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Automated Identification of Vehicular Accidents from Acoustic Signals Using Artificial Neural Networks

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Abstract: *As a consequence of its critical impact upon societies, the occurrence of vehicular traffic accidents is a globally studied phenomenon. Much effort has been directed towards the understanding and identification of causal factors, with the intention of minimising the occurrence. In a related area, the development of methods for the identification and classification of vehicles has also received necessary attention. However, little work has been done on the development of methods for the identification of motor vehicle accident occurrences. Thus, this work sought to develop an automated system for the identification of motor vehicular accidents. It utilises an artificial neural network approach to estimate the probability of occurrence, based on recorded acoustic signals. More specifically, it first characterises accident acoustic signals by 9 selected signal features, in both the time and frequency domains. It then develops a dual layer artificial neural network, which accepts as its input the 9 characterising signal features and as its output calculates the probability of occurrence. The system was built and tested in the MATLAB environment, utilising 22 sample signals in the design phase and a further 53 for testing. An evaluation of the system found it have an accuracy of 86% and a precision of 76%, with a 100% identification of actual accidents. Additionally, it was found that the system prioritises the time domain signal features over those of the frequency domain, in the identification process. These results validate the structure of the system used and demonstrate its potential for real-world applications.*

Keywords: *Vehicular accident detection; artificial neural network; signal processing; time domain; frequency domain; acoustic signals*

1. Introduction

Road safety is a global concern. The World Health Organisation reports that there were 1.25 million road traffic deaths in 2013 alone (WHO, 2017). The impact of this phenomenon is far reaching and many countries have been aggressively seeking to counteract it. Accordingly, much effort has been directed into the research of various aspects of accident occurrences. Many researchers have investigated the causal factors in the occurrence of accidents (de Ona et al., 2013; Dadashova et al., 2016; Mujalli and de Ona, 2011). The primary goal in most of these instances has been to understand what causes accidents, with the intention of minimising their occurrence. Similarly, other researchers have sought to develop methods for identifying road conflicts (Cafiso et al., 2017) or for assessing the likelihood of an accident occurrence in a particular location (Li et al., 2017). Further, some investigators have developed methods for reconstructing accidents, based on data gathered from the scene of an accident (Li et al., 2017; Evtiukov et al., 2017). Yet further, some researchers have developed methods for the determination of the level of injury of a vehicle's occupants, upon the occurrence of an accident (Kononen et al., 2011; Delen et al., 2006).

A related field of study of particular interest, is the detection and identification of motor vehicles. Several researchers have used vibration and/or acoustic data, coupled with signal processing techniques, to develop effective vehicle recognition and detection methods. Wu et al. conducted significant work in this area and were among the first to utilise a frequency spectrum principal component analysis approach for vehicle sound recognition (Wu et al., 1999). George et al. (2013 a) also used vehicle sound signals to detect and classify vehicle types in an Indian context. They developed an algorithm that processed the acoustic data and allowed for vehicle detection, then used a neural network for classification. George et al. (2013 b) have advocated for the use of wavelet analyses in their detection and classification techniques. Yet in another case, Ozgunduz and Turkmen (2010) designed a vehicular classification system using a Mel frequency Cepstral coefficient algorithm and extracted features of the acoustic data which was then reduced by using a vector quantisation algorithm.

Despite these efforts, little work has been done on the development of methods for identifying the actual occurrence of accidents. Currently, accident identification primarily relies on visual recognition. In many cases, this is based on reports by person(s) involved in the accident or by bystanders. In others, the analysis of real time traffic camera data allows for accident identification. However, this is limited by several environmental factors such as the state of the vehicle's occupants, the presence of bystanders and their willingness to assist, lighting conditions and the level of monitoring of traffic camera data. In-vehicle collision systems provide an effective alternative. However, this too is limited by the make and model of the vehicles involved and the level of support system architecture in a particular location.

In light of this, this work presents an automated approach for the identification of vehicular accidents. It utilises a combination of an artificial neural network and some selected signal processing techniques, to identify the occurrence of an accident based on acoustic signal data. Such an approach can be incorporated into existing traffic management systems or form the basis for a standalone system. In so doing, it can facilitate faster response times to critical accidents and increase the chances of saving an injured occupant's life.

