Research Article

Evaluating the Properties of Railway Ballast Using Spectral Analysis of Ground Penetrating Radar Signal Based on Optimized Variational Mode Decomposition

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1. Introduction

The structure of a railway track typically consists of a superstructure and a substructure. The load of the track needs support. Ballast, which is part from the substructure, is the key element to support and transfer the load. Ballast typically consists of angular aggregate that is uniformly graded to provide enough structural capacity and air voids. In practice, rails and sleepers need a relatively dry environment to maintain its maximum performance, and air voids can reduce water drainage and keep the rails and sleepers away from moisture. Over time, general steps to produce ballast were gradually fouling fine materials when filling the air voids; however, the strength and drainage capabilities were compromised. The moisture in the fouling material tends to exacerbate the decrease in strength [1–4]. Ground-penetrating radar (GPR) has been used as a viable technique for quick and nondestructive inspection of the actual condition of railway ballasts [4, 5]. GPR has the ability to produce geophysical images in the following ways. Firstly, GPR measures reflected electromagnetic (EM) waves transmitted in the form of radar pulses in the microwave band of the radio spectrum. Then, a transmitting di-pole antenna radiates EM pulses into the ground, and a receiving dipole antenna measures variations in the reflected signal in a time-domain profile. Finally, the structural properties of the ballast can be inferred from the responses given by those interface reflections. Particularly, using GPR can estimate and monitor the track stiffness indirectly by detecting the ballast layer which is the most important and dominant component in track stiffness. The research has demonstrated the relationship between the parameter of track stiffness with ballast layer and subgrade condition, which shows the promising future use of GPR to estimate the track load carrying capability [1–5]. GPR has been used to quantify the ballast fouling. If the fouling procedure is contaminated by other fines, the mechanical properties of the ballast will be degraded, which will finally lead the railway track into an unstable condition. The research presents the results of experimental studies on the strong relationship between
ballast stiffness and clay fouling. The ballast stiffness is
decreased with the increased severity of fouling. GPR
time-domain signal of ballast has been used to generate an
assessment index for fouling evaluation. Time-domain analysis
does not consider the frequency-dispersive properties of
ballast media and the signal phase; however, it is easy to filter
out electromagnetic interference in the frequency domain. 
Many attempts used the frequency spectrum analysis to
detect the fouling level of ballast, thanks to the Fourier
transform, and time-domain GPR data can be successfully
converted to the frequency domain. Silvast et al. [6] showed
that in a clean ballast, the area of a signal spectrum in the
frequency domain is bigger than that of fouled ballast. Leng
and Al-Qadi [7] used the short-time Fourier transform
(STSF) to investigate the time variation of the frequency
spectrum of the GPR signal. They graphically demonstrated
the variation of the frequency energy with the ballast depth
under different fouling conditions and used the STFT ap-
proach on GPR data to quantify railroad ballast fouling, and
the result showed that the time-frequency technique was
able to reveal changes in ballast fouling over depth. Shao
et al. [8] used GPR to evaluate the track ballast conditions at
the network level [8]. They proposed a method that used the
maximum peak of the spectrum of the frequency domain to
automatically assess the condition of ballast and developed
an algorithm that can extract magnitude spectra at salient
frequencies and classify ballast conditions by support vector
machines. Al-Qadi et al. [9] interpreted GPR data and
evaluated the fouling of the ballast by a wavelet transform
(WT) technique invented by themselves. Then, they sum-
marized and compared processing techniques for time-
frequency GPR signal that can be used to evaluate the level of
railway ballast fouling. Bianchini Ciampoli et al. [10] ana-
yzed the spectral data of GPR and assessed the geometric
properties of the ballast. Fontul et al. [11] investigated and
assessed the railway track condition at the network level in
the frequency domain using GPR data. They quantified the
shift and deformation of the frequency spectrum with
changing ballast parameters such as aggregate size and then
illustrated the maximum shift of frequency spectrum, re-
garding them as a function of the dimension of the aggregate
particles. The above methodologies revealed a good reli-
bility and effectiveness in monitoring the ballast health. The
possibility of characterizing the ballast stiffness can also be
proved. Recent related work can be found in [12].

For classifying the ballast, results from existing experi-
ments showed that many approaches are efficient enough to
represent and analyze GPR signals. Furthermore, when it
comes to the classification of patterns, typical and important
features can be extracted from those approaches. Therefore,
it can be concluded that GPR is an effective and efficient tool
to evaluate the thickness and fouling levels of ballast.

