Turkish Journal of Electrical Engineering & Computer Sciences

http://journals.tubitak.gov.tr/elektrik/

Research Article

Turk J Elec Eng & Comp Sci
(2019) 27: 2817 – 2832

doi:10.3906/elk-1807-258

Patient comfort level prediction during transport using artificial neural network

Željko JOVANOVIĆ[1,*], **Marija BLAGOJEVIĆ**[1], **Dragan JANKOVIĆ**[2], **Aleksandar PEULIĆ**[3]

[1]Faculty of Technical Sciences, University of Kragujevac, Čačak, Serbia
[2]Faculty of Electronic Engineering, University of Niš, Niš, Serbia
[3]Faculty of Engineering, University of Kragujevac, Kragujevac, Serbia

Received: 24.07.2018 • **Accepted/Published Online:** 22.02.2019 • **Final Version:** 26.07.2019

Abstract: Since patient comfort during transport is a matter of paramount importance, this paper aims to determine the possibilities of applying neural networks for its prediction and monitoring. Specific objectives of the research include monitoring and predicting patient transport comfort, with subjective assessment of comfort by medical personnel. An original Android application that collects signals from an accelerometer and a GPS sensor was used with the aim of achieving the research goals. The collected signals were processed and a total of twelve parameters were calculated. A multilayer perceptron was created in the proposed research. The evaluation results indicate acceptable accuracy and give the possibility to apply the same model to the next patient transport. The root mean square error was 0.0215 and the overall confusion matrix prediction accuracy was 90.07%. Moreover, the results were validated in real usage. The limitations and future work are highlighted.

Key words: Patient comfort, artificial neural network, android application, accelerometer

1. Introduction

While the comfort of passengers is regarded as one of the most significant features of vehicles, a problem arises when it comes to its measuring. The difficulty lies in the fact that comfort is dependent on numerous factors. In general, the acceleration (vibration) that passengers feel during a ride is considered to have the greatest impact on the comfort they experience. The three most important factors that are responsible for the vibration in a vehicle are the vehicle's condition, the driver's skills (driving style), and road conditions. Although the condition of the vehicle is determined based on numerous characteristics, it is generally accepted that suspension and tires influence vibration to the greatest extent. The effect of vibration on humans in various situations was addressed in [1, 2]. However, it must be noted that the transport of patients should be regarded as a specific category of transportation since patients are passengers with mental or physical health problems and the comfort of the ride affects the mental and physical conditions of even healthy passengers. Therefore, the effect of vibrations, noise, temperature, and other subjective parameters could be even greater when it comes to patients since these can exacerbate their already existent health problems. There are two types of patient transport: primary transport and secondary transport. Primary transport [3] is the movement of patients from the scene of an accident or the onset of illness to the first hospital contact, where their injuries or illnesses can be stabilized and treated. It is usually undertaken by paramedics and it is called prehospital care. Secondary transport [4] is the movement of the patient after initial treatment and may include transfer to specialized facilities within the same

*Correspondence: zeljko.jovanovic@ftn.kg.ac.rs

hospital (intrahospital transfer) or transfer from one hospital to another for continuing clinical care (interhospital transfer). Road ambulance vehicles are mostly used for patient transport from or between places of treatment. In many instances, these vehicles must provide medical care to the patient; therefore, they are specifically designed for patient transport and should be aligned with the regulations presented in [5]. This European standard outlines the requirements for the design, testing, performance, and equipping of road ambulances used for the transport and care of patients. The design of emergency medical service (EMS) vehicles, as shown in [6], specifies a number of recommendations for patient transport. The transport of patients with severe head injuries was presented in [7], whereas the adequate transport of patients with spinal injuries was described in [8]. The most significant recommendations relate to careful and steady transport of patients. Having this in mind, this paper focuses on the monitoring and prediction of patient transport comfort in EMS vehicles. The purpose of the research is to determine the possibilities of applying neural networks in predicting patient comfort. The specific aims of the research relate to monitoring and predicting the comfort of patients during transport. The results were obtained using the subjective evaluation of comfort by medical staff in EMS vehicles. An Android application presented in [9] was used to collects signals from an accelerometer and GPS sensor. Moreover, the results were validated in real usage. This paper also puts an emphasis on the potential to use the prediction algorithm in emerging and rapidly developing technologies. The remainder of this paper is structured in the following way: Section 2 presents the related work, Section 3 focuses on the research methodology, Section 4 presents the obtained results, and the final conclusions are shown in Section 5.

2. Related work

This section presents the previous work related to patient comfort during transport and the application of neural networks in predicting it. As mentioned above, riding comfort is regarded as one of the primary characteristics of vehicles and the acceleration (vibration) of the vehicle during the ride is generally considered the most significant factor that affects the comfort of the passengers. The general term that relates to the vibrations (mechanical oscillations) of any frequency that are transferred to the human body is whole-body vibration (WBV). An overview of current standards and regulations regarding WBV was given in [10]. These are:

- ISO Standard 2631-1 (1997) [2];
- British Standard 6841 (1987) [11];
- ANSI S3.18:2002 [12];
- European Directive 2002/44/EC [13];
- Control of Vibration at Work Regulations [14].

The International Standard Organization (ISO) presented a popular and useful criterion for ride comfort (ISO 2631) [2], which addresses the effects of vibrations on a passenger. Comfort levels are defined according to [2]. Only vertical axes are used for the classification of comfort levels.

