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Modeling extreme loads acting on steering components using driving events

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ABSTRACT

Forces during steering events, such as curves and maneuvers, cause large stresses on steering components. In this paper, we formulate a model for the lateral loads causing fatigue damage of the steering components. Steering events are identified using a Hidden Markov model on the CAN (Controller Area Network) bus data. The CAN data is available on all vehicles, thus the model is applicable across many types of vehicles. To identify the events, the observation from CAN data is modeled by a multivariate generalized Laplace (GAL) distribution. An explicit formula for the expected fatigue damage is given. Results are validated using measured lateral acceleration.

1. Introduction

Fatigue is a process of material deterioration caused by variable stresses which may lead to failures of metallic components. Only parts of loads causing large oscillations influence the fatigue life. Knowledge about the variability of external loads can be used to design market specific vehicles. In this study we consider steering components for which the large stress oscillations occur during turnings which will be called *driving events*.

The paper deals with two problems: The first is development of methods to estimate some market specific statistical characteristics of driving events, e.g. the frequency of events. The second is computation of the expected damage for a steering component.

There exist a large number of different markets and customer types for which one would like to know the load acting on vehicles. Field measuring of forces is both time consuming and costly. Thus it is proposed to use statistics of occurrences of driving events to describe load environments encountered by vehicles. In this paper we present means to estimate driving events statistics using CAN (Controller Area Network) bus data, which is available for all vehicles. Since the driving events are not recorded in CAN data we extract them using a hidden Markov model (HMM) [6], where each event represents a hidden state.

The idea of using HMMs to find driving events is not new, see Maghsood and Johannesson [18,17], Mitrović [21,22] and [1]. The novelty of our approach is to use a multivariate generalized Laplace model (GAL) as the distribution of the observation process in the HMM. Recent results show that Laplace models are well suited to describe responses measured on driving vehicles, see [27,16,4]. In previous works, the observation process has been discretized by using thresholds. The continuous model, used here, has two main advantages over the discrete version. First, in the discrete model one has to manually set the threshold levels, whereas the continuous model is entirely estimated from the actual data. Second, the continuous model can easily be extended to incorporate multivariate sources of information, which is not easy for the discrete threshold approach.

Using the hidden states above, we get a sequence of driving events, which we model with a Markov chain (MC). The MC is specific to the market or customer type, and since it is vehicle independent we use it to describe the variability of expected load environment. However, fatigue life depends on vehicle responses and properties of the steering component used. Consequently given a model for load environment, one needs to evaluate expected damage for a component. This is done as follows: using laboratory tests or designed measurements on test trucks, a distribution of loads acting on a component during a driving event is found. By attaching independent random variables, with the event specific distributions derived above, on each steering event, we have constructed a reduced load model. By the Markov property for the reduced load model a closed form formula for the expected damage is derived. Modeling load sequences by Markov chains is not new, see e.g. [3,8–11,13,15,25,28]. However, the presented formula was not given previously in the literature and the stringent proof of the result is presented in the Appendix.

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Finally, we validate our method on a real data set, with field measurements of loads acting on a steering component in a Volvo truck. First, we show that the steering events found in CAN data are responsible for the large oscillation of forces acting on steering component. This is done by constructing a reduced load, which consists only of the extreme load values occurring during steering events. If the damage from the reduced load is close to the observed damage computed using continuously measured forces, we conclude that the steering events accurately capture the variability of the load. Second, we verify that the expected damage of the reduced random load is close to the observed damage.

The paper is organized as follows. The theory and some preliminaries are presented in Section 2. The proposed load model and the way for detecting driving events are presented in Section 3. In Section 4, measured data are used to validate the models and to illustrate the results.

2. Theory and preliminaries

In this section, theory and known results needed in this paper are presented. We start with a short description of HMMs and the generalized asymmetric Laplace distribution used to detect the sequence of driving events in CAN data. Further counting rainflow cycles procedure is presented in Section 2.2, while definition of damage index is given in Section 2.3.

2.1. Event identification using HMMs with Laplace distribution

Hidden Markov models [6] are one of the most useful statistical models to identify the patterns in signals. The model consists of two processes: a hidden, that is not observed, Markov chain $\{S_t\}_{t=0}^{\infty}$ and a observed process $\{Y_t\}_{t=0}^{\infty}$. Conditioning on $\{S_t\}_{t=0}^{\infty}$, the observed process $\{Y_t\}_{t=0}^{\infty}$ is a sequence of independent random variables with distributions depending only on S_t.

In this paper, Y_t has the generalized asymmetric Laplace distribution (GAL), see [14]. As mentioned in the Introduction the Laplace distribution has recently been successfully used to describe the loads acting on vehicles.