2. System Design

2.1 General Approach

By virtue of the phenomenon's nature, there are a number of attributes that can be considered and examined in seeking to detect the occurrence of an accident. Some of these include visual imagery, vibration data, scents/odors and sounds. However, not all of these features are as easily quantified and recorded, and the level and type of information provided by each feature varies significantly. Notwithstanding this, the work done on vehicle detection methods suggests that acoustic data samples provide a wealth of information that can be used for accident identification, if processed correctly. In keeping with this, this work sought to use acoustic sample data as the primary data source for a proposed identification system.

Figure 1 shows a typical acoustic sample recorded for an accident. It can be seen that the accident is defined by a distinct rise in the amplitude of the acoustic signal and for a short period of time. This pattern repeats itself for most of the acoustic samples examined. Given the repetitive nature of the pattern, the use of an artificial neural network was considered to be a feasible approach for identifying its occurrence within a recorded signal.

2.2 Identification of Signal Features for Characterisation

The efficacy of neural networks in pattern matching and identification, has been steadily increasing over the past few years. Two key contributing factors have been the increasing computational power of computing systems and the growing access to more detailed data sets. However, despite this increase in computational power, there are still some evident limitations, i.e., the processing of large data sets by a neural network does present a challenge for most standard computers. For instance, the car accident acoustic sample of Figure 1, which is 2.5 seconds long and sampled at 44.1 kHz, contains 110,250 data points. Attempts to directly utilise this sample in an artificial neural network, have proven to be memory-intensive for a current, standard desktop computer. Accordingly, an alternative approach to utilising the acoustic data in an artificial neural network had to be developed.

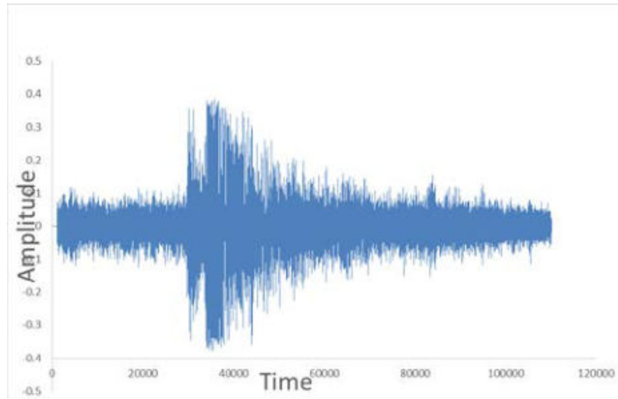

Figure 1: Sample of accident acoustic data signal – Amplitude versus Time

As an alternative, it was considered that a signal can be represented in both the time and frequency domains. In keeping with this, either presentation of the signal presents unique aspects of the data. Accordingly, the signal can be characterised by the features of either representation, or a combination of both. Thus, the authors posit that if a unique subset of the signal's features in both the time domain and the frequency domain are identified, such that these features are influenced by the occurrence of an accident. Then, this subset can be used to identify the presence of an accident. Key to this proposition is that the features must vary specifically with the occurrence of an accident.

In so doing, they provide both a basis set for representing the accident signal and for assessing the presence of an accident within a wider signal. However, it is unclear which of the many signal characteristics in the time or frequency domain would be critical in assessing the occurrence of an accident. In light of this, a number of well-known signal features and characteristics were examined, to determine their level of influence in accident identification from acoustic sample data. Table 1 gives the list of the features assessed in this work.

3. Data Sets and Data Acquisition

For the purposes of training and evaluation of the system, acoustic samples of various accidents were required. However, due to limited funding availability, the recreation and/or simulation of real time vehicular accidents were not feasible in this work. Alternatively, existing accident data sets were used. These comprised of data obtained from various crash intuitions namely Insurance Institute for Highway Safety (IIHS) and European New Car Assessment Programme (Euro Ncap). Both institutions conduct crash testing on a wide range of vehicles and various types of collisions (e.g., head-on, and small overlap). The sampling frequency for audio capture used in these data sets, was given as 44100 Hz for both institutions. The distance from the microphone to the point of impact was not given; however, it was known to vary for both. The acoustic data was converted to a wav format from these mp3's for greater accuracy of representation. The vehicle type and accident details for the various samples examined, are presented in Table 2.