Correlations between GPR parameters, such as the di-
electric permittivity and the area of the frequency spectrum
as well as the fouling level, have been concluded and assured
by previous studies and experiments. However, it is difficult
to find efficient methods or specifications to quantify the
level of fouling of the ballast. In one word, it is still
challenging to determine the level and type of the fouling of
the ballast layer from GPR analysis.

With the help of joint time-frequency analysis (JTFA),
interpretation of GPR data was no longer a heavy task. 
However, a lot of traditional JTFA methods, including STFT
and WT, were limited in application because low time-
frequency (TF) resolution and mode mixing cannot be solved perfectly. Although the most popular tools for JTFA
are based on the Fourier transform method, under the
limitation of the uncertainty principle, however, these
methods cannot be used to analyze the GPR signal because
they failed to show the information about the local frequency
variations.

Recently, the variational mode decomposition (VMD),
which encompasses multiple adaptive Wiener filter groups,
has been widely used to process GPR signal, because it
showed a good robustness in overcoming the disadvantages
of mode aliasing, small end effects, and pseudocomponents
when compared to other traditional TF analysis algorithms
for GPR [13, 14]. This innovative VMD method also has a
solid theoretical foundation in decomposing the adaptive
and quasiorthogonal signals [15]. In solving problems, such
as mode-mixing, noises, and samplings, VMD successfully
shows its advantages in effectiveness and robustness com-
pared to the conventional time-frequency methods. For
time-frequency resolution, the VMD-based spectrum can
provide a higher resolution, which also performs better than
conventional JTFA methods. Sensitivity to data is another
feature of the VMD method. In other words, the decom-
position parameters, which include the number of extracted
modes and are a critical factor for the performance of the
method, were determined mainly through the engineering
experience. Those inaccurate operations will cause a low
method performance, and thus, the accuracy of the outcome
will be compromised. Therefore, it is crucial to find an ef-
fective and accurate way to determine the parameter. Liu
et al. [16] proposed a new approach to choose the parameter
and analyze the signals. In his research, he firstly found out
the eddy current signal and the frequency spectrum of it, and
then, he chooses the number of extracted modes based on
the peak point of the spectrum. Next, he analyzed the
correlation coefficient between the original and rebuilt signal
in mechanical rotor system diagnosis. Shi and Yang [17]
developed a revised VMD method for the vibration signals
of a wind turbine, and they optimized the number of extracted
modes [17]. Isham et al. reviewed a variety of
improved VMD and wide applications in rotating ma-
achinery diagnosis [18]. Particularly, Li et al. [19] developed
a genetic algorithm-based VMD and applied it in fault di-
agnosis recently [19], and they developed an advanced
optimization method for system diagnosis and recognition
[20]. Ni et al. [21] developed a fault information-guided
VMD (FIVMD) method for extracting weak signals to
minimize the effects of background noise and/or interfer-
ences [21].

In this research, we choose the optimized VMD-based
TF analysis method for ballast GPR signal processing, be-
cause it performs better than the conventional JTFA and WT
methods. In other words, the method we choose can accurately capture the spectral features; thus, the TF resolution can be higher, and the TF spectrogram of the GPR signal based on optimized VMD can be much smoother and sparser. The implemented optimized VMD algorithm was chosen to calculate the modes of the original nonlinear GPR signal of railway ballast collected in Huntington, WV in Feb. 2022 by 400 MHz air-coupled antennas, and the Hilbert transform was chosen to compute the instantaneous frequency of the decoupled modes. The instantaneous frequency of the GPR signal was established based on the optimized VMD. The spectra of GPR signal based on optimized VMD method were applied to evaluate dry and wet fouled ballast in field test and compared the conventional TF spectrum methods and illustrated the superiority. The experimental results of GPR with dry and wet fouled ballasts demonstrate that, by comparison with the feature extraction method of conventional spectrum methods such as spectrogram and wavelet, the feature extraction method based on the optimized VMD has much better separability and quantitative identification capability.

The rest of this paper is structured as follows. Section 2 presents the theoretical background of the optimized VMD algorithm and introduces the specific steps of the optimized VMD algorithm. Section 3 presents the field experiment details, including GPR equipment, test site, materials/real ballast in railway, and main steps of the proposed fault feature extraction method. Section 4 carries out the signal processing and compares the results of the optimized VMD algorithm with spectrogram and wavelet results. Section 5 gives the conclusion of this paper.