Both standards and regulations presuppose that acceleration magnitude, frequency spectrum, and duration represent the crucial exposure variables, which may lead to potential harmful effects. The Serbian national standard that relates to this field is ICS 13.160 (SRPS ISO 2631-1:2014, Mechanical vibration and shock: Evaluation of human exposure to whole-body vibration, Part 1: General requirements). The proposed research highlights the subjective assessment of comfort, while the calculated values were used for neural network training. The impact of vibration duration and the amount of rest between successive vibrations were analyzed in [15]. No significant differences were found in discomfort between 15-s or 20-s vibration exposure, nor between 5-s and 10-s rest duration for any type of vibration exposure. The research presented here applied the same driving conditions for the testing of the decision interval with 10-s and 15-s durations. The relationship between discomfort and the vibration total value for different axes of vibration was given in [16]. A number of statistically significant differences were observed in discomfort between the different axes of vibration for similar ranges of vibration total values. Less discomfort was typically associated with single axis vertical vibrations than with multiaxis vibrations. This finding implies that the frequency weighting scheme presented in ISO 2631-1 does not achieve interaxis equivalence. Consequently, it is necessary to conduct a more detailed analysis of multiaxis vibration that will lead to changes in the ISO 2631-1 weighting factors. Accordingly, all three axes were included in the prediction of comfort in the proposed research. An accelerometer is a device that can detect and measure static gravity influence, as well as dynamic movement influence. The authors of [17–19] devised automotive real-time observers and an attitude estimation system based on an extended Kalman filter (EKF). The authors of [20] detected road potholes with high-pass filtered accelerometer data. A high-pass (HP) filter was used for passing high-frequency vibrations in the proposed research. The use of mobile health devices is becoming increasingly common in this field of research since they have sensors (accelerometers, gyroscope, GPS), multicore processors, etc. The conclusion that the authors of [21] reached was that mobile technologies may transform care delivery across populations and within individuals in the foreseeable future. The authors of [22] outlined a mobile sensing system for road irregularity detection using Android OS-based smartphones. Only the Z-axis was used in their calculations. However, the calculations in the present paper were performed over all three axes. The authors of [23] considered the problem of monitoring road and traffic conditions in a city using smartphones. Smartphones were also used in the proposed research, but to monitor and predict patient transport comfort levels, not to detect the cause of discomfort. According to the ISO 2631-1 standard, exposure to WBV brings health risks. The authors of [24, 25] concluded that ISO 2631-1 comfort prediction results did not match self-reported results for heavy machinery routines for construction, forestry, and mining vehicles. Since the subjective experience of the comfort level was different from the predicted one, in the proposed research neural networks (NNs) are implemented in order to predict subjective comfort. The relation between disability retirement and workers' exposure to WBV was the subject of many papers. A strong association between these was shown in [26]. The authors of [27] concluded that both the age and the weight of drivers were important. Although this was not taken into consideration in the proposed research, it will be considered as an additional input parameter in a future work. Very few papers deal with neural network implementation in predicting patient comfort during transport. Neural networks were successfully implemented in drug transport modeling and simulation in [28]. As opposed to the research conducted in [28], in the proposed research patient transport comfort is analyzed using artificial neural networks. In [29], neural networks were implemented to predict ice jam occurrence. The authors of [29] found that the application of neural networks could be more successful for this issue than the application of other techniques of data mining, thereby concluding that NNs provide early warning and permit rapid and effective mitigation of ice jams. Provided that the true data-generating process is unknown and hard to identify, which was the case in this study, the authors of [30] suggested the implementation of neural networks. Such an approach involved creating, testing, and evaluating models of neural networks [30]. Neural networks were also successfully applied in the analysis of the quality of public transport in [31]. In [32], unlike in the proposed research, a Bayesian network was used for identifying the mode of transport: walking or cycling. The authors in [33] proposed decentralized intelligent transportation systems with distributed intelligence based on classification techniques. By analyzing the related research in the application of neural networks for predicting comfort levels, one can observe similarities and differences with the proposed method of each shown survey. The analysis of related research has found that neural networks have been used in the analysis of various transportation problems. However, very few studies dealt with transport comfort using the aforementioned techniques. In this sense, the proposed research is innovative in its approach, with its purpose of determining the possibility of implementing artificial neural networks for the presented research problem.

3. Materials and methods

In this section the methods and materials for analysis are presented. In order to collect the data for patient comfort monitoring, an Android application was developed to calculate several parameters and passengers' subjective comfort levels during patient transport. The collected data are further used to train, test, and validate the neural network in order to detect the subjective patient comfort level.

3.1. Android application for patient transport comfort monitoring

For patient transport comfort monitoring, an Android application was developed. It is based on three axes' accelerometer data calculations. The development of the main application functionalities was presented in [34] and full functionalities were presented in [9]. In order to collect parameters for patient transport comfort analysis, accelerometer calculations, GPS monitoring, and main application threads are created using RxJava [35]. The developed Android application algorithm is presented in Figure 1.

After application parameters are set up, the accelerometer and GPS threads start. At the beginning, the application calibrates the accelerometer axis orientation as follows: X is the movement direction, Y is the lateral movement direction, and Z is the vertical movement direction. Thanks to these, it is possible to analyze the discomfort cause direction, with axis discomfort as follows:

- Z-axis: ertical discomfort,
- Y-axis: lateral discomfort,
- X-axis: moving direction discomfort.

After the calibration, the comfort calculation is performed. Live three-axis acceleration caused by the vehicle's vibrations are plotted on the phone display. After the decision time interval expires, the application requests the user to enter the subjective comfort level (comfortable; medium uncomfortable; uncomfortable). The marked comfort level is presented in the display's upper right-hand corner with a green, yellow, or red light bulb, respectively. Calculated and subjectively marked data are saved to KML and TXT files. Implemented calculations are presented in the next section.

3.2. Implemented calculations

The application is designed to calculate accumulated vibrations in standard time intervals according to Eq. (1):

$$a_{zRMS} = \sqrt{\frac{1}{n}\,(a_{z1}^2 + a_{z2}^2 + \cdots + a_{zn}^2)}. \tag{1}$$

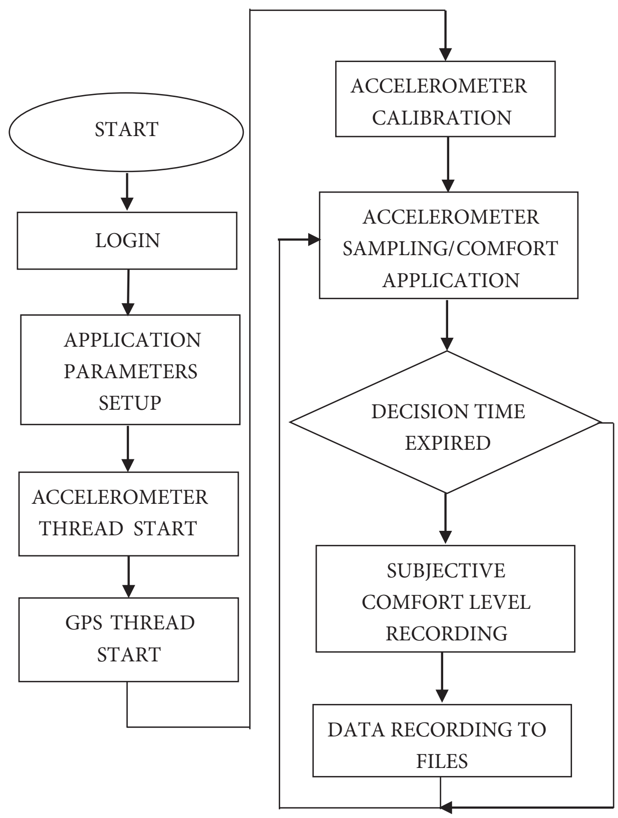

Figure 1. Algorithm of the developed Android application.