The GAL distribution is defined by the following parameters: δ – location vector, μ – shift vector, $\nu > 0$ – shape parameter, and Σ – scaling matrix and denoted by $GAL(\delta, \mu, \nu, \Sigma)$. The one-dimensional GAL distributions dependences on the shape parameter, ν, is illustrated in Fig. 1. An important property of the $GAL(\delta, \mu, \nu, \Sigma)$ distribution is that it has an explicit formula for the probability density function (pdf), namely

$$f(y) = \frac{1}{\Gamma(\lambda)\sqrt{2\pi}}\left(\frac{\sqrt{(y-\delta)^T\Sigma^{-1}(y-\delta)}}{c_2}\right)^{(\nu-d/2)/2} e^{(y-\delta)\Sigma^{-1}\mu}$$

$$K_{\nu-d/2}\left(c_2\sqrt{(y-\delta)^T\Sigma^{-1}(y-\delta)}\right),$$

where d is the dimension of Y, $c_2 = \sqrt{2+\mu^T\Sigma^{-1}\mu}$ and $K_{\nu-d/2}(.)$ is the modified Bessel function of the second kind. A convenient representation of a random variable Y having GAL distribution is

$$Y = \delta + \Gamma\mu + \sqrt{\Gamma}\Sigma^{1/2}Z,$$

where Γ is the Gamma distributed with shape ν and scale one, while Z is a vector of d independent standard normal random variables.

2.2. Rainflow cycle

The rainflow cycle count algorithm is one of the most commonly used methods to count cycles. The method was first proposed by Matsuishi and Endo [19]. Here, we shall use the definition given in [24] which is more suitable for statistical analysis of damage index. Assume that a load x has N local maxima. Let M_i denote the height of ith local maximum. Denote by m_i^+ (m_i^-) the minimum value in forward (backward) direction from the location of M_i until x crosses M_i again. The rainflow minimum, m_i^{rfc}, is the maximum value of m_i^+ and m_i^-. The pair (m_i^{rfc}, M_i) is the ith rainflow pair and $h_i(x) = M_i - m_i^{rfc}$. Fig. 2 illustrates the definition of the rainflow cycles.

Counting rainflow cycles is equivalent to counting the number of interval upcrossings by a load, denoted by $N^{osc}(u, v)$, see [26,2] for multivalued loads.

Remark 1. Note that some local maxima cannot be paired with any of local minima in x. It will happen when the corresponding rainflow minimum m_i^{rfc} lies before or after the period that load was measured. The sequence of maxima and minima which could not be paired by means of rainflow method is called the residual and has to be handled separately. Here, we let maxima in the residual form cycles with the preceding minima in the residual.

2.3. Fatigue damage index

The most common way to define fatigue damage, using rainflow cycles, is the Palmgren–Miner (PM) rule [23,20]

$$D_\beta(x) = \alpha\sum_{i=1}^{N} h_i(x)^\beta, \tag{1}$$

where α, β are material dependent constants. The parameter α^{-1}

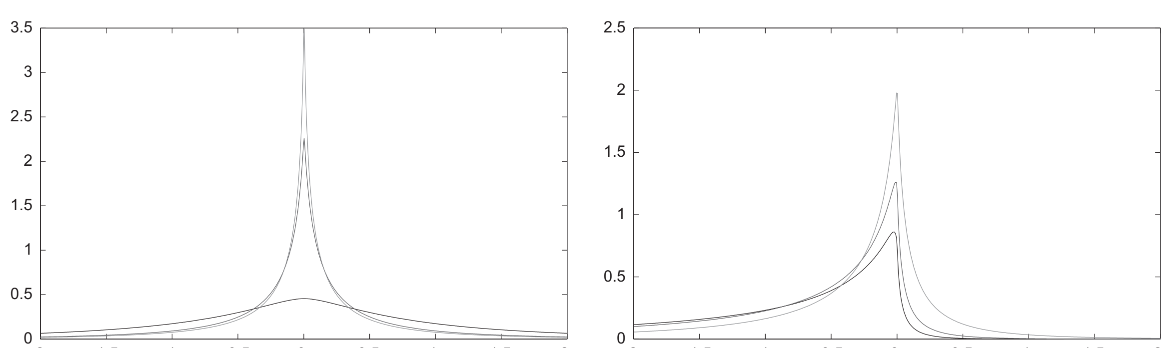

Fig. 1. The figures illustrates the one-dimensional GAL pdf dependence of the shape parameter ν. For the figure to the *left* the parameter μ is zero giving symmetrical pdf, while to the *right* μ is negative.