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Wild Life Passer Species Recognition From A Technical Passage Through Data Fusion Of A Wireless Sensor Network

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Abstract. This paper presents a Wireless Sensor Network (WSN) system which was created as a project about protecting wildlife using sensor networks following the assistance of the department of Electrical and Computer Engineering of the Democritus University of Thrace. An automated process was implemented, regarding the recognition of a passenger (ie human, wolf, bear, etc.) traversing a box-shaped underground passage, such as the ones located along main highways fusing Width, Height and Weight values. These were measured using low-cost distance (beam) and weight (S-type load) micro-sensors and stored in a central repository. Moreover, the information provided by the WSN was analyzed, via a variety of methods including a neural pattern recognition network as well as clustering algorithms, which were able to recognize the kind of passenger, with certainty scores over 90%. The main concern, regarding the future, is the evaluation of these passages in respect to their effectiveness, i.e. whether they are frequently utilized by animals. This information was further analysed by appropriate information systems, in order to provide insights about the effectiveness of such mitigation structures.

Keywords: data fusion, data mining, neural pattern recognition networks, wireless sensor networks, wildlife protection, clustering, visualisation

INTRODUCTION

Nowadays, the increasing rate of accidents, involving the passage of protected wildlife species from highways (for instance animals such as the brown bear *Ursus arctos* and grey wolf *Canis lupus* from Egnatia Highway, which is the longest commercial road in Greece, measured over 670 km) have caused a negative effect in both the natural habitat and the transportation between urban centers [1]. To illustrate the problem, in Germany, 16.4% of roe deer *Capreolus capreolus* newborns is annually killed in highway accidents, while the respective percentages of wild boar and deer are 3.9% and 2.2%. Furthermore, according to [2] in Germany, in 1976, 66,744 accidents involving wildlife and passing vehicles were recorded amounting to insurance compensations up to 51 million dollars, while in 1988, 145,636 accidents were recorded amounting to 210 million dollars. In Greece, fragmentary evidence is also available thought ecological groups, such as *Callisto* and *Arcturos* and from the personal records of researchers. It is noted that during the period 1995-2011, 53 incidences of brown bear deaths occurred in the main national road network and especially in Western Macedonia while during the period 2009-2015, 25 collisions between vehicles and brown bears happened in Egnatia Highway. Throughout the past, a number of protective measures were presented and tested, in order to ensure the safe passage of the animals such as the construction of mitigating structures (underground, above-ground, box-shaped, inhibited or not by flora). Underground, box-shaped tunnels were manufactured along the Egnatia motorway vertical axe *VA-45.0*, thus, dramatically reducing the number of annual accidents.

[1]The system was developed under the auspices of the ALPINE project [1], *A Low-Power, Intelligent, sensor NEtwork architecture, for environmental management*. ALPINE was funded by the Hellenic General Secretariat of Research and Technology

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RELATED WORK

Recent advances in micro-electro-mechanical systems and in low-power wireless network technology have created the technical conditions to observe and react according to the physical phenomena of their surrounding environment. Regarding WSN nodes used, some challenges, which we needed to comprehend were regarding several approaches in this area target like the life span, energy consumption [3] and control. This is the main reason why WSN have been increasingly entailed and developed primarily targeting real time applications, such as those supporting the general public in urban settings [4] and environmental monitoring applications, both indoor [5] and outdoor [6]. The most important projects on which we relied were Zebra Net [7, 8], Wildsensing [9] and GreatDuckIsland [6] that constitute the initials WSNs, created for monitoring wildlife. Throughout this publication, we set our primary focus in the development of a Wireless Sensor Network with MANET [10] features. ALPINE WSN nodes interact both with tagged and untagged animals. Tagged animals are bears equipped with either commercial or custom radio-colars, developed in the ALPINE project. As far as we are aware, the only alternative approach to species recognition of untagged animals is using image processing, e.g., [11],[12], however this is usually performed off-line, using static images, taken as snapshots and it is error-prone.Lastly, in terms of mathematical analysis we studied the usage and effect of pattern classification, pattern recognition [13] and clustering algorithms [14] to our final proposed system.