This calculation is performed for all three axes (RMS_X, RMS_Y, RMS_Z). Beside these values, for every acceleration sample, the application calculates the magnitude of all three axes' accelerations according to Eq. (2):

$$a_{iRMS} = \sqrt{a_{xi}^2 + a_{yi}^2 + a_{zi}^2}, \tag{2}$$

where a_{xi}, a_{yi}, and a_{zi} are the X-, Y-, and Z-axis accelerations for the ith sample and a_{iRMS} is the magnitude of all three axes' accelerations. Using these values in the decision time interval, a_{RMS} is calculated according to Eq. (3):

$$a_{RMS} = \sqrt{\frac{1}{n}\left(a_{1RMS}^2 + a_{2RMS}^2 + \ldots + a_{nRMS}^2\right)}, \tag{3}$$

where a_{iRMS} is the ith magnitude of all three axes' accelerations and n is the number of samples.

According to the ISO (ISO2631-1:1997), the weighting factors for the X- and Y-axis are 1.4 while for the Z-axis it is 1.

Exposure to WBV, based on weighting factors, is calculated with the following formula (ISO2631-1:1997):

$$a = \sqrt{1.4^2 a_x^2 + 1.4^2 a_y^2 + a_z^2} \quad [\mathrm{m/s^2}]. \tag{4}$$

Although many researchers use the k-factor (i.e. 1.4) for the accelerations along the X- and Y-axes when evaluating WBV, as noted in the application of ISO 2631, there is debate about this number due to ambiguity regarding the axes to be evaluated. The ambiguity comes from the anomalous use of a multiplying factor of 1.4 for ax and ay. Guidance is only provided regarding the evaluation of health effects of WBV, not the effects of WBV on comfort. As an alternative, the vector sum of the RMS accelerations with no weighting factor can be used (ISO 2631-1:1997), as in Eq. (2).

This formula is being used with many machinery devices to measure the acceleration.

Beside these calculations, maximum magnitude values (APEAK) and their axis values (APEAK_X, APEAK_Y, APEAK_Z) are calculated. For detected APEAK the GPS data (latitude, longitude, altitude, speed, time) are stored. For the analysis of suffered vibrations all three axes' maximum accelerations are calculated. According to these, after the decision time interval the next values are stored in predefined file formats:

- IDT: location marker ID
- RMS_X: Eq. (1),
- RMS_Y: Eq. (1),
- RMS_Z: Eq. (1),
- ARMS: Eq. (3),
- APEAK: Eq. (2),
- APEAK_X, APEAK_Y, APEAK_Z: axis values for APEAK sample,
- LATITUDE,LONGITUDE, TIME, SPEED: GPS data for APEAK sample,
- MAX_X, MAX_Y, MAX_Z: maximum detected absolute values by axes,
- COMFORT: subjectively marked comfort level (0 = comfortable; 1 = a little uncomfortable; 2 = uncomfortable).

In order to measure the real acceleration of the device, the contribution of the force of gravity must be eliminated. This is achieved by applying a HP filter over raw accelerometer data according to Eq. (5):

$$\mathrm{HPX}_i = \mathrm{HPX}_{i-1} - \left((\mathrm{RX} \cdot f_c) + \mathrm{HPX}_{i-1} \cdot (1 - f_c) \right), \tag{5}$$

where HPX_i is the ith HP-filtered X-axis acceleration, RX is raw X-axis acceleration data, and $f_c = 0.1$ is the filter coefficient that cuts 10% of the lower frequencies. Raw and filtered data for all three axes are presented in Figure 2a and Figure 2b, respectively.

As presented in Figure 2, the gravity influence is eliminated without significant loss of information. Since the phone was almost in an ideal vertical position the gravity impact was largest on the X-axis. The HP-filtered data calculations in Eqs. (1)–(3) were performed for all three axes. Cumulative signals with marked calculated data are presented in Figure 2c. In the presented data sample's signal, APEAK_Z is also the maximum detected value for the Z-axis acceleration (MAX_Z) in the decision interval. Maximum values for the X- and Y-axes are detected from the aPeak sample. All calculated data presented in Figure 2c are presented in Table 1.

According to the calculated results, the vertical (Z) axis had a higher RMS value, while the moving direction (X) axis and lateral (Y) axis had lower RMS values. The application is improved with sensitivity level determination, as shown in Figure 3.

