EFFECTIVE PROFILE ESTIMATION FOR TRACTOR DYNAMICS ON AGRICULTURAL TERRAINS
/
基于拖拉机动力学特性的农田地面有效不平度估计

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ABSTRACT
For tractor operation on deformable terrains, accurate terrain profiles are critically needed to determine the dynamic tractor response, which is affected by the terrain roughness. Effective profiles for tractors operating on agricultural terrains were identified in this study. A novel technique, called independent component analysis (ICA), was used to estimate the effective profiles. ICA can use a known system dynamic response (observed signals) to identify road-induced excitation. In this context, tractor wheel vibration signals were used as observed signals, and the ICA method was used to estimate the source signals, which are the effective profiles of the terrain. The proposed approach was validated by comparing the estimated profiles with those measured by a profiling apparatus in the time and frequency domains. The calculated root mean square error RMSE and the relative error E_f *between the measured and estimated profiles showed that the proposed approach can be used to accurately estimate road profiles. A group of grass-field roughness data was taken as an example to compare the characteristics of the original and effective profiles, and the parameters of the effective profiles, such as the RMS, roughness index* C *and waviness* W *were found to noticeably change during the interaction between the tractor wheel and the terrain soil.*

摘要
拖拉机在可变形地面上运行时，准确了解地面不平度特征是研究受地面不平激励的拖拉机动态响应的关键因素。本文研究拖拉机在农田地面上作业过程中地面有效不平度的识别问题，采用独立分量分析（ICA）这种新方法来估计农田地面的有效不平度，通过系统的动态响应（观测信号），ICA 可识别路面的不平激励源。为此，以拖拉机车轮振动信号为观测信号，采用 ICA 方法对地面有效不平度的源信号进行估计，为了验证该方法的有效性，在时域和频域将估计的不平度与通过不平度测试装置实测的不平度进行了比较，计算实测不平度与估计不平度之间的均方根误差 RMSE 和相对误差 E_f*，结果可知该方法能很好地估计地面不平度。以一组田间草地不平度数据为例，通过比较草地原始不平度与有效不平度特征可知，在拖拉机车轮与地面土壤相互作用过程中，有效不平度特征参数 RMS、不平度系统 C 和频率指数 W 均发生了明显的变化。*

INTRODUCTION
Agricultural tractors typically operate on rough field terrain, and the terrain roughness generates particularly noticeable vibrations. Severe vibration affects the work efficiency and service life of a tractor, increases the compaction of agricultural field soil, and gravely endangers the health of the tractor driver (*Becker et al, 2014; Cutini et al, 2017; Gialamas et al, 2016*). Therefore, a slow velocity is typically used in the design of agricultural tractors to reduce the magnitude of vibrations and thereby improve ride comfort and handling. To analyse terrain surface roughness as an excitation source for tractor dynamics, the surface profiles on which agricultural tractors usually operate need to be investigated. However, measured surface profiles usually cannot be directly used as the input excitations in a tractor vibration analysis. The vibration from tractors travelling on soft terrain surface may be significantly modified by the dynamic interaction between the tractor with the soil, mainly because of energy losses from soil compaction and elastic waves (*Hildebrand et al, 2008*).

Determining the tractor dynamic response on deformable terrain requires accurate terrain profiles. Previous studies have shown that the displacement excitations of tractor vibration while traversing soft terrain are not original, but effective profiles of the terrain surface that is, the equivalent excited displacements of the terrain that cause the tractor wheels to jump up and down along the longitudinal plane (*Fassbender et al, 1997;*

Liu et al, 1999). The effective profile is an intermediate variable in the interaction process between tractor the wheel and the terrain soil. Therefore, a considerable number of studies have been performed to develop terramechanics models considering the terrain surface roughness, soil properties, wheel load, tire size and pressure, tread pattern and other factors for off-road applications (*Taheri et al, 2015; He et al, 2018*).