SENSORS, MATHEMATICAL MODEL AND DATASETS

The main objective, when placing the sensors, was to extract valuable information, regarding the crossing of a passer through the tunnel. In order to measure the passer's height, a distance (beam) sensor was placed at the ceiling of the passage, near its entrance, so as to ensure its instant activation. Moreover, three weight (S-type) sensors were installed before the entrance of the tunnel, in order to measure the attribute of Weight. It should be noted that the specific number of sensors placed in the tunnel was calculated with respect to the passage's narrow entrance's width and each sensor's dimension, so as to cover the tunnel's length and width and to ensure that the passer will step on at least one weight sensor generating a value. Furthermore, width was measured by two distance sensors, diametrically placed on the walls in equal distance from the entrance and simultaneously providing values. Lastly, the measurement of length was acquired by placing an additional distance sensor on the left-hand side wall further down along the passage at the same height as the opposing width sensors.

The equations used in order to analyze the raw sensors' data provided in XML format were the following:

$$Width(cm) = PassageWidth - (DistanceFromLHSWall(time) + DistanceFromRHSWall(time)) \tag{1}$$

$$Height(cm) = PassageHeight - DistanceFromCeiling(time) \tag{2}$$

$$Weight(cm) = Mean\,(LeftWeightSensor(time), MiddleWeightSensor(time), RightWeightSensor(time)) \tag{3}$$

$$Speed(m/sec) = DistanceBetweenTwoLHSConsecutiveSensors/TimeIntervalBetweenTheirReadings \tag{4}$$

$$Length(cm) = Speed * (time_{S_2-last} - time_{S_2-first}) \tag{5}$$

By applying our case study values, i.e., those of the K81 tunnel with a width and height of 350 cm and equipped with the sensors $S_1, \cdots, S_7$, the following formulae are derived:

$$Weight(kg) = \overline{(S_5(value_5, time) + S_6(value_6, time) + S_7(value_7, time)} \tag{6}$$

$$Width(cm) = 350 - (S_1(value_1, time) + S_2(value_2, time)) \tag{7}$$

$$Height(cm) = 350 - S_4(value_4, time) \tag{8}$$

$$Speed(m/sec) = Distance(S_3, S_2)/(time_{S_3} - time_{S_2}) \tag{9}$$

$$Length(cm) = Speed * (time_{(S_2-last)} - time_{(S_2-first)}) \tag{10}$$

where $S_i(value_i, time)$ represents a sensor observation with value $value_i$ at instant $time$. The difference $(time_{S_3} - time_{S_2})$ denotes the interval from when the passer was first seen by sensor S_3 and last seen by sensor S_2. Similarly, $time_{(S_2-last)} - time_{(S_2-first)}$ is the difference between the last and first seeing of the animal by sensor S_2. Due to the non-zero dimensions of the paws (regardless if the passer is human), each passer usually steps on at least two weight sensors simultaneously. Consequently, in order to calculate this variable, the average function can be applied. Note that all calculations use the International System of Units hence generated distance and weight sensor values are in *cm* and *kg*, respectively:

$$S_4 = 0 \wedge S_5! = 0 \wedge S_6! = 0 \Rightarrow Weight = \overline{S_5 + S_6} \tag{11}$$

$$S_i(value_i, time) \neq 0.\forall i \in [4, 5, 6] \tag{12}$$

$$S_i(0, time).\forall i \in [4, 5, 6] \Rightarrow Weight(cm) = 0 \tag{13}$$

$$S_4! = 0 \wedge S_5 = 0 \wedge S_6! = 0 \Rightarrow Weight = \overline{S_4 + S_6} \quad , \quad S_4! = 0 \wedge S_5! = 0 \wedge S_6 = 0 \Rightarrow Weight = \overline{S_4 + S_5} \tag{14}$$

Although we were familiar with data for all the dimensions, we have excluded length, since it is a value that is primarily distinctive in studies regarding ground, quadruped animals, whereas, in our data set, we have also included human (biped) and flying species. Finally, we designed a taxonomy that consists of the following passer classes: *(brown) bear, (gray) wolf, (Greek) shepherd dog, flying species* and *human*. We also designed the following datasets:

