Potholes vs. speed bumps: a multivariate time series classification approach

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Abstract. In this work, we present a preliminary approach to distinguish potholes from speed bumps by analyzing the acceleration values sensed by a mobile device. The information of the accelerometers is gathered by an experimental mobile application developed to automatically detect potholes. A driver, who has previously installed the application in her smartphone, places the device in a fixed position inside the vehicle. Thus, this application records the accelerometer oscillations and the place where the vehicle transits. Then, if the road is damaged, the vibrations produced in the vehicle can be captured by the accelerometers indicating the pothole. However, in a road there are other structures that can produce similar effects: speed bumps. In both potholes and street bumps, the accelerometers of the mobile device produce a sequence of oscillations in the three axis (X, Y and Z). We model these sequence as multivariate time series and then we classify these by using a temporal classification approach. The preliminary results were carried out with real-world data and showed a promising accuracy.

Pothole detection, multivariate time series classification.

1 Introduction

Maintaining the road infrastructure free of potholes is a difficult task. Several works have been proposed to solve the problem of detecting potholes by using mobile devices [2,5,1]. All these works share the idea that the potholes can be detected analyzing the acceleration values sensed by a mobile device. However, not all vibrations in a vehicle are produced by potholes. The road infrastructure usually has speed bumps and other structures that produce vibrations in a vehicle, but they cannot be considered road defects. This fact produces a large number of false positives, which degrades the accuracy of the pothole detection.

In this work, we propose a supervised learning approach based on temporal classification to distinguish potholes from speed bumps. An experimental mobile application records the accelerometer oscillation and GPS information. With this information, we can identify if an vibration event represents a pothole or a speed bump. Each event is composed of a sequence of oscillation produced by the accelerometer of the mobile device. These sequences include the oscillations since the event occurs until the vehicle stabilizes (i.e. the oscillations disappear). An entry of a sequence is composed of a three pair of values (the raw value of the accelerometer and its difference with the previous value) for axis X, Y and Z. We model these sequences as a multivariate time series.

A multivariate time series is a sequence of numerical vectors [8]. In this article, we use a supervised learner for multivariate time series to classify the events recorded by the mobile device. This supervised learner is based on a generic constructive induction technique to allow for domains where instances exhibit recurring substructures [3]. These substructures are extracted, and a clustering algorithm is used to construct synthetic attributes based on the presence or absence of certain substructures. Then, standard learners can be applied. The experiments were carried out using real-world data and showed an accuracy of 63.64% in the differentiation of potholes and two types of speed bumps (speed humps and street gutter).

The rest of the article is organized as follows. Section 2 briefly describes the approach to detect potholes and some related concepts. In Section 3, we present the preliminary results. Finally, Section 4 informs the conclusions and future work.

Fig. 1: Example of a speed hump included in the experiments.

2 Approach description

When a vehicle transits in a road, potholes and others structures affect its stability. These variations in the vehicle stability can be detected by the accelerometers of a mobile device (i.e. an smartphone). An accelerometer provides data on the acceleration of the three coordinate axes with (almost) continuous updates. This allows us to detect the slightest movements. Thus, placing the device in a fixed position inside the vehicle, the mobile movements can reflect the movements of the vehicle. Then, we can detect the presence of potholes or street bumps in the road, and its severity in terms of destabilization of the vehicle, by analyzing the accelerometers information. Moreover, if we combine this information with geolocation information, we can determine where these events occur. We name these events as stability events. Particularly, we consider two types of speed bumps: speed humps and street gutter (a depression running parallel to a street designed to collect rainwater, but that usually crosses perpendicular streets). Figures 1 and 2 show two examples of speed humps and street gutter, respectively.

The accelerometer information gathered by the application are tuples *acc={rawX, diffX, rawY, diffY, rawZ, diffZ}*. The variables $rawX$, $rawY$ and $rawZ$ correspond to the acceleration values sensed by the sensors in the axis X, Y and Z, respectively. Moreover, the variables $diffX$, $diffY$ and $diffZ$ represent the differences between the actual raw values and the previous one. After losing stability, the vehicle takes several seconds to stabilize again. For this reason, each stability event is composed of several tuples *acc*. Then, we define a stability event as a sequence $se = \{(t_1, acc_1), (t_2, acc_2), ...(t_n, acc_n)\}$, where acc_i is the accelerometer information in time i within the stability event *se*.

In this context, a sequence *se* represents a multivariate time series. A multivariate time series is a sequence of numerical vectors [8]. Several approaches have been proposed to classify multivariate time

Fig. 2: Example of a street gutter included in the experiments.

series when a class can be associated with it [4,7,6,8]. Particularly, Kadous and Sammut [3] propose a feature construction technique that parameterizes sub-events of the training set and clusters them to construct features. Once obtained the features, a standard classifier is built to classify new instances. Some of the components that can be applied to construct features are global extractors (duration, mean, minimum and maximum and mode of a variable of the sequence), and the following metafeatures:

- Increasing: it detects when a sequence is increasing.
- Decreasing: it detects when a sequence is decreasing.
- Plateau: it detects when a sequence is not changing.
- LocalMax and LocalMin: it detect when a sequence has a local maximum or minimum, respectively.
- RLE: Run-Length Encoding is a process where a single value repeated several times is encoded as that value, its starting point and its duration.

During the experimental results, we use the Kadous and Sammut approach. However, it is worth noticing that other multivariate time series approaches can be applied.

3 Preliminary results

The experiments were carried out with real-world information extracted from Tandil, Buenos Aires, Argentina. In total, 48 journeys were processed. Moreover, we manually identified 24 potholes, 54 speed

		Actual Class			
		Pothole	Speed hump	Street gutter	Precision
Predict.	Pothole	42	13	7	0.677
	Speed hump	6	20	2	0.714
	Street gutter	7	5	8	0.4
	Recall	0.764	0.526	0.471	

Table 1: Confusion matrix and metrics.

humps and 33 street gutters in the streets through which the vehicle transited. Then, taking into account the potholes and the speed bumps identified, we extracted 371 stability events, particularly: 184 events associated to potholes, 128 events associated to speed humps, and 59 events associated to street gutters. In average, each event was compound of 19.04 tuples *acc*.

To run the experiment we used *TClass*[1]. *TClass* is the implementation of the approach to classify multivariate time series proposed by Kadous and Sammut in [3]. Since *TClass* allow us to define different feature extractors, we test different configurations to find the best one considering the accuracy of the classification.

The best results were obtained by using the global extractors *duration, mean*, *min* and *max* over the 6 attribute of the sequences: *rawX, diffX, rawY, diffY, rawZ* and *diffZ* by using a J48 classification tree. The accuracy of the approach was 63.64%. Table 1 shows the confusion matrix and precision and recall metrics for each class. The best precision and recall were obtained predicting speed humps and potholes, respectively. In contrast, the worst individual metrics were obtained by predicting street gutter. We think that this is because of the low number of stability events produced by the street gutter in the dataset.

Moreover, we grouped the speed hump and street gutter in a common class, in order to differentiate potholes from speed bumps. Considering this grouping, the accuracy increase to 70%.

4 Conclusions and future work

In this work, we propose a preliminary approach that allows us to distinguish between potholes and speed bumps. This approach allows us to reduce the number of false positives produced during the pothole detection process. Moreover, this approach is key if we want to make available the application in multiple cities with the least effort. The preliminary results obtained from real-world data were promising.

Future work will focus on a more extensive experimentation. Moreover, we will analyze the use of other multivariate time series classification approaches.

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