A framework for terrain profile estimation is developed in this study for tractors operating on agricultural terrains. Previous studies have been based on steady-state tire operation, linearized classical terramechanics models, or on computationally expensive algorithms that are not suitable for real-time estimation (*Dallas et al, 2020*). To address these shortcomings, a novel technique called independent component analysis (ICA) is used in this study to extract effective profiles for terrains that affect tractor dynamics. The ICA does not require a long computation time and is easy to use. This technique only requires the dynamic responses of the studied system, as collected by sensors, such as accelerometers and the suspension deflections. A related study was carried out to estimate the road profiles that affect vehicles by using the ICA technique, showing that the ICA can adequately identify road disturbances (*Ben Hassen et al, 2017*). Another study showed that the ICA can be used to accurately estimate road profiles both in the time and frequency domains, even in the presence of payload or speed variations (*Chaabane et al, 2019*). However, no studies have been performed thus far on identifying effective profiles for vehicles operating on deformable terrains. Experimental validation of application of the ICA technique to this research field is essential.

MATERIALS AND METHODS

Independent component analysis (ICA)

The Independent component analysis (ICA) is based on blind source separation (BSS). This method consists of recovering source signals knowing based only on a mixture of observed signals (*Ben Hassen et al, 2017*). The ICA uses the dynamic responses of the system (observed signals) to identify road excitation. In this paper, the tractor wheel response (vibration) signals are regarded as observed signals, and the effective terrain profiles produced by the interaction between the tractor wheel and the terrain soil are regarded as the source signals. The problem of using response signal analysis to determine the effective profiles of the terrain is equivalent to using ICA to extract the source signals from the observed signals.

Figure 1 is a schematic of the ICA procedure.

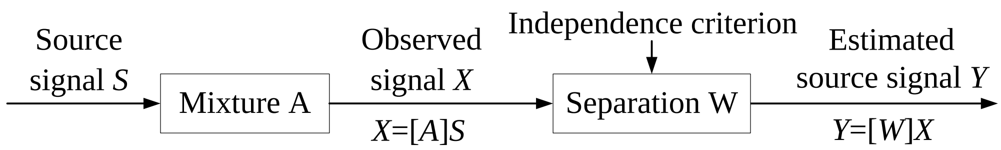


Fig. 1 - Schematic of ICA procedure

Within the ICA method, the observed signals $\{X(t)\}$ can be described as follows:

$$\{X(t)\} = [A]\{S(t)\} \tag{1}$$

where $\{X(t)\}$ and $\{S(t)\}$ represent signals observed by sensors and the source signals, respectively, and $[A]$ is the mixing matrix.

$$\{X(t)\} = \begin{bmatrix} x_1(t) \\ x_2(t) \\ \vdots \\ x_n(t) \end{bmatrix}, \quad A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix}, \quad \{S(t)\} = \begin{bmatrix} s_1(t) \\ s_2(t) \\ \vdots \\ s_n(t) \end{bmatrix}$$

The source separation principle consists of determining a separating matrix $[W]$ to estimate the source signals $\{Y(t)\}$ as follows:

$$\{Y(t)\} = [W]\{X(t)\} \tag{2}$$

where $[W]$ denotes the separating matrix and $\{Y(t)\}$ denotes the vector of source signals.

$$\{Y(t)\} = \begin{bmatrix} y_1(t) \\ y_2(t) \\ \vdots \\ y_n(t) \end{bmatrix}, \quad W = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1n} \\ w_{21} & w_{22} & \cdots & w_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1} & w_{n2} & \cdots & w_{nn} \end{bmatrix}$$

The key task in the ICA method is to identify the separating matrix $[W]$ to estimate the source signals $\{Y(t)\}$.

Assumptions and pretreatments of ICA

To find the estimated sources, some assumptions must be satisfied to ensure that the source separation procedure is effective (*Akrout et al, 2012*).

The first hypothesis is that the components of source signals are statistically independent of each other. In fact, the source signals must be uncorrelated since the hypothesis is respected. Two signals s_1 and s_2 are uncorrelated if and only if their covariance is equal to zero. Then, the following relation can be written (*Hyvärinen and Oja, 2000*):

$$Cov(s_1, s_2) = E(s_1, s_2) - E(s_1)E(s_2) = 0 \tag{3}$$

where:

$Cov(s_1, s_2)$ is the covariance of signals s_1 and s_2. $E(s)$ denotes the variance of the variable s.

The second hypothesis required by the ICA is the non-Gaussianity of the sources. The normalized kurtosis function is commonly used to measure the non-Gaussianity and can be expressed as follows (*Akrout et al, 2012*):

$$Kurt(s) = E\{s^4\} - 3(E\{s^2\})^2 \tag{4}$$

When $Kurt(s) > 0$, the signal s is super-Gaussian; when $Kurt(s) < 0$, the signal s is sub-Gaussian; when $Kurt(s)=0$, the signal s is Gaussian; the stronger the non-Gaussianity of the signal s is, the farther the value of $Kurt(s)$ is from 0.