- *7-Input Dataset* was derived by scenarios manually simulated by generating multiple test raw data that were used in order to train and evaluate the data fusion models. It should be noted that in a realistic scenario sensor values may present fluctuations depending on which part of the animal body is observed by each sensor so, in order to cater this, a 2% - 4% error has been introduced in our data set. In cooperation with "Callisto" we studied and produced data, referring to both male and female passers. In particular, we incorporated 21 male bears, 21 female bears, 21 male wolfs, 21 female wolfs, 21 bird species, 21 shepherds and 21 humans. All results were carefully selected, in order to form an accurate data sample, without bias or overfitting.
- *3-Input Passer Dataset* contains instances of the above taxonomy. It includes individuals of both genders and was customized to treat them as a whole equity, regardless of their sex. The dataset was created by the equations which were previously presented. That is the reason why, while defining the passers' dimensions, a big interval dispersion occurs to each of their dimension.
- *Body Dataset* is a free dataset we used for modeling human dimensions as realistically as possible from the University of San Jose which contains age, weight, height, and gender values of 507 individuals [15] .

PATTERN NEURAL NETWORK PROPERTIES AND CONFIGURATION

An Artificial Neural Network (ANN) is a system that processes information similarly to the biological nervous system of our brains. Each neural network constitutes a large autonomous quantity, which evaluates information and predicts results, based on its level of complexity (neurons, hidden layers) and general behavior parameters (training, testing and evaluation data).

Our first approach was to create a Neural Network(NN) that would display whether our passer is human-1- or not-0- (one output class). In order to achieve this goal, we created a NN using the NN Toolbox in Matlab and more specifically the Pattern Recognition and Classification application, for a NN consisting of 2 hidden layers and 7 inputs each corresponding to one sensor which gave satisfying results. Finally, we enlarged our data set with human males and females [15] and repeated the previous experiment with the results formated as a confusion matrix. Our second approach, included five output classes, which were linked to the kind of passer: human, brown bear, grey wolf, Greek shepherd dog and bird species (bat or pigeon). The results were odd because the system could not fully comprehend the sensors' interrelationship (e.g. Sensor 1 and 2 as width or Sensor 5,6 and 7 as weight). As a result, we constructed a new NN, which consisted of the following inputs: weight, height and width. At first, we defined one output with a Boolean logic of human (1) or not (0) and we did not encounter any complications. Afterwards, we simply adjusted the previous five outputs and concluded that this method was the most efficient, by far. Consequently, we conducted several comparisons and experimental testing, to ensure that we have chosen the best available allocation. We present the testing using the *3-Input Passer Dataset* for 5 output classes. Finally, we have additionally incorporated 507 human samples as derived from the *Body Dataset* in our testings and which are presented in Table 1. It is observed that for each combination of inputs-outputs and data sample length the optimal percentage rate is selected based on the convergence of the training and validation curves examined and that for the case of the optimal system with 3 inputs and 5 outputs, the optimal configuration is 50-35-15 as shown in Figure 1 where the Training and Validation curves converge, while the score is high (95.4%). This is verified by the ROC curves that are situated in the top left region. Moreover, the overall system score regarding the NN consisting of 7 inputs is worse than the overall system score of the NN of 3 inputs for the great majority of the percentages presented with the exception of 70-15-15 where the overall score is similar which could be to due to training percentage rate (70%). For each set of parameters (each column indicates the used percentage rates) the results are notably improved when an integration of additional data samples occurs and especially in the case of the 15-15-70 percentage where the overall system score arises rapidly from 78.2% to 94.5% (Table 1).

Finally, the change which occurred when implementing our mathematical model (leading to 3 inputs), in comparison to processing the raw data (7 inputs), is superior to the one when we enlarge our dataset's length. From the different testings, we have selected the ones with high Overall System score as well as high Validation Sample Rate and in each case scenario we used approximately 30-65 iterations while the max number was set in 100, 6 validation checks, random data division, scaled conjugate gradient and cross-entropy performance, all in accordance with Matlab's standards so as to ensure the quality of results. In addition, the application generated the confusion matrix (CM), the receiver operating characteristic (ROC), the training performance, the training state and the error histogram plot, for each test, which were used to validate the above results.