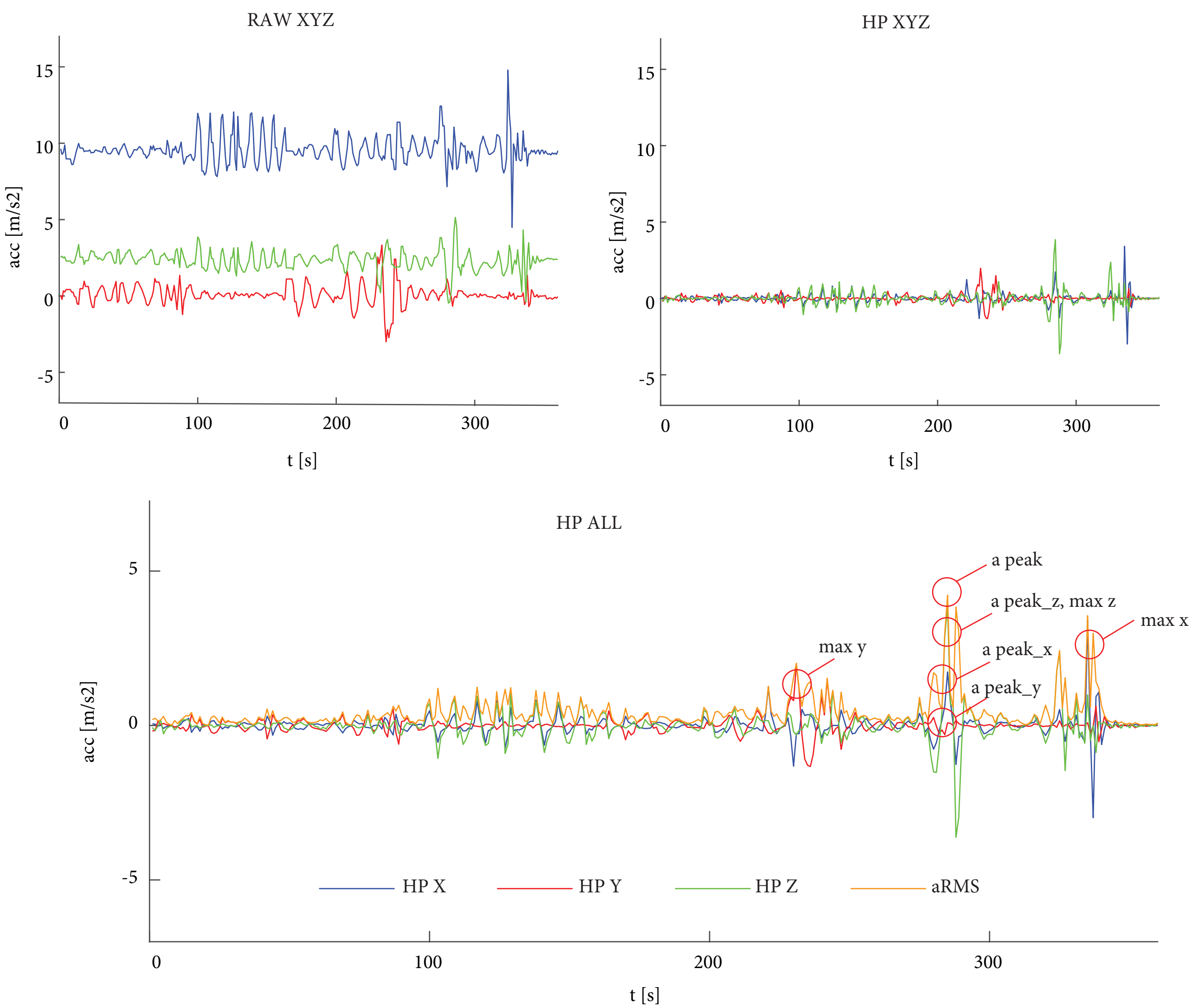

Figure 2. Raw and HP-filtered acceleration data for all three accelerometer axes: a) raw XYZ; b) high pass XYZ; c) decision interval signals for all three axes with marked calculated data.

Table 1. Calculated data.

RMS_X [m/s^2]	RMS_Y [m/s^2]	RMS_Z [m/s^2]	ARMS [m/s^2]
0.287	0.238	0.401	0.548
$APEAK_X$ [m/s^2]	$APEAK_Y$ [m/s^2]	$APEAK_Z$ [m/s^2]	APEAK [m/s^2]
1.731	0.084	3.846	4.218
MAX_X [m/s^2]	MAX_Y [m/s^2]	MAX_Z [m/s^2]	Speed [km/h]
3.414	1.975	3.845	46.35

The sensitivity thresholds were determined experimentally in cooperation with medical staff. For example, Category 1 sensitivities include groups I, O, and P; Category 2 includes group G diagnosis; and Category 3 includes diagnoses C, D, F, K, and N. Diagnosis groups are as defined by the World Health Organization (International Statistical Classification of Diseases and Related Health Problems (International Classification of Diseases), 10th Revision - Version: 2010, Vol. 1, 2010).

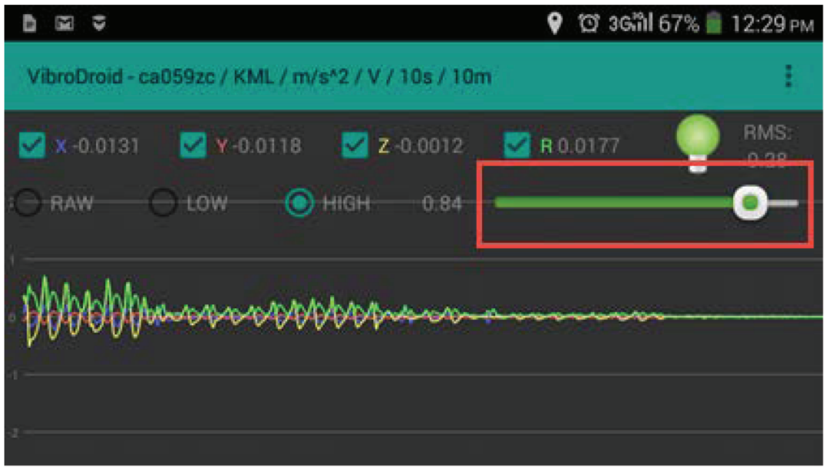

Figure 3. Sensitivity level.

3.3. Android application usage in patient transport monitoring

The proposed research application presents the usage of an EMS vehicle (type B) in Čačak, Serbia. The application is used for the secondary type of patient transport between Čačak and Belgrade medical institutions. The example of one transport between Čačak and Belgrade is given in Figure 4. For validation, in this research a completely new route is used: Čačak-Užice. Besides the driver and a patient, two medical staff members are present during every transportation to provide necessary medical care if needed. Patients who participated in the transport had cardiac problems with arrhythmia. For future work it is planned to gather data for different types of medical diseases and also different types of roads. The phone with the installed Android application was attached to the windshield using a phone holder, as presented in Figure 4. This phone position is also useful for the driver, who is able to monitor vibration signals plotted on the display and to adjust the driving style accordingly.