The final hypothesis is that the number of observed signals is more than or equal to the number of source signals.

To extract different sources from an unknown mixture, pretreatments of the observed signals is required for the ICA. These pretreatments are centering and whitening. Centering corresponds to subtracting the mean vector $E(X)$ of a signal and is expressed as follows:

$$\bar{X} = \{X\} - E(X) \tag{5}$$

The ICA algorithm exhibits higher convergence for whitened observations. The measured signals $\{X\}$ are transformed to white signals $\{\tilde{X}\}$ with uncorrelated components and a variance of unity (*Hyvärinen and Oja, 2000*):

$$\{\tilde{X}\} = [M]\{X\} \tag{6}$$

Here, $[M]$ is the whitening matrix determined by the eigenvalue decomposition of the observed signal covariance matrix:

$$\{M\} = [D]^{-1/2}[U]^T \tag{7}$$

where $[U]$ is the orthogonal eigenvector matrix and $[D] = \mathrm{diag}(d_1, d_2, ..., d_n)$ is the eigenvalue diagonal matrix.

ICA algorithm

After the necessary pretreatments have been performed, the recovered signal can be separated. Note that the separating matrix $[W]$ must satisfy the criterion of following a non-Gaussian distribution.

Therefore, the kurtosis function defined by Zarzoso and Comen must be maximized as the normalized fourth-order marginal cumulates (*Zarzoso and Comon, 2010*):

$$K(w)=\frac{E\left\{|y|^{4}\right\}-2E^{2}\left\{|y|^{2}\right\}-\left|E\left\{y^{2}\right\}\right|^{2}}{E^{2}\left\{|y|^{2}\right\}} \tag{8}$$

After the first column of the separating matrix $[W]$ has been determined, the ICA uses deflation to extract the estimated sources. Therefore, each source is selected once by multiplication by the exact factor (*Zarzoso and Comon, 2010*).

Application of the ICA for the estimation of effective profiles

The ICA analysis is used in this paper is to identify effective profiles for tractors operating on agricultural terrains. The original surface profiles of nondeformable roads are considered effective profiles in vehicle dynamic analysis (*Pacejka, 2012*). Therefore, the proposed approach can be validated by comparing the estimated profiles identified by the ICA method with the profiles measured by a profiling apparatus during tractor travel on hard roads.

Previous studies have laid a foundation for the validating the approach proposed in this study. A profiling apparatus for measuring agricultural terrain profiles was designed in a previous study (*Yan et al, 2019*). The profiling apparatus was mounted on the front counterweight of a tractor, as shown in Figure 2, and the terrain surface profiles were measured dynamically for parallel tracks during tractor driving. Details on the testing and analysis of agricultural terrain profiles can be found in *Wang et al (2020*), in which the profiling tests were carried out in a field road, a grass field and a corn stubble field, as shown in Figure 2.

a) Profiling apparatus *b) Field road*

c) Grass field *d) Corn stubble field*

Fig. 2 - Profiling apparatus and agricultural terrain profiling measurement

RESULTS AND ANALYSIS

Assumption judgment of the ICA for road profile estimation

As previously mentioned, some hypotheses must be satisfied for ICA application. First, the components of the source signals must be statistically independent of each other. Considering the excitation of the vehicle dynamic response, the independence of the terrain profiles have mainly been tested by investigating the correlation between the left- and right-wheel profiles that the tractor wheels are subjected to. Profiling tests were carried out on three types of agricultural terrains: grass fields, corn stubble fields and field roads. Figure 3 shows the statistical results obtained from a data analysis of the covariance of the profiles for the left- and right-wheel tracks calculated using Eq. (3). Among the 30 groups of covariance data, the maximum and minimum values were 7.51×10^{-4} and 4.7×10^{-4}, respectively, and the mean value was 1.92×10^{-4}, which is close to 0. Therefore, the source signals of the terrain profiles on the left- and right-wheel tracks can be considered to be independent of each other.