Table 1: Acoustic signal features examined to determine effectiveness in accident identification

Signal feature	Domain
zero crossing rate	Time
short time energy	Time
Fundamental frequency	Frequency
Bandwidth	Frequency
Signal amplitude mean	Time
Signal power	Time
Frequency envelope	Frequency
Variance	Time
Spectral crest	Frequency
Spectral flux	Frequency

Table 2: Types of vehicles for which data was acquired

	Micro-car	Small	Midsize	Large
small overlap		√		√
moderate overlap	√		√	
front			√	
side crash	√		√	
trailer underride		√		√
head on			√	

As opposed to one type, various types of collisions were used to ensure variability in the accident features examined. The aim of this approach was to increase the system's likelihood of identifying a random accident. A total of 45 vehicular accident samples was used in the development of the system.

Additionally, simulated accident data was obtained from a test rig that was setup for the purposes of the work. The test rig consisted of a weighted automobile front bumper, suspended in mid-air by a pulley system. The bumper was lifted to a height of 12 feet and then allowed to fall and strike a metal sheet, which was fitted with an accelerometer. A microphone was positioned 10 feet away from the drop site, to record the acoustic data. The data was recorded at a sampling rate of 44,100 Hz. A picture of the setup is shown in Figure 2. Some of the amples recorded here were used in the identification of the set of key signal features. Additionally, acoustic samples taken of a jackhammer in operation and of random noises were also recorded for use in assessing key signal features.

Figure 2: Image of simulated accident testing setup

4. Results and Discussion

4.1 Identification of Key Signal Parameters

The signal features presented in Table 1 were assessed for all of the test signals previously mentioned. Various plots were made to examine the performance of each characteristic. The results obtained here were used to determine which characteristics were most suitable for classification of an accident. Figure 3 shows the plot of normalised mean signal amplitude against signal variance.

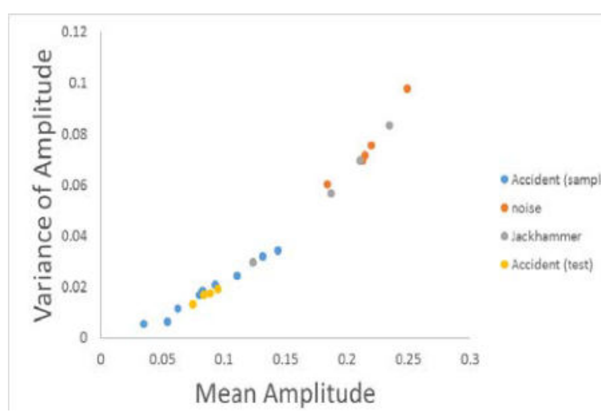

Figure 3: Pot of mean amplitude vs. variance

It can be observed from the figure that an accident is easily characterised by the variance of the amplitude time plot. The variance of the accident signals is found to be lower and exhibits less variability than the other signals examined. An examination of the normalised, mean amplitude shows that for an accident signal, the values are much lower than the other signals considered. This is due to the fact that accident signals contain localised points of very high amplitude, with the remaining portion of the signal having significantly lower values. On the contrary, noise signals generally do not have notable localised peaks and consequently their normalised means are higher. Accordingly, both features are suitable for characterisation.

Figure 4 illustrates the changes in the fundamental frequency and the zero-crossing rate of the signal. From the figure, it is evident that the values of the zero-crossing rate are much higher for both sets of accident signals, as compared to other signals considered. Accordingly, this is a suitable signal feature for characterisation. Conversely, the fundamental frequency demonstrates a high degree of variation and does not show any specific relationship for the signals considered. In keeping with this, the fundamental frequency serves as a poor characteristic and its use would lower the efficacy of the system.