Thirty patients from Čačak medical institutions were transported to other medical institutions in Serbia for necessary medical treatment. Their medical conditions demanded special equipment only present in specialized medical institutions outside of Čačak. During the first five cases, the application was tested in real conditions and the medical staff were trained for its appropriate usage. Others were used for data collection for neural network training and testing. The comfort decision interval was set to 10 s. After its expiry, one of the medical staff members in consultation with the patient marked the subjective comfort level among comfortable, medium uncomfortable, and uncomfortable. Calculated data and comfort level were saved to KML and TXT files in the phone's internal memory. Upon completion of the transportation, XML and TXT files were transferred from the phone's memory to a computer for further analysis. The KML file is displayed using the Google Earth program, as shown in Figure 4. The marker color presents the 10-s marked comfort level (green

= comfortable; yellow = a little uncomfortable; red = uncomfortable).

(a) (b)

Figure 4. a) Implemented application usage, b) appearance of saved KML file.

The patient transport comfort statistics on the route from Čačak to Belgrade are shown in Table 2. The average values of all calculated data are presented.

Table 2. Transportation statistics.

Statistics	Value
Total interval number	25,290
Comfortable interval number	454 – 53.8%
A little uncomfortable interval number	363 – 43%
Uncomfortable interval number	26 – 3.2%
Average RMS_X	0.1258 [m/s^2]
Average RMS_Y	0.129 [m/s^2]
Average RMS_Z	0.2607 [m/s^2]
Average ARMS	0.3202 [[m/s^2]
Average APEAK	1.0704 [m/s^2]
Average MAX_X	0.4894 [m/s^2]
Average MAX_Y	0.4527 [m/s^2]
Average MAX_Z	1.0024 [m/s^2]
Average speed	55.51 [km/h]
Average altitude	209.76 [m]

Results shows that 53.8% of the intervals were comfortable, 43% were a little uncomfortable, and 3.2% were very uncomfortable. Based on the average RMS axis values, the Z-axis (vertical) detected most of the causes of discomfort along the way. The average APEAK value is over 1 m/s^2, which means that a large number of intervals had a stronger shock in at least one sample.

3.4. Neural networks: selection of data

The survey was conducted on one route, Belgrade-Čačak, thirty times. The distance between these two cities is 150 km. The number of recorded points for thirty transports and the descriptions thereof are given in the context of Table 1.

3.4.1. Preprocessing and data transformation:

This phase involves solving the problem of incomplete and incorrect data. In this study, incomplete values were ignored, because, as stated in [36] and [37], where techniques for solving this problem were compared, this approach has proved to be the most appropriate.

3.5. Neural network: model creation

Here, a multilayer perception, which is one of the backpropagation neural networks, was used. This is a multilayer algorithm and learning was monitored. The neural network algorithm was used to create a network that could contain three layers of neurons in this study: the input layer, hidden layer (which is optional), and output layer.

Figure 5 shows the neural network structure, chosen input, and output parameters, and also the key attribute (marker id).

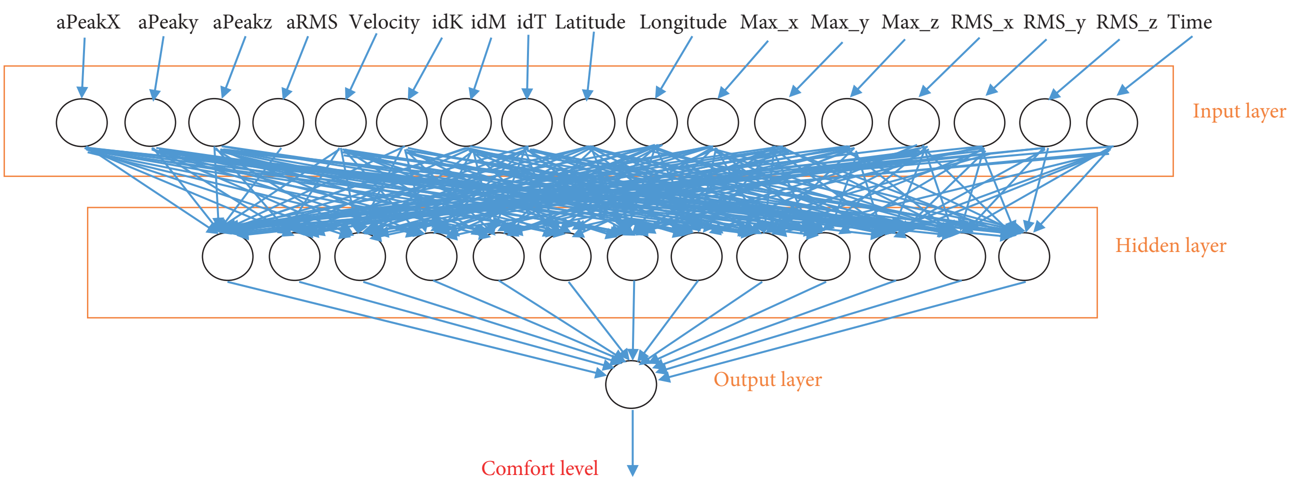

Figure 5. Structure of neural network.

3.6. Evaluation of neural network model

For model evaluation in this research, 30% of data was used for testing and 70% of the data was used for training the neural network. Evaluation was done in two ways: a confusion matrix and root mean square error (RMSE).

Root mean square error is calculated according to the following:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=0}^{n-1}(t_i - o_i)^2}, [37] \quad (6)$$

in which ti is the calculated output given by way of the community, oi is the actual output for case i, and n is the wide variety of instances in the pattern. The error is averaged in keeping with the number of output variables and associated with the variety of instances wherein the pattern is calculated. The confusion matrix [38] is determined between the target class and output class. The diagonal cells in each table display the number of cases that were labeled correctly, and the off-diagonal cells show the misclassified cases. The blue cell at the bottom right suggests the whole percentage of correctly categorized instances (inexperienced) and the whole percentage of misclassified cases (in pink). Gray cells numbered 1, 2, and 3 in the fourth row show the popularity accuracy of comfortable, slightly uncomfortable, and uncomfortable styles, respectively. Gray cells numbered 1, 2, and 3 inside the fourth column of the confusion matrices represent the precision or positive predictive value (PPV) and negative predictive value (NPV) of comfortable, slightly uncomfortable, and uncomfortable styles, respectively. The high quality and NPVs are the proportions of positive and negative consequences in confusion checks, which are true positive and true negative results. Mathematically, the PPV and NPV can be expressed as:

$$PPV = \frac{TP}{TP + FP}, \qquad NPV = \frac{TN}{TN + FN}, \tag{7}$$

where TP is the true positive rate, FP is the false positive rate, TN is the true negative rate, and FN is the false negative rate. The receiver operating characteristic (ROC) curve is a graphical technique that illustrates the overall performance of a classification. The curve is created by plotting the actual high quality against the false positive rate. In a perfect balance of positive and negative results, the ROC curve is positioned in the upper left. The training and checking of the classifiers was completed with the use of the pass-validation methodology. The dataset was divided at random into k distinct units. Training is accomplished on ok-1 sets and the ultimate set is tested. For all of the variable training and check units, this is repeated. Averages of all k effects are the category results.