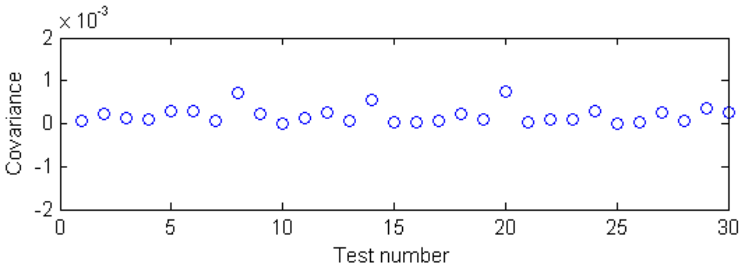
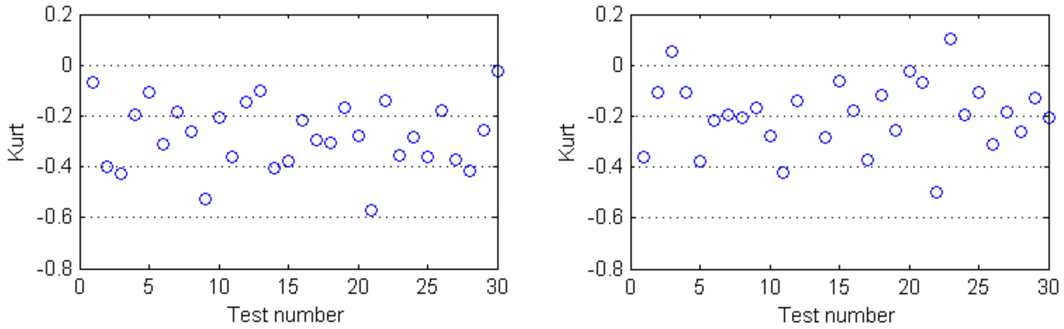


Fig. 3 - Statistical results for profile covariance on left- and right-wheel tracks

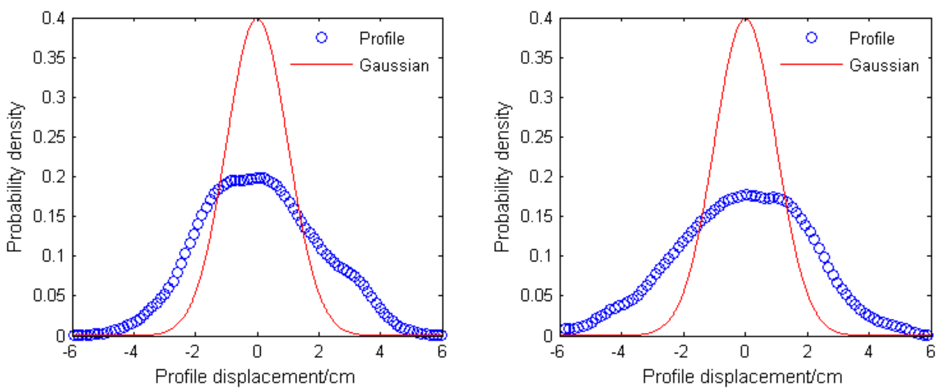
Figure 4 shows the statistical results obtained from a data analysis of the Kurt values of the measured agricultural terrain profiles calculated using Eq. (4). Figure 4 a) shows that the Kurt values for all 30 measured profiles of agricultural terrains (grass and corn stubble fields) are less than 0.



a) Grass and corn stubble fields *b) Field road*

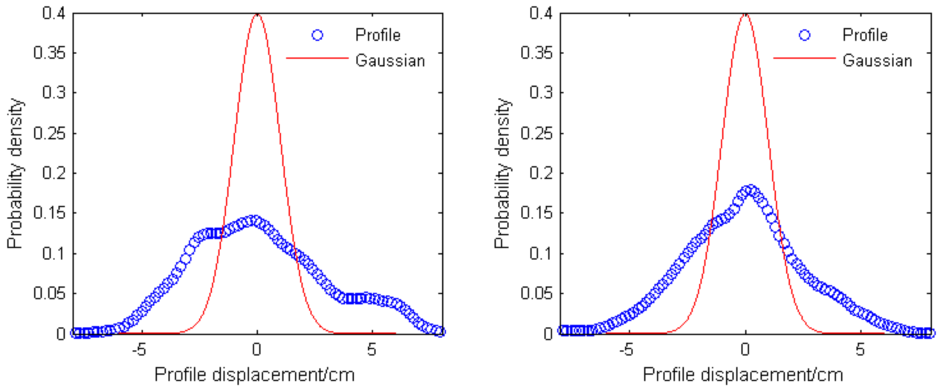
Fig. 4 - Statistical results for Kurt values of terrain profiles