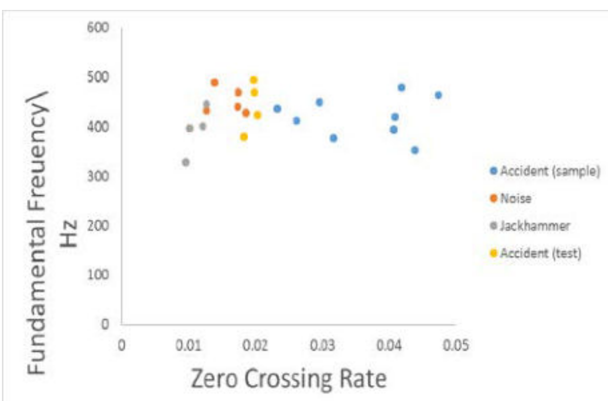

Figure 4: Plot of zero crossing rate vs. Fundamental frequency

An examination of the bandwidth values in Figure 5, shows that it is difficult to differentiate an accident signal from those of the other signals considered. Accident signals have wider bandwidth ranges than the other signals, making characterisation difficult. Conversely, accident signals can clearly be distinguished by the spectral crest values. The spectral crest values for both sets of accident signals are visibly lower than the other signals considered. Accordingly, the spectral crest was selected as a feature for characterisation, while bandwidth was not.

An examination of Figure 6 shows no clear relationship or correlation between the occurrence of an accident and the maximum energy or the energy flux. These two signal features are dispersed through a large area, and hence attempts to use them for accident characterisation may introduce some error into the system. Consequently, both parameters were not included in the final subset used to develop the system.

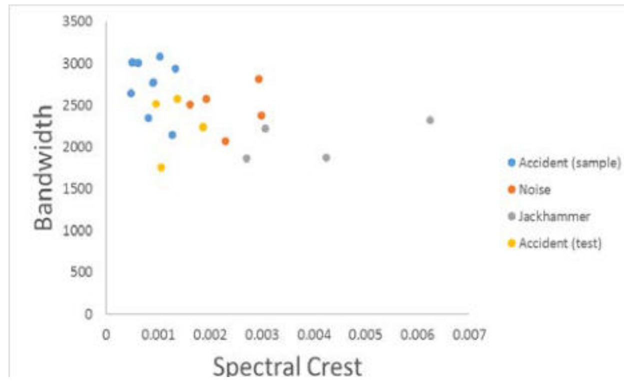

Figure 5: Plot of bandwidth vs spectral crest

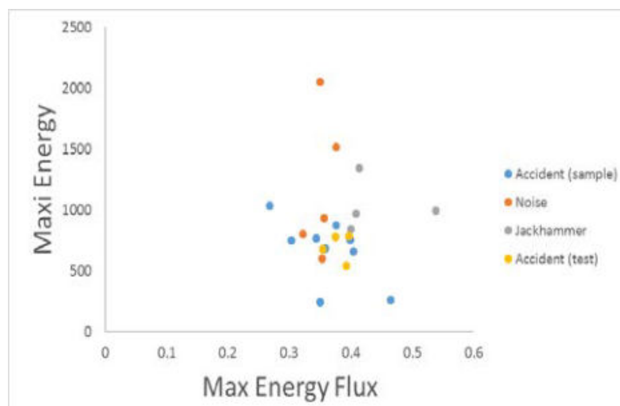

Figure 6: Plot of energy flux vs. Maximum energy

Figure 7 displays the frequency envelopes of the accident and noise signals tested. The signals have been converted into the frequency domain using a fast Fourier transform. An analysis of the graph shows a distinct difference between the noise signal (blue) and the accident data (black). It can be seen that the frequencies present within the accident signals are more stochastic as compared to the noise signals. Additionally, the amplitudes of the frequencies that are present in the accident signals are larger than those of the noise. Accordingly, the frequency envelope was chosen as a feature for accident characterisation.

4.2 Network Development and Architecture

Based on the previous analysis, 9 signal features were identified for the characterisation of accident signals. The features include both time domain and frequency

