

PERFORMANCE IDENTIFICATION OF RACING MOTORBIKE BY ACOUSTIC MEASUREMENT

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Abstract

To know the performance and characteristics of competition vehicles has always been a common aim in the motorsport world. This paper focuses on the development of a procedure to extract the straight-line performance of a racing motorcycle by measurement of the exhaust noise signal. The method is divided into three phases. In the first one an acoustic signal from the motorbike exhaust is acquired. The second phase performs an engine order tracking by means of an autoregressive (AR) spectrogram, based on an adaptive Kalman filter. In the third phase, the signal associated with the extracted order is fitted by a mathematical model of the motorcycle. In this procedure, Doppler effect, time delay and microphone distance from the path are taken into account. Finally, an approximation of engine torque and power curves, as well as mass and drag coefficients, is given. The procedure has been validated comparing the numerical results with the data acquired on-board of the Yamaha race motorcycle. Correlation shows a good match between the predicted curves and the actual ones, giving confidence in the capability of the method to evaluate the performance of competition motorcycles.

INTRODUCTION

The aim of this work is to investigate the performance of different motorbikes analyzing their engine exhaust noise. The Authors' intention is to identify the bike and the engine performance by the processing of a signal acquired with a microphone placed along the straight.

The ability to track the dynamic contents of the signal, and thus to extract the necessary information, is strongly related to the kind of the spectrogram used to process the data. Using a Kalman filter to estimate time varying coefficients of the model, Authors could realize high resolutions spectrogram. For the case at hand, it is worth-while remembering that the engine order to track is influenced by the Doppler effect and it has no linear relation with the engine rpm. The Authors developed a mathematical model capable of considering the Doppler effect, the gear shift, and the bike position with respect to the one of the microphone. Fitting such a model to the acquired data in the least square sense allows to extract engine rpm, bike speed and acceleration.

MEASUREMENTS

In order to establish the characteristics and performances of different motorbikes, data of the various vehicles has to be acquired. To minimize the acquisition hardware and to simplify the data processing, the measurements were performed with a single free field microphone, placed on the pit wall at about three quarters of the longest straight section of the Doha Circuit in Qatar. This set up has different advantages: firstly the motorbike is closing into the microphone position on an almost straight path, thus simplifying the elimination of the noise frequencies shifts due to the Doppler effect. Secondly, being at the end of a long stretch of the circuit, different gear changes can be highlighted and identified. The motorbikes pass in front of the microphone at the highest gear, this being very helpful to distinguish between the frequency shifts due to the Doppler effect the measured frequencies of the approaching vehicles will be higher than the actual ones, while lower for the ones that are getting away from the microphone position.

Since the interest in the frequency content of the signal is limited to the first 3-5 harmonics of the fundamental rpm signal, the sampling frequency was limited to 6000 Hz. To consider the effect of the air temperature on the sound propagation, some temperature and humidity measurements were also performed.

METHODS

After the measurement, the processing is done in two parts: firstly the parametric spectrogram of the signal, then the curve fitting of the data that latter providing the

engine and bike performance.

Parametric Spectrogram

It has been assumed that an autoregressive data structure is the best one to fit the acquired motorbike data for its intrinsic generality and peak matching capabilities. An *autoregressive process* (AR) for a real data series x(t) is a representation in the form

$$x(t) = -\sum_{k=1}^{M} a_k(t) x(t-k) + e(t)$$
(1)

where the prediction error, e(t), is white gaussian noise, [2]. It means that the successive samples of the signal are predicted as linear combinations of the M previous values. The Kalman filter allows to estimate the coefficients $a_k(t)$ of an autoregressive process starting from a data series z(t) corrupted by white noise. The state space equations of such a dynamic process, can be written, using matrix notation, as

$$\mathbf{a}(t) = \mathbf{a}(t-1) + \mathbf{e}(t) \tag{2a}$$

$$z(t) = \mathbf{z}^{\mathrm{T}}(t) \,\mathbf{a}(t) + q(t) \tag{2b}$$

where $\mathbf{a}(t) = [a_1(t), a_2(t), \dots, a_M(t)]^T$ is the *process vector* and z(t) the *measurement variable*. The AR coefficients can be estimated using the recursive algorithm, [4]

$$\mathbf{P}(t) = \mathbf{P}(t) + \mathbf{Q}_e(t) \tag{3a}$$

$$\mathbf{K}(t) = \mathbf{P}(t) \mathbf{z}(t) \left[\mathbf{z}^{\mathrm{T}}(t) \mathbf{P}(t) \mathbf{z}(t) + 1 \right]^{-1}$$
(3b)

$$\hat{\mathbf{a}}(t) = \hat{\mathbf{a}}(t) + \mathbf{K}(t)[z(t) - \mathbf{z}^{\mathrm{T}}(t)\,\hat{\mathbf{a}}(t)]$$
(3c)

$$\mathbf{P}(t) = \left[\mathbf{I} - \mathbf{K}(t) \,\mathbf{z}^{\mathrm{T}}(t)\right] \mathbf{P}(t) \tag{3d}$$

where $\mathbf{z}(t)$ is the observation vector $\mathbf{z}(t) = [z(t), z(t-1), \dots, z(t-M+1)]^{\mathrm{T}}$ and \mathbf{Q}_e is the *drift matrix* of the prediction error in the process equation; \mathbf{Q}_e is a diagonal matrix since the prediction error is white noise. The algorithm is entirely specified by $\mathbf{P}(0)$, $\hat{\mathbf{a}}(0)$, $\mathbf{Q}_e(t)$ and the sequence of data z(t).