In Figure 4 b), the Kurt values of two of the 30 field road profiles are greater than 0, and the Kurt values of the other 28 profiles are less than 0. Figure 5 presents the probability densities of one group of profiles measured for grass and corn stubble fields, showing that agricultural terrain profiles follow a sub-Gaussian distribution and meet the non-Gaussianity of the sources required for the ICA method to be applicable.



a) Left track of grass field *b) Right track of grass field*

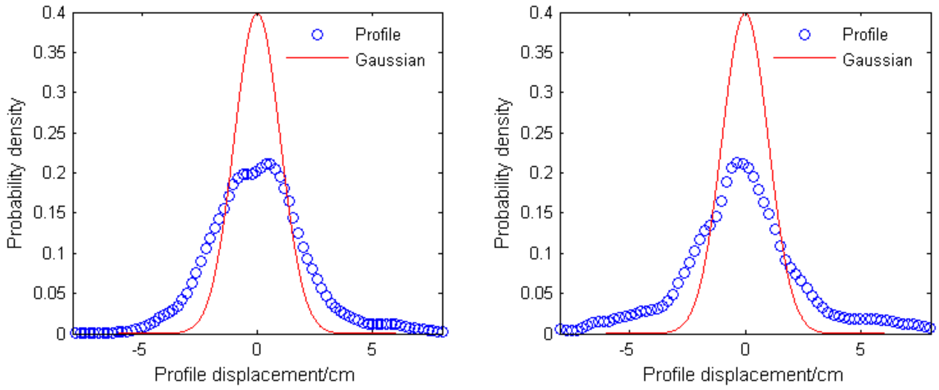
Fig. 5 a,b - Probability density distribution of agricultural terrain profiles



c) Left track of the corn stubble field *d) Right track of the corn stubble field*

Fig. 5 c,d - Probability density distribution of agricultural terrain profiles

Figure 6 shows the probability densities of one group of field road profiles. Therefore, it can be considered that the field road profile signals generally obey a sub-Gaussian distribution and meet the non-Gaussianity of the sources required by the ICA method.



a) Left track *b) Right track*

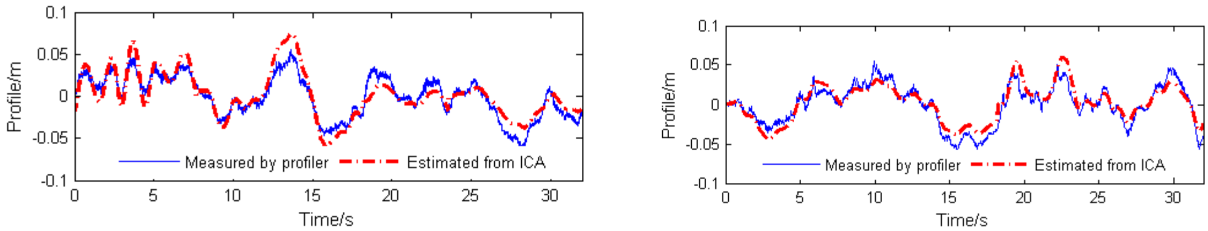
Fig. 6 - Probability density distribution of field road profiles

Road profile estimation using the ICA

As the tractor travels along a terrain, the terrain profile excites the tractor wheel and generates wheel vibrations. Therefore, the tractor wheel vibration signals are used as the observed signals in the ICA method to estimate the source signals, which are the effective profiles of the terrain. The proposed approach is validated by comparing the estimated profiles with the profiles measured by a profiling apparatus during tractor travel on hard field roads.

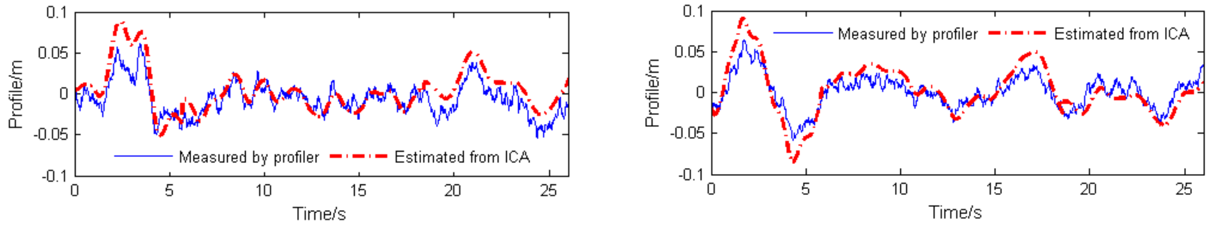
Two accelerometers were attached to the ends of the front axle at the centres of the tractor's front wheels to measure the vertical acceleration of each front wheel and one accelerometer was attached at the midpoint of the front axle to measure the axle vertical acceleration for use as comprehensive background noise in the ICA analysis. The terrain profiles traversed by the tractor wheels were measured synchronously by the profiling apparatus mounted on the front counterweight of the tractor.