TABLE 1. Neural Network tests for 3 inputs(width,height,weight) and 5 output(kind of passer) classes for the final data set

Training-Validation-Testing Rates(%)	70-15-15	15-15-70	15-70-15	35-15-50	35-50-15	50-35-15
Training Sample Rate(%)	90.4	98	99	97.8	96.5	94.5
Validation Sample Rate(%)	91.8	96.9	96.1	94.9	95.4	96.1
Testing Sample Rate(%)	84.7	93.2	87.8	97.2	99	96.9
Overall System(%)	89.8	94.5	95.3	97.1	96.3	95.4

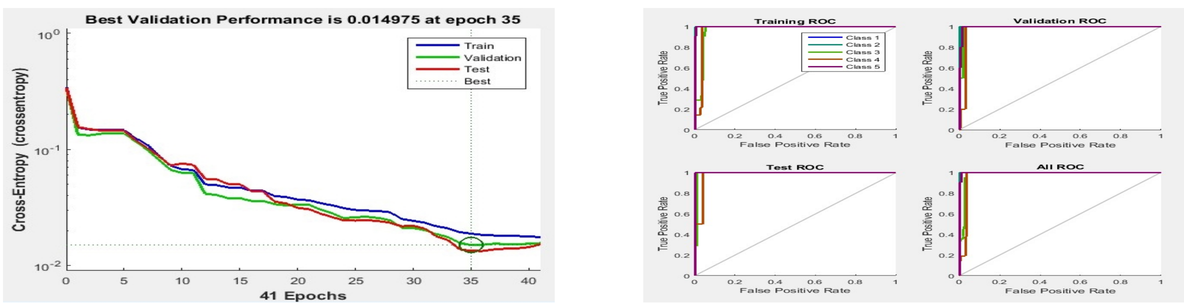

FIGURE 1. Performance plot and ROC curves for the optimal system as derived from Table 1 for the 50-35-15 case.

CLUSTER OF DATA

After successfully constructing a neural network system which may predict the kind of passer, we proceeded to ascertaining its validity. For this reason, after preprocessing the raw data and implementing the previously mentioned equations, in order to calculate Width, Height and Weight we clustered them using Simple K-means and X-means algorithm [14]. We have conducted our experiments on each case for Euclidean, Manhattan and Chebyshev distance, in order to select the optimal results. During our testings we have observed that Manhattan distance for big data samples and for a small number of clusters, is not greatly affected by the outliers. During our testings, we have not excluded any outliers, regarding the inputs of our system. Primarily, Weka has been utilized to verify the ontology of our *3-Input Passer Dataset* for which we know the "ground truth" and the NN's final recognition result set, which we do not. It should be noted that the latter refers to processing real data(*7-Input Pilot Data-set*). The clustering results are presented in the following manner: instances of the training set (samples) are shown in Real axis and the variable of interest (classification variable) in Imaginary axis. As we know the "ground truth" of our datasets and the Matlab prediction of our NN, by associating the sample id with the type of passer (e.g. samples 0-21 human, 22-64 bear etc.) we were able to identify the passer which we were trying to cluster and thus verify the validity of the clustering's centroid.

Our first experimental testings concerned the distinction among humans and bears, characterized by the following features: Width, Height and Weight. We generated a database of 549 samples out of which 42 from the *3-Input Passer*

Datase and 507 from the *Body Dataset*, where samples 0-506 were humans and the rest were bears. In addition, we executed the X-means clustering algorithm, in order to determine whether the clustering would correctly separate each case study. As a result, two clusters were created, the first representing humans and the second bears. The results were that bear samples were located to the upper high region denoting high weight values, which fully characterises them. We replicated the experiment using both Euclidean and Manhattan distance however Euclidean distance was chosen due to the smaller distortion of the centroids. Next, we attempted to cluster all classes together for the integrated *3-Input Passer* and *Body Datasets* comprising of 634 instances applying the Manhattan distance. The results were satisfying after setting the maximum number of classes to four, which, in most cases, correctly identified humans, flying species, bears and Canis subspecies (grey wolf and Greek shepherd dog) as shown in Figure 2 for their Weight attribute. This is particularly interesting, as it can be used as a tool by the Egnatia Highway personnel, in order to give a first account of the passer that is crossing the passage, in a given period of time which is significant in determining the effectiveness of the mitigating structure, in respect to being used by wildlife and especially bears. By repeating the previous experimental procedure, using real observations, as derived from the Alpine project (*7-Input Pilot Dataset*) we were confident about the kinds of passers that traversed the passage during the pilot's program period of 2 months.