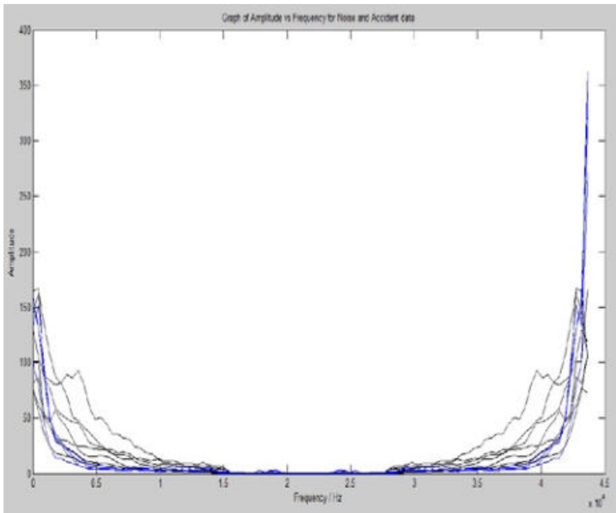

Figure 7: Frequency envelope of various acoustic events

domain identifiers. The time domain features selected were the energy flux, mean amplitude, power, zero crossing rate and variance; whereas the frequency domain features include frequency envelope, bandwidth, spectral crest and variance. In so doing, this allows for the reduction of an accident signal having 110,250 points to 9 characteristics. Figure 8 shows the sequence of computational steps within the final system.

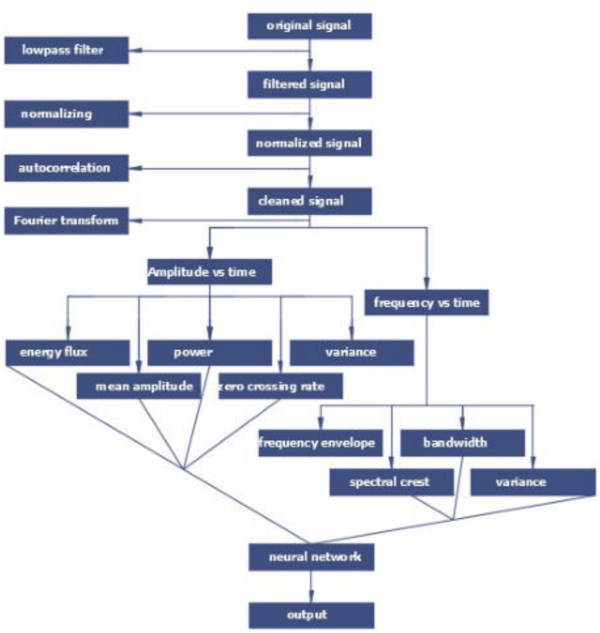

Figure 8: Final system architecture

The development and subsequent analysis of the network's performance was done using MATLAB 2015. This process entailed two primary decisions: a determination of the number of layers in the network and a determination of the number of neurons required for accurate functionality. The previous analysis indicated that the characteristics of an accident signal are not linearly separable. In keeping with this, a multilayer approach was considered to be more suitable. More specifically, a dual layer configuration was implemented, with a hidden layer containing a linear function and an output layer.

Figure 9 shows the final architecture of the neural network. The batch training method was selected as the basis for training the network, using a sample set of 22 signals. This was implemented with randomly determined batches, using a gradient descent algorithm via the MATLAB interface. This approach minimises the loss function as a means of adjusting function weights and improving the network performance. MATLAB subsequently validates the network with a subset of samples.

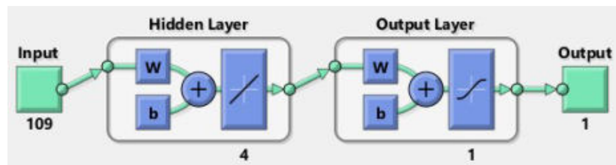

Figure 9: Final architecture of the neural network

The determination of the most suitable number of neurons was effected via the pruning approach. The proposed sequence of computational steps in Figure 8 was implemented using a test network having 11 neurons in the hidden layer. This test network was trained and validated as previously discussed. Subsequently, its performance was assessed via the examination of key network characteristics. More specifically, the root mean squared error (R^2 value) relative to a set target value was calculated for the test network, which was indicative of its ability to observe trends.

Nine other test networks were subsequently developed, using a different number of neurons in the hidden layer, ranging from 10 to 2 neurons. Each test network was trained, validated and assessed in a manner that was identical to that of the 11-neuron network. Three of the test networks were found to have R^2 values of 0.999, indicating the ability to accurately differentiate between a car accident signal and the other test samples. Using Ockham's razor principle, four neurons were selected as the most suitable number of neurons to be used in the network. Accordingly, the final system architecture consisted of 2 layers with four neurons in the hidden layer. This system is such that 109 points are inputted based on the 9 characterisation features and a probability value is outputted.