The obtained results are presented by the following Figures 7, 8 and 9 for tractor speeds of 2.56 km/h, 3.58 km/h and 5.41 km/h, respectively. Figures 7-9 show there is good agreement at each tractor speed between the estimated profiles identified by the ICA and the profiles measured by the profiling apparatus.



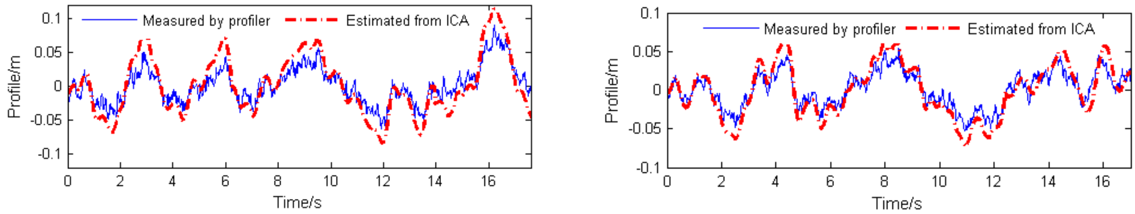
a) Left track *b) Right track*

Fig. 7 - Profiles of hard field roads measured at a speed of 2.56 km/h and obtained by ICA analysis



a) Left track *b) Right track*

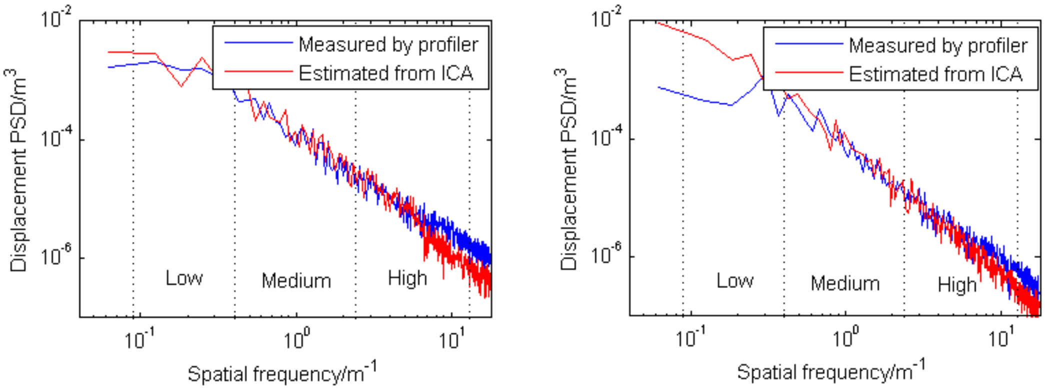
Fig. 8 - Profiles of hard field roads measured at a speed of 3.58 km/h and obtained by ICA analysis



a) Left track *b) Right track*

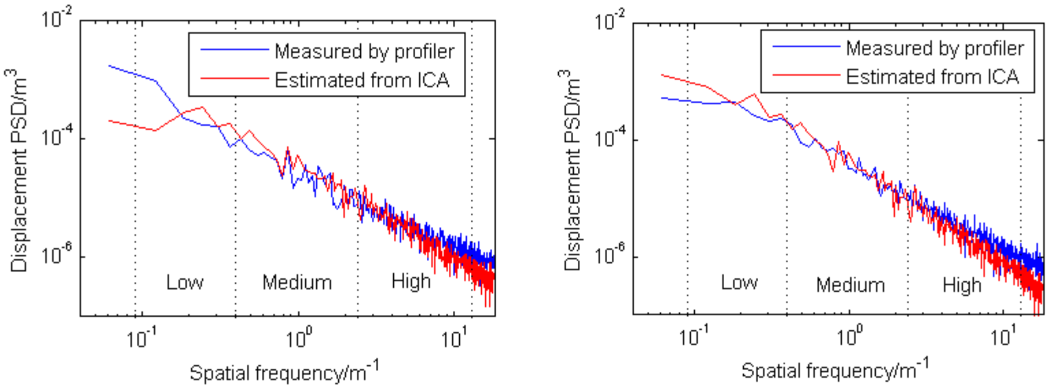
Fig. 9 - Profiles of hard field roads measured at a speed of 5.41 km/h and obtained by ICA analysis