4. Results and discussion

This section provides the results of evaluation regarding the RMSE and confusion matrix. Results are also given regarding Data Mining Extension (DMX) queries together with a discussion of the research.

4.1. Results of evaluation

This section provides results related to types of evaluation as described in Section 3.6. The RMSE value in this research is 0.0245. Compared to similar work in [39] and [40], the RMSE has an acceptable value. Figure 6 shows the confusion matrix and the ROC curve.

Based on the results for the confusion matrix, we can discuss the following aspects:

- 124 cases were classified correctly as 1, whereas 7 cases were classified incorrectly as 2;
- 97 cases were classified correctly as 2, whereas 9 cases were classified incorrectly as 1 and 6 cases were classified incorrectly as 2;
- 6 cases were classified correctly as 3, whereas 3 cases were classified incorrectly as 2.
- The confusion matrix shows that there are no incorrect classifications from states 1 to 3 and vice versa.

ROC analysis was also employed to evaluate the performance of the proposed method in classifying patterns into one of three classes. The ROC curve graphs in Figure 6 demonstrate the accuracy rate of pattern classification. In order to predict the accuracy rate of recognition, the graphs are plotted between true positive rates and false positive rates.

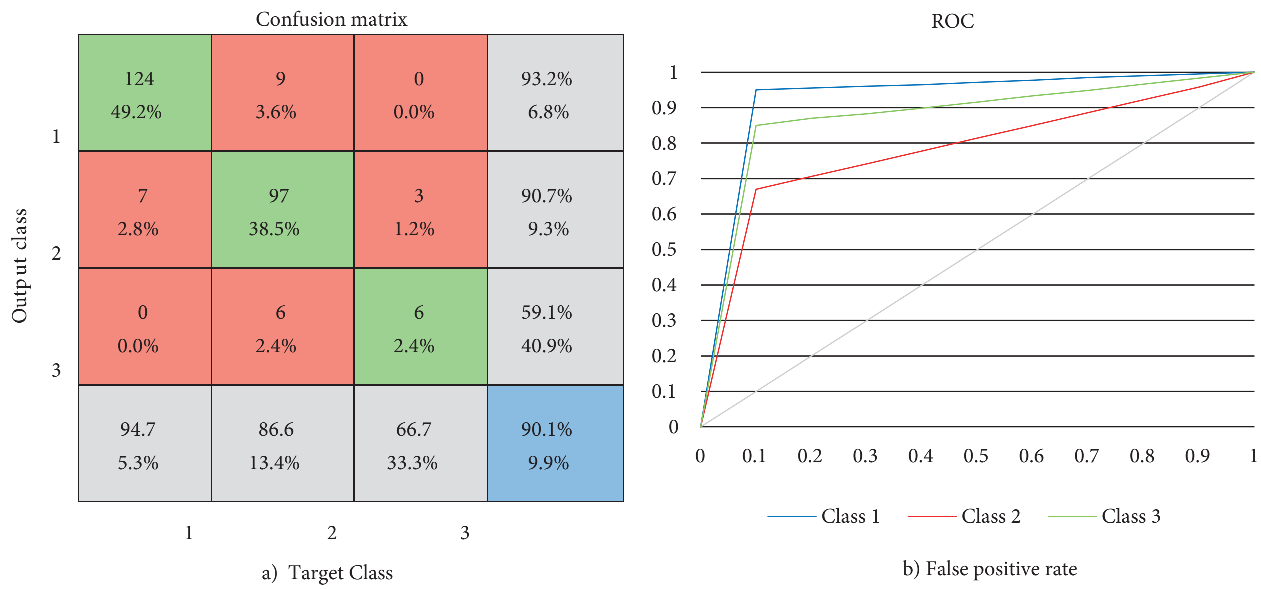

Figure 6. a) Confusion matrix; b) ROC curve.

The classifiers are trained and tested using 10-fold cross-validation to ensure exhaustive testing with all samples. According to this technique the dataset is divided at random into a set of K = 10 distinct sets. Then training is performed on K - 1 sets and the remaining set is tested. This process is repeated for all possible K training and test sets. The classification results are averages of all K results.

4.2. Results: testing neural networks

The testing of neural networks in this research was conducted via DMX query [41]. The aim of using a DMX query is related to creating queries against the model in order to get the desired results and an answer to the research questions is obtained. In this study, the goal was to obtain the predicted probability of access to certain modules. DMX queries can be created within Microsoft Visual Studio 2008, using a wizard, or queries can be written directly within Microsoft SQL Server Management Studio 2008 after the selection of models and types of queries. We used singleton queries for the predictions. The following is an example of a query:

```
SELECT [Tacke].[Comfort], Predict ([Comfort])
From [Tacke]
NATURAL PREDICTION JOIN
(SELECT '0.1132' as [aPeak], '0.0657' as [a RMS], '43.8882666' as [Latitude],
'20.340825' as [Longitude], '0.115509704' as [Max X], '-0.067291334' as [Max Y],
'0.791438103' as [Max Z]) AS t
```

This anticipated comfort on the basis of entered parameters for Apeak, a_{RMS}, Latitude, Longitude, Max X, Y Max, and Max Z. Requests allowed us to change input parameters and test values for the user's needs. As a result, the comfort level was predicted as 0, which represents comfortable transport. Bearing this in mind, the results obtained through testing the neural network can be discussed with regard to the importance of using DMX queries. The above-mentioned queries can be used successfully for the specific needs of users, listing the selected input parameters and obtaining results from different perspectives in relation to the selected function prediction.