4.3 System Performance

The system was tested using a number of new data sets, i.e., signals that had not previously been used in the development and training of the system. These data sets consisted of 16 car accidents signals obtained from the Insurance Institute of Highway Safety (IIHS), 7 simulated accident signals, 12 noise signals, 9 sample signals of impact strikes on different materials, and 9 other sample signals of noises likely to be recorded on the roadway (e.g., emergency sirens and jackhammering). Of the 53 tests on the system conducted, Figure 10 presents the results of 36 outputs of the network. Table 3 presents a confusion matrix for the predictions made by the system.

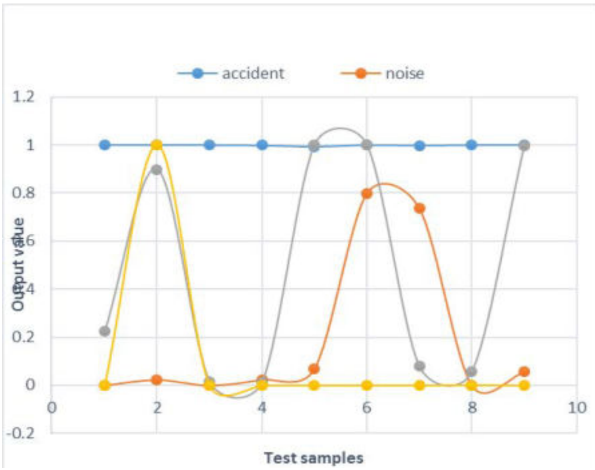

Figure 10: Results of Classifications– System Output for Acoustic Data

Table 3: Confusion matrix for predictions made by system

	Predicted: No accident	*Predicted: Accident*	
Actual: No accident	*23*	*7*	*30*
Actual: Accident	*0*	*23*	*23*
	23	*30*	

In keeping with Table 3, the following performance criteria can be evaluated:

Accuracy = (true positive + true negative)/total = 86%
True positive rate = True positive/ Actual positive = 100%
False positive rate = False positive/ Actual no = 30.4%
Precision = True positive/ predicted yes (when it predicts yes, how often is it correct) = 76%

4.4 System Behaviour

In examining the system, some key relationships and behavioural trends were identified. One of these concerns the issue of the incorrect classification of the impact strike signals. It was noticed that impact strike signals where a high force was used, had a higher chance of being classified as an accident. This false positive classification occurred both with strikes to steel and polyethylene materials. Although the natural frequencies of both steel and polyethylene of similar masses contrast greatly, both were still classified as a car accident. This suggests that the neural network gives precedence to characteristics in the time domain, as opposed to those in the frequency domain. This is likely a consequence of the fact that the features in the time domain display a greater correlation with the occurrence of a car accident, than those in the frequency domain.

A second key behavioural trend concerns the nature of the probability values obtained. The outputs for the tests conducted showed a range of values between 0.7 - 1.0, to predict the occurrence of an accident. Conversely, probabilities of 0 - 0.21 were found in cases where the system suggested that an accident did not occur. These ranges of probability values allowed for clear interpretations to be made on whether or not an accident did occur. This result was a consequence of the sigmoid function in the hidden layer. Its insertion reduces the probability of having instances where the neural network predicts a 50% chance of the occurrence of a car accident. These results serve to validate the structure of the system used.

5. Conclusion

This paper presented the work done on the design of an automated system for identifying vehicular accidents, using acoustic signal data and utilising an artificial neural network approach. The system was based upon the identification of key signal features that were used to characterise an accident acoustic signal. A total of nine signal features was identified with five being time domain features and four of the frequency domain. These features allowed for large data signals to be represented by a much smaller data set; in so doing significantly decreasing the computing requirements of the system.

The system was designed and tested using MATLAB. In designing and training the system, 22 signals were used. These signals consisted of actual accident recordings, simulated accident data and other recorded acoustic data. The system was subsequently tested using 53 additional signals that were not used in the design phase. An evaluation of the system's performance found that it had an accuracy of 86% and a precision of 76%, with a 100% identification of actual accidents. Testing also served to identify that the system prioritises the time domain signal features, due to a greater correlation between changes in these values and the occurrence of an accident.

With correct incorporation into a wider traffic management and/or emergency system, the approach presented here has the potential to significantly increase the likelihood of identifying vehicular accidents. In so doing, it can increase the response time of emergency personnel and increase the potential for saving lives.

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