Figures 10, 11 and 12 are the power spectral density curves corresponding to the measured and ICA analysis results of the field road profiles shown in Figures 7, 8 and 9, respectively. The PSD spectrum clearly shows a loss of content for the high-frequency band using the ICA method. This result is obtained because that the measured profiles reflect the up-and-down motions of the profiler wheels on the road, where the profiler wheels are considerably smaller than the tractor tires and can sense the relatively high-frequency components of the terrain profile. Nevertheless, there is good agreement between the measured profiles and the profiles estimated by the ICA. The small discrepancy between the measured and estimated profiles in the low-frequency band does not affect the vehicle response (*Fauriat et al, 2016*).



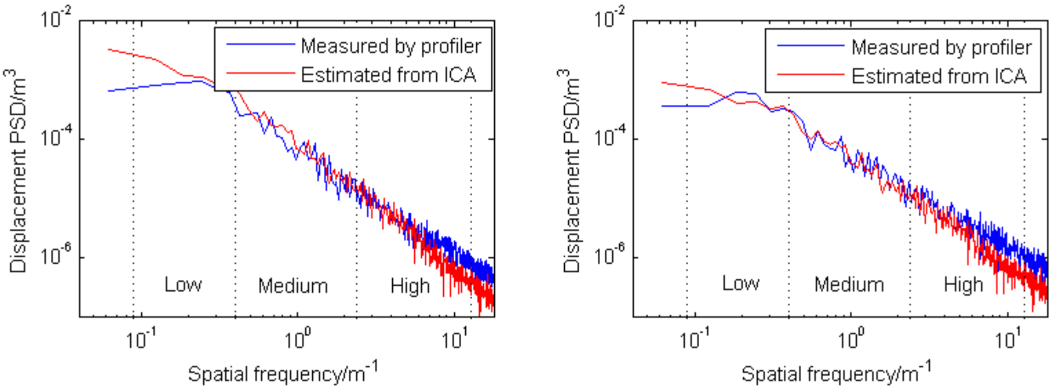
a) Left track *b) Right track*

Fig. 10 - Power spectral density of field road profiles measured at a speed of 2.56 km/h and estimated by the ICA



a) Left track *b) Right track*

Fig. 11 - Power spectral density of field road profiles measured at a speed of 3.58 km/h and estimated by the ICA



a) Left track ***b) Right track***

Fig. 12 - Power spectral density of field road profiles measured at a speed of 5.41 km/h and estimated by the ICA

The ICA efficiency was analysed by calculating the root mean square error $RMSE$ and the relative error E_f between the measured and estimated profiles. These error measures are defined as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(y_i - s_i)^2}{N}} \tag{9}$$

$$E_f = \frac{1}{N}\sum_{i=1}^{N}\frac{y_i - s_i}{s_i} \times 100\% \tag{10}$$

where: y_i is the profile estimated using the ICA at time instance i ; s_i is the profile measured by the profiler for time instance i ; and N is the number of measured points for the terrain profiles.

The calculated $RMSE$ and E_f for Figures 7-9 are shown in Table 1.

Table 1

***RMSE* and *E* between the measured and estimated profiles**

Test speed (km/h)	*RMSE* (m)		*E$_f$* (%)	
	Left track	Right track	Left track	Right track
2.56	0.0038	0.0046	5.6	8.1
3.58	0.0042	0.0045	7.7	7.2
5.41	0.0054	0.0037	8.9	6.8

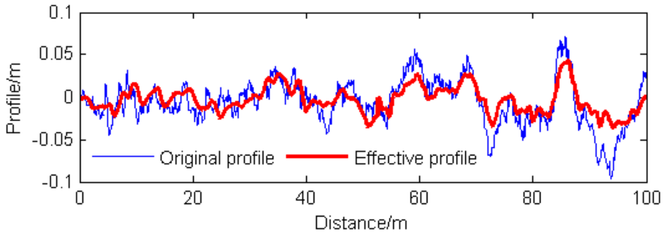
The results in Table 1 show that the $RMSEs$ range from 3.8 mm to 5.4 mm, and E_f values range from 5.6% to 8.9%. The E_f values for the profiles estimated by the ICA in this paper are close to the obtained using the Kalman filtering theory in reference (*Fauriat et al, 2016*). Therefore, the proposed approach was validated, showing that the ICA is adequate for effective profile estimation.