4.3. Validation in real usage

For system validation in real usage, another transportation was conducted for Čačak-Užice, Serbia. The generated KML file is shown in Figure 7.

Figure 7. Generated KML file for Čačak-Užice transport.

Every marker comfort level is validated using the presented neural network model. Real usage validation results are presented using the confusion matrix and ROC curve. Figure 8 shows the generated confusion matrix and the ROC curve.

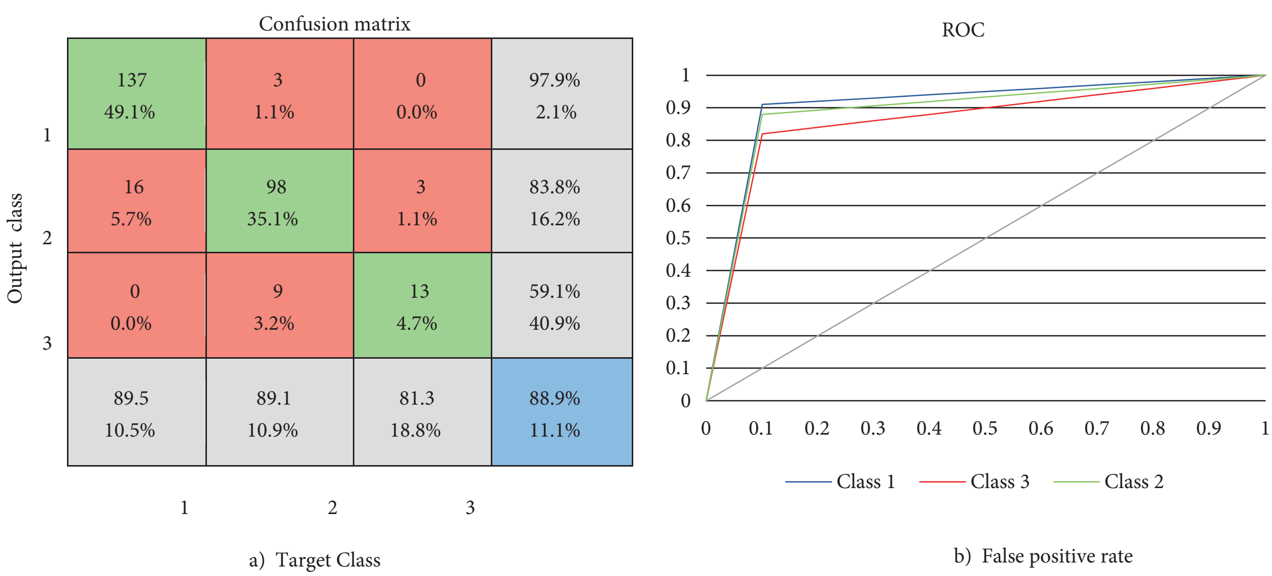

Figure 8. The confusion matrix (a) and ROC curve (b) for Čačak-Užice.

As presented in Figure 7, overall precision is 88.9% which is 1.2% less than the results presented in Figure 5.

These results are satisfying since the measurement was conducted on a new route that was not used for the neural network training.

5. Conclusion

We can draw conclusions in several areas:

- Analysis of comfort in the transport of patients:
  According to the results, comfort levels can be estimated with satisfactory accuracy. The proposed approach highlights the potential to use the prediction algorithm in emerging and rapidly developing technologies. The evaluation results indicate acceptable accuracy and give the possibility to apply the same model to the next patient transport. The results enable further work on determining the transport's impact on the patient's medical condition. In this paper we analyzed the transportation of patients with one type of medical problem (cardiac problems). As future work, we plan to analyze other types of medical problems and include them as additional input values in the neural network. Then the neural network could be trained to predict comfort levels according to patients' medical problems and transport parameters.

- Android applications:
  After examining the results obtained by the created Android application we can conclude the advantages and disadvantages of the application. The created application is mobile and simple to install and use. The limitations of the application are real-time neural network predictions, which are implemented offline. Future work will address real-time neural network implementation.

- Applying neural networks in predicting patient comfort during transport:
  Neural networks, based on the presented results, can be used successfully to predict patient comfort during transport. The created model gave satisfying accuracy and could be applied for future patient transport. Future work in the field of neural networks relates to the creation of Web-based applications that receive input data and, as a result, provide the comfort level and driving style recommendations.

Acknowledgments

The work presented in this paper was funded by Grant No. TR32043 and III44006 for the period of 2011-2019 from the Ministry of Education and Science of the Republic of Serbia.

References

[1] Griffin M. Handbook of Human Vibration. London, UK: Elsevier Academic Press, 1996.

[2] ISO. Standard by Technical Committee ISO/TC 108/SC 4. Human Exposure to Mechanical Vibration and Shock, ISO 2631-1 Mechanical Vibration and Shock - Evaluation of Human Exposure to Whole-Body Vibration - Part 1: General Requirements. Geneva, Switzerland: ISO, 1997.

[3] Coats T, Davies G. Prehospital care for road traffic casualties. British Medical Journal 2002; 324 (7346): 1135.

[4] Gray A. Secondary transport of the critically ill and injured adult. Emerging Medicine Journal 2004; 21 (3): 281-285.

[5] British Standards Institution. British-Adopted European Standard. BS EN 1789:2007+A2:2014: Medical Vehicles and their Equipment - Road Ambulances. London, UK: BSI, 2014.

[6] Ferreira J, Hignett S. Reviewing ambulance design for clinical efficiency and paramedic safety. Application Ergonomics 2005; 36 (1): 97-105.

[7] Ferdinande P. Recommendations for intra-hospital transport of the severely head injured patient. Intensive Care Medicine 1999; 25 (12): 1441-1443.

[8] Theodore N, Aarabi B, Dhall S, Gelb DE, Hurlbert RJ. Transportation of patients with acute traumatic cervical spine injuries. Neurosurgery 2013; 72 (Suppl. 2): 35-39.

[9] Jovanovic Z, Bacevac R, Markovic R. Information system for the centralized display of the transport comfort information. Facta Universitatis Series Electronics and Energetics 2017; 30 (4): 5547-5570.

[10] Paschold H, Mayton A. Whole-body vibration: building awareness in SH&E. Professional Safety 2011; 56 (4): 30.