Due to variable SNR, for the investigated signals, it is not appropriate to use a constant value for the diagonal elements of the \mathbf{Q}_e matrix, as in [4]. The Authors propose to use a *trust function*, [5], originated by the ratio between the RMS value of the observation vector and its variance $q(t) = \text{rms } \mathbf{z}(t) / \text{var } \mathbf{z}(t)$. The data series q(t)is low filtered and scaled by the ratio between γ_q and the maximum value of q(t). The value γ_q , depends on the measurement and on the directionality of the microphone. The covariance matrix $\mathbf{Q}_e(t)$ is calculated as the product of the identity matrix I and q(t). The low track capability of the Kalman filter requires for an over modelling of the signal in order to describe sudden changes in frequency such as gear shift and the bike passing by the microphone. For these reasons a trial determination of the model order M is required. In any case, the model order depends above all from the source and not from the measurements.

The *time-varying AR power spectrum* of an autoregressive process x(t) is given by

$$S_{AR}(e^{j\omega}, t) = \frac{\sigma_e^2(t)}{\left|1 + \sum_{k=1}^M a_k(t) e^{-jk\omega}\right|^2} , -\pi < \omega < \pi$$
(4)

As the interest of the work was focused on the identification of signal frequencies, the estimation of $\sigma_e^2(t)$ was neglected. Specifically, only the *time-varying frequency function* was used, [3]

$$F_{AR}(e^{j\omega}, t) = \frac{1}{\left|1 - \sum_{k=1}^{M} \hat{a}_{k}(t) e^{-jk\omega}\right|^{2}} , -\pi < \omega < \pi$$
(5)

as $-\hat{a}_k(t)$ is the estimation of $a_k(t)$ at the time instant t. Finally, to increase the statistical property of the signal, the estimated parameters $\hat{a}(t)$ were average over a fixed time interval, yielding a smoother time-varying frequency function.

Using the peak matching capability of the AR model, the order tracking problem was quickly solved. Due to the required over determined modelling, some hint points have to be provided to extract the order from the spectrogram. These hint points are the initial and final instant of each gear.

Curve Fitting

The *frequency signal* f(t), extracted from the AR spectrogram must be fitted with a model to calculate bike and engine performances. The first thing is to observe that



Figure 1: Time frequency analysis of the signal.

frequency-speed ratio is constant for each gear since frequency is proportional to rpm and rpm is proportional to overall gear ratio $\tau = \text{rpm/speed}$.

The frequency signal f(t) is Doppler shifted, moreover due to the distance d between bike path and the microphone, the frequency signal f(t) has to be corrected to obtain the frequency $f_0(t)$ of the exhaust noise using the expression

$$f(t) = \frac{f_0(t)}{1 \mp \frac{v(t)\cos\theta(t)}{c}} \tag{6}$$

where c is the speed of sound, v(t) the speed of the bike and $\theta(t)$ the angle formed by the line that goes from the source to the microphone and the bike path. The angle $\theta(t)$ is connected to the bike position x(t) and the distance d by $\theta(t) = \arctan[d/x(t)]$.

The Authors propose a time linear decreasing engine torque model for each gear to solve the bike differential equation of motion, [1]. Since the rear wheel force can be calculated from the engine torque, it is possible to calculate the bike speed v(t) and the distance x(t) by numerical integration and the equation (6) can be solved respect to $f_0(t)$. To correct for the delay t_d caused by the acoustic wave speed, the speed of sound c and the distance of the bike from the microphone $s(t) = \sqrt{x^2(t) + d^2}$, are taken into account, $t_d = s(t)/c$. As s(t) is a result of model fitting, an iterative procedure was used to determine the correct time t.

The curve fitting starts from the last gear of the frequency signal, that is the gear of the bike when it passes by the microphone. Curve fitting parameters are: the distance x_1 between last gear shift and the microphone position, the frequency-speed ratio $\tau_{\rm f}$, the orthogonal distance between bike path and the microphone d and the bike speed during the last gear shift v_1 . The maximum and minimum engine torque $T_{\rm e1}$ and $T_{\rm e2}$, bike mass m and drag h are also determinable parameters. For other gears the numerical integration of the motion equation is performed backward over time, using as initial values, the starting values of the previous gear.

The final results of the curve fitting are the corrected time serie t, the bike characteristics: acceleration a(t), speed v(t), position x(t) and the rear wheel force $F_{\rm r}(t)$. Moreover the real exhaust noise carrier frequency $f_0(t)$, the frequency-speed ratio $\tau_{\rm f}$ of each gear and the engine torque $T_{\rm e}$ and power $P_{\rm e}$ as function of rpm are obtained.

RESULTS

The first results are the comparison between the data measured from the microphone of the Yamaha M1 bike exhaust noise and the data collected by the onboard data-logger. This results represent the model validation phase, figure 2. In figure 3 and

4 are represented the performance of four different MotoGP bikes (Doha MotoGP of Qatar, 06-08/04/2006). Figure 5 and 6 instead represent the performance of four different SuperBikes (Doha, World SuperBike Race of Qatar 23-25/02/2006).













Figure 4: Different MotoGP bikes engine performance.



Figure 5: Different SuperBikes performance on the straight.



Figure 6: Different SuperBikes engine performance.

CONCLUSION

The paper describes a procedure to determine the racing bikes characteristic using a microphone signal acquired during the bike competitions. It is based on parametric spectrogram definition and curve fitting procedures. Comparative results between data logged on the real bikes and the one obtained with proposed procedure showed high degree of accuracy and investigative capabilities.

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