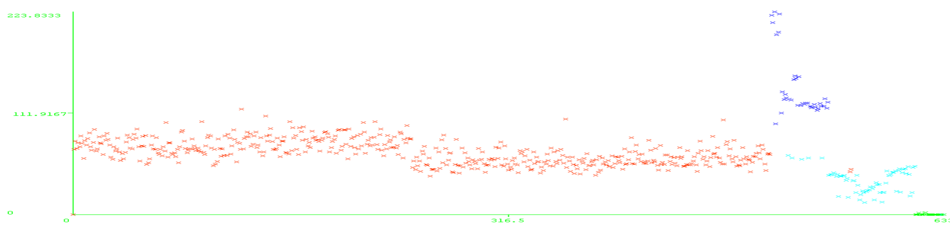

FIGURE 2. Clustering results of the X-means algorithm using Manhattan distance, for a big data set of 634 instances where red represent human, blue bears,light blue Canis subspecies and green flying species in accordance with the variable of Weight.

RESULTS

First and foremost, we were able to construct a neural network, capable of predicting the kind of passer with a probability of 95.4 % for rates of: 50% for Training, 35% for Validation and 15% for Testing, as evident in Figure 1. K-means as well as X-means algorithm were able to instantly separate our sample in two instances, human and animals for all the used distances. This technique leads to extremely accurate outcomes, resulting to the identification of all different classes and in several cases, passers could even be separated in male or female. After conducting several testings on each kind (bear-human, bear-wolf, etc.), we concluded that the sole cases where passers would be falsely recognized, were the grey wolf and the Greek shepherd, which may not be distinguished from each other as the variable of weight is far more crucial in the identification of the passer, than height or width.

Hence, for each data set, we have validated our results with clusters of data as well as extreme cases, such as an obese person (high weight), a child (small height and weight) or a fox (extremely low weight and height) and it is able to instantly segregate not only ground species from bird species but most of the other species too. For the 76 passers that actually crossed the K81 tunnel during the pilot application, we have concluded that 18 were wolfs, 8 were birds/bats and 50 were Greek shepherds. Although the area is densely populated by bears, it comes as a surprise that not a single one has crossed our sensors' line of sight and after consulting with *Callisto*, we have concluded that the bears' absence was due to their special way of thinking. For future notice, we recommend the construction of animal-friendly above-ground passages, instead of tunnels, although it may be expensive. In addition, environmental barriers (bushes, trees, plants) are proposed, so as to indicate the available route to the animals.

CONCLUSIONS AND FURTHER WORK

We have studied and proposed a method for measuring usage frequency of K81 passage, by means of data fusion of WSN data and have produced an objective evaluation of the proposed pattern recognition techniques using cluster analysis and implemented method, by developing cluster analysis. Under this scope, we were able to easily determine whether the tunnel's usage was frequent or not and by which species. While the purpose of our study was to evaluate the effectiveness of the tunnel, our model also provides valuable information regarding the protection of certain endangered species, which inhabit these areas, such as the brown bear (months of hibernation or immigration to warmer climates etc).

This paper may be used as a stepping stone for additional research projects and applications. First of all, we may add night-vision cameras, so as to test the validity of our NN results, in action and capture real time photos/video, so as to instantly analyze the kind of passer on any given time. As a result, when our system produces a false prediction, we can update our dataset or insert a new output class. Moreover, further research is required regarding pattern recognition, so that the system would recognize a flock or a crowd passing and record it in the right output. In addition, the creation of NoSQL databases should be considered, due to the multi column listed sensors' received readings. It is indicative that, for the study of the passage K81, each query required 2-3 seconds, in order to be executed and additional time to load on the user's screen, thus hindering the performance of multiplex queries. This task is crucial, especially if we aim to create a large database which would automatically connect with all available passages throughout Egnatia's road network. Finally, the system should be user-oriented and reconstructed to a simple graphical user interface, in order to supply future analysts with all the necessary tools, so as to examine our methods and possibly ameliorate the results.

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