[11] BSI. Standard BS 6841, Guide to Measurement and Evaluation of Human Exposure to Whole-Body Mechanical Vibration and Repeated Shock. London, UK: BSI, 1987.

[12] American National Standards Institute. ASA S2.72-2002/Part 1 / ISO 2631-1:1997 (R2012). Washington, DC, USA; American National Standards Institute, 2002.

[13] European Union. Directive 2002/44/EC, Vibration - Safety and Health at Work - EU-OSHA. Brussels, Belgium: EU, 2002.

[14] HSE. The Control of Vibration at Work Regulations. Guidance on Regulations (L140), 104. London, UK: HSE, 2005.

[15] Dickey J, Oliver M, Boileau P. Multi-axis sinusoidal whole-body vibrations: Part I - How long should the vibration and rest exposures be for reliable discomfort measures? Journal of Low Frequency Noise Vibration and Active Control 2006; 25 (3): 175-184.

[16] Dickey J, Eger T, Oliver M. Multi-axis sinusoidal whole-body vibrations: Part II - Relationship between vibration total value and discomfort varies between vibration axes. Journal of Low Frequency Noise Vibration and Active Control 2009; 26 (3): 195-204.

[17] Cuadrado J, Dopico D, Perez J. Automotive observers based on multibody models and the extended Kalman filter. Multibody System Dynamics 2012; 27 (1): 3-19.

[18] Lee J, Park E, Robinovitch S. Estimation of attitude and external acceleration using inertial sensor measurement during various dynamic conditions. IEEE Transactions Instruments Measurements 2012; 61 (8): 2262-2273.

[19] Blanco-Claraco J, Torres-Moreno J, Giménez-Fernández A. Multibody dynamic systems as Bayesian networks: applications to robust state estimation of mechanisms. Multibody System Dynamics 2015; 34 (2): 103-128.

[20] Eriksson J, Girod L, Hull B. The pothole patrol: using a mobile sensor network for road surface monitoring. In: Proceedings of the 6th International Conference; Breckenridge, CO, USA; June 2008. pp. 29-39.

[21] Shaw R, Steinberg, D, Bonnet J. Mobile health devices: will patients actually use them? Journal of the American Medical Informatics Association 2006; 23 (3): 462-466.

[22] Mednis A, Strazdins G, Zviedris R, Kanonirs G, Selavo L. Real time pothole detection using Android smartphones with accelerometers. In: International Conference on Distributed Computing in Sensor Systems and Workshops; Ottawa,Canada; 2011. doi: http://dx.doi.org/10.1155/2015/869627

[23] Mohan P, Padmanabhan V, Ramjee R. TrafficSense? Rich monitoring of road and traffic conditions using mobile smartphones. In: 6th ACM Conference on Embedded Networked Sensory System; Rayleigh, NC, USA; 2008. pp. 1-29.

[24] Plewa K, Eger T, Oliver M. Comparison between ISO 2631-1 comfort prediction equations and self-reported comfort values during occupational exposure to whole-body vehicular vibration. Journal of Low Frequency Noise, Vibration and Active Control 2012; 31 (1): 43-53.

[25] Grenier S, Eger T, Dickey J. Predicting discomfort scores reported by LHD operators using whole-body vibration exposure values and musculoskeletal pain scores. Work 2010; 35 (1): 49-62.

[26] Tüchsen F, Feveile H, Christensen K, Krause N. The impact of self-reported exposure to whole-body-vibrations on the risk of disability pension among men: a 15 year prospective study. BMC Public Health 2010; 10: 305.

[27] Ayari H, Thomas M, Dor S. A design of experiments for statistically predicting risk of adverse health effects on drivers exposed to vertical vibrations. International Journal of Occupational Safety and Ergonomics 2011; 17 (3): 221-232.

[28] Munish P, Yashwant P, Vijau S, Tipparaju S, Moreno W. Artificial Neural Network for Drug Design, Delivery and Disposition. Amsterdam, the Netherlands: Academic Press, 2015.

[29] Massie D, White K, Daly S. Application of neural networks to predict ice jam occurrence. Cold Regions Science and Technology 2002; 35 (2): 115-122.

[30] Karlaftis M, Vlahogianni E. Statistical methods versus neural networks in transportation research: differences, similarities and some insights. Transportation Research Part C: Emerging Technologies 2011; 19 (3): 387-399.

[31] Garrido C, De Oña R, De Oña J. Neural networks for analyzing service quality in public transportation. Expert Systems and Applications 2014; 41 (15): 6830-6838.

[32] Xiao G, Juan Z, Zhang C. Travel mode detection based on GPS track data and Bayesian networks. Computers, Environment and Urban Systems 2015; 54: 14-22.

[33] Osaba E, Onieva E, Moreno A. Decentralised intelligent transport system with distributed intelligence based on classification techniques. IET Intelligent Transportation Systems 2016; 10 (10): 674-682.

[34] Jovanovic Z, Bacevic R, Markovic R. Android application for observing data streams from built-in sensors using RxJava. In: 2015 23rd Telecommunications Forum; Belgrade, Serbia; 2015. pp. 918-921.

[35] Christensen B, Nurkiewitz T. Reactive Programming with RxJava. Sebastopol, CA, USA: O'Reilly Media, 2016.

[36] Grzymala-Busse J, Hu M. A comparison of several approaches to missing attribute values in data mining. In: International Conference on Rough Sets and Current Trends in Computing; Canada; 2000. pp. 378-385.

[37] Harper G. Viability of artificial neural networks in mobile healthcare. PhD, Goteburg University, Oulu, Finland, 2011.

[38] Kohavi R, Provost F. Glossary of terms special issue on applications of machine learning and the knowledge discovery process. Machine Learning 1998; 30 (2/3): 271-274.

[39] Chukwu A, Nwachukwu S. Analysis of some meteorological parameters using artificial neural network method for Makurdi, Nigeria. African Journal of Environmental Science and Technology 2012; 6 (3): 182-188.

[40] Senkal S, Ozgonenel O. Performance analysis of artificial and wavelet neural networks for short term wind speed prediction. In: 8th International Conference on Electrical and Electronics Engineering; Bursa, Turkey; 2013. pp. 196-198.

[41] Blokduk G. Data Mining Extensions. Brisbane, Australia: Emereo Pty. Ltd., 2018.