Comparison of original and effective profiles for deformable terrain

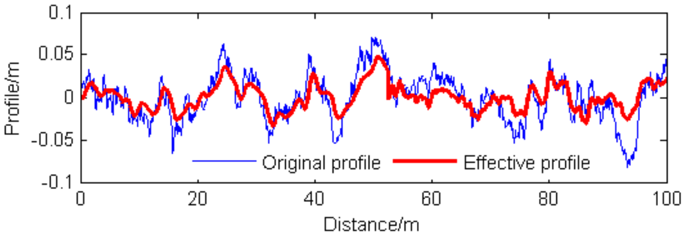
One group of grass field roughness data was taken as an example to investigate the relationship between the original and the effective profiles for deformable terrain. The original profile of the grass field measured by the profiler was compared with the effective profile identified by the ICA method.

Figure 13 shows the original and effective profiles of a group of grass fields for left- and right-wheel tracks. The figure shows that the terrain profiles were flattened and filtered by the tractor wheel during the interaction between the wheel and the soil.

In Figure 13, the calculated *RMS* values of the original profiles of the grass field on the left- and right-wheel tracks are 24.7 mm and 26 mm, respectively, whereas the corresponding values for the effective profiles are 19.8 mm and 20.7 mm, respectively.



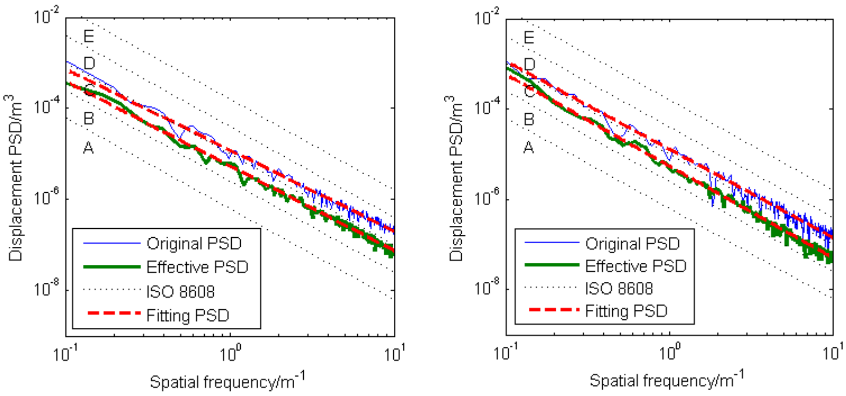
a) Left track



b) Right track

Fig. 13 - Profiles of agricultural grass field

Figure 14 shows the *PSD*s of the original and effective profiles presented in Figure 13. In Figure 14, the roughness index *C* of the original profiles for the left- and right-wheel tracks are 1182×10^{-8} and 1254×10^{-8}, respectively, and the corresponding waviness *W* values are 1.78 and 1.95, respectively. The roughness index *C* of the effective profiles for the left- and right-wheel tracks are 438×10^{-8} and 452×10^{-8}, respectively, and the corresponding waviness *W* values are 1.91 and 2.01, respectively. This result indicates a higher ratio of the shortwave energy to all the wavelength energies for the original profile than for the effective profile.



a) Left track *b) Right track*

Fig. 14 - Power spectral density of grass field profiles

CONCLUSIONS

The obtained results show that the ICA is suitable for estimating a true road profile. The proposed approach can be used to identify the effective profiles of a deformable field terrain as the ground excitation sources of vehicle dynamics without using complex terramechanics models and field soil parameters. Therefore, the ICA technique exhibits considerable potential for the dynamic analysis of agricultural tractors and implements. A comparative analysis of the characteristics of the original and effective profiles in both the time and frequency domains showed that the parameters of the effective profiles, such as the *RMS*, roughness index *C* and waviness *W* changed noticeably during the interaction of the tractor wheel and the terrain soil. Therefore, the effective profiles should be used instead of using the original profiles to analyse the dynamic response of vehicles excited by a deformable terrain.

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