one epoch is:

$$E(w,\theta) = \sum_t \left(y^t - Y^t\right)^2 \quad (3)$$

Training of the MLP neural network is the adaptation of weights (w and θ values) after each epoch in such a way that the SSE will be reduced to an acceptable level. The main algorithm for this training is the gradient descent based back propagation algorithm for which the details can be found in [12]. Essentially, the weights can be updated in batch (after each epoch) or online (after each input vector is applied) where the error at output is used to update the weights connecting the hidden layer to the output nodes in such a way that this update will reduce the error. There are two more parameters of interest: the learning rate and the momentum term. The learning rate is used to scale the weight update that is proportional to the derivative of the error. The momentum term is used to adjust weight updates based on previous updates [12]. Both adaptive learning rates and momentum term have been used in the training phase of this work in order to speed up convergence, that is, reduction of the SSE to the acceptable level.

The inputs of our problem can be categorized into two types:

o "Analog" inputs for which the magnitude has a meaning, such as the speed of traffic, temperature, wind speed, humidity, and the time (hour) of the accident. Those inputs are

normalized according to their maximum values for compatibility with binary inputs.

o "Discrete" inputs for which an encoding is necessary, such as the segment of the road, weather condition, month and day of the accident, and the holiday indicator.

Due to the need for an encoding, some inputs are represented in an extended manner: Table 2 summarizes the way how the inputs are extended. This extension has increased the actual number of inputs applied to the MLP neural network; however, several trials without such an extension have shown that the effective training of the network cannot be achieved in most cases.

TABLE 2.
REPRESENTATION OF INPUTS.

INPUT	REPRESENTATION
Segment of the road	Extended to twenty binary inputs: regions R1 to R20
Average speed before event	Normalized
Average speed after event	Normalized
Air temperature	Normalized
Road temperature	Normalized
Wind speed	Normalized
Humidity	Normalized
Weather condition (rain, snow, fog)	Extended to three binary inputs: rain, snow, fog
Month of event	Extended to twelve binary inputs: January to December
Day of the week	Extended to seven binary inputs: Mon. to Sunday
Holiday indicator	Binary value
Hour of the event	Normalized

The outputs (except the time to recovery) are represented as binary values where the severity level is extended to three outputs. Time spent to reach the average speed before accident is also normalized. Several trials have shown that the MLP learning is not feasible, if all outputs are included in a single network. Hence, for each of the output variable, a different MLP network is trained where the adaptation of weights has displayed different characteristics. In summary, the framework of the expert system is based on a collection of 9 MLP neural networks with 50 inputs and one output each.

IV. NUMERICAL EXPERIMENTS

The expert system is to be used within a more comprehensive information system that is capable to generate events (accidents) and the related data based on sensory information. Unfortunately, this system is under development; hence, the expert system for accident severity prediction is experimented using synthetic data generated using a simulation tool: A sample of 2000 data events have been generated based on the real data available from the 2010 statistics in Turkey [13]. The statistics include data for the accidents reported by the police where different categorizations are available: severity of the accident with respect to weather condition, month, day, time (all separately). Based on this data, samples have been generated that resemble the same statistical distribution (proportions) in the severity of the accidents according to the abovementioned factors. Obviously, the generation scheme has regarded logical correlations between severity and need for services, e.g. an accident with fatalities or injuries absolutely needs police, ambulance and towing. Then, 1600 of the sample events have been chosen for training and 400 events have been used for validation. Several different MLP models with one and two hidden layers have been experimented which are listed in Table 3. The performance of the MLP neural network has been measured as the percentage of correct classification in all the binary valued outputs, namely the severity levels, and needs for police, ambulance, rescue, fire, and towing. The output of a binary variable is considered to be 1 if the MLP output is greater than 0.5. The performance (best performances among a collection of tens of runs with different learning rates, momentum terms and initial weights) of the different models for the same training and validation data sets, are also given in Table 3. The experiments suggest that employing 2 hidden layers may improve both the training and the validation performance. The probabilistic nature of the input and output samples makes it difficult to obtain a generalization over 90% in the training set. When the outcome is investigated for the severity only, a better performance is measured as some of inconsistent outcomes in the validation set are eliminated. The simulations indicate that the MLP models are capable of estimating the severity of the accident up to 88% correctly and the misclassification of an accident with fatality or injury as "material damage only" counts for less than 4%.

TABLE 3.
EXPERIMENTS AND PERFORMANCE OF MLP MODELS

Model	No of hidden layers	No of neurons	Training Performance (%)	Validation Performance (%)
1	1	30	87	73
2	1	40	88	78
3	1	50	91	81
4	1	60	90	78
5	2	30+2	85	81
6	2	30+4	87	80
7	2	40+2	93	85
8	2	40+4	88	82

V. CONCLUSION AND FUTURE WORK

In this work, we have developed a neural network based framework for the prediction of road accident severity and the necessary actions to be taken after an accident event is registered. This expert system is supposed to be triggered by an event based system that continuously monitors the sensors on the motorway. Such a tool can be used both for action planning in case of an accident, and for the purpose of predicting outcomes of what-if scenarios so that traffic management can take necessary measures before an accident happens. Preliminary analyses suggest that MLP neural networks can be exploited for such a purpose. On the other hand, several important factors have to be investigated thoroughly: Some statistical analyses (e.g. principal component analysis, clustering) can be useful to figure out the effective factors among the inputs for the expert system so that the input dimension can be reduced and the MLP neural network can be trained efficiently. The performance of the expert system should also be checked using more reliable real life data. Finally, the expert system can be complemented by other statistical and neural network methods for obtaining a more reliable tool based on the opinions of several "independent" decision makers.

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