2. Theoretical Background

2.1. Basic Theory for the Variational Mode Decomposition (VMD) Method. VMD is a method for the decomposition of the nonrecursive signal. This method can decompose a real-valued input nonlinear signal into a series of modes [15]. Through the VMD method, the signal $f(t)$ can be decomposed into $n$ number of intrinsic mode functions (IMF).

$$f(t) = \sum_{k=1}^{n} u_k(t).$$

Each mode can be defined by the following equations (the amplitude-frequency modulation signal):

$$u_i(t) = A_i(t) \cos \{\phi_i(t)\},$$

where $u_i(t)$ represents the $i$th mode; $A_i(t)$ represents the instantaneous amplitude; $\phi_i(t)$ represents the instantaneous phase. Define $\omega_i(t) = \varphi_i'(t)$ as the instantaneous frequency. Both $A_i(t)$ and $\omega_i(t)$ vary much slower than $\varphi_i(t)$. Thus, over a sufficiently long interval $[t-\eta, t+\eta]$, where $\eta = 2\pi/\omega_i(t)$, the mode $u_i(t)$ can be considered as a pure harmonic signal. The amplitude of that is $A_i(t)$, and the instantaneous frequency is $\omega_i(t)$. The core function of VMD is to calculate the center frequency and bandwidth of the extracted modes to display different components in the signal. Each mode is closely surrounded the center pulsation $\omega_0$ and its bandwidth can be calculated by the squared L2-norm of the gradient. VMD can be expressed by following equations that are solving the solution of a constrained variational problem:

$$\begin{aligned}
\min_{\{u_i\},\{\omega_i\}} & \left\{ \sum_{i=1}^{K} \frac{1}{2} \left\| \sum_{j=1}^{K} \delta(t - t_j) \ast u_i(t) \right\|_{L^2}^2 + \frac{1}{2} \sum_{i=1}^{K} \left\| f(t) - \sum_{i=1}^{K} u_i(t) \right\|_{L^2}^2 \\
& + \int_0^\infty \left( \frac{\hat{\lambda}(t)}{\sum_{i=1}^{K} \hat{u}_i(t)} \right) \left( \frac{\hat{X}(\omega) - \sum_{j=1}^{K} \hat{u}_j(\omega) + \lambda(\omega)/2}{1 + 2\alpha(\omega - \omega_n)} - \omega_0 \right) \dot{\omega}_n d\omega\right\},
\end{aligned}$$

where $K$ represents the number of modes; $\{u_i\} = \{u_1, u_2, \ldots, u_K\}$ represents the set of estimated modes; $\{\omega_i\} = \{\omega_1, \omega_2, \ldots, \omega_K\}$ represents the set of center frequencies that corresponds to the estimated modes; $\delta(t)$ represents the gradient function; $\delta(t)$ represents the Dirac distribution.

Through the Lagrangian multiplier $\lambda$ and the quadratic penalty factor $\alpha$, the constrained variational problem degraded into an unconstrained problem which can be described by the augmented Lagrangian function presented as follows:

$$L(\{u_i\}, \{\omega_i\}, \lambda) = \alpha \sum_{i=1}^{K} \left\{ \frac{1}{2} \left\| \sum_{j=1}^{K} \delta(t - t_j) \ast u_i(t) \right\|_{L^2}^2 + \frac{1}{2} \left\| f(t) - \sum_{i=1}^{K} u_i(t) \right\|_{L^2}^2 + \frac{1}{\lambda} \sum_{i=1}^{K} \hat{u}_i(t) \left( \frac{\hat{X}(\omega) - \sum_{j=1}^{K} \hat{u}_j(\omega) + \lambda(\omega)/2}{1 + 2\alpha(\omega - \omega_n)} - \omega_0 \right) \right\}.$$

This problem can be solved by searching the saddle point of the above equation. The way to find that point is using the alternate direction method of multipliers. From (3), we can summarize the modes in the frequency domain by updating each mode $u_i$ and its center frequency $\omega_i$ constantly:

$$\begin{aligned}
u_i^{n+1}(\omega) &= \lambda^n(\omega) - \sum_{j=1}^{K} \gamma_j u_j(\omega) + \lambda(\omega)/2 \\
\omega_i^{n+1} &= \gamma \omega_0 \frac{\int_0^\infty \omega_0^2 \mu(t) \dot{\omega}_n d\omega}{\int_0^\infty \left| u_i(t) \right|^2 d\omega}.
\end{aligned}$$

where $n$ represents the number of iterations. The operator $\lambda$ of the Lagrange algorithm is represented as follows:

$$\lambda_{n+1}(\omega) = \lambda_n(\omega) + \tau \left( \hat{X}(\omega) - \sum_{i=1}^{K} \hat{u}_i^{n+1}(\omega) \right),$$

The above equation will not terminate until the following equation is true:

$$\sum_{i=1}^{K} \left\| u_i^{n+1} - u_i^n \right\|_{L^2}^2 < \varepsilon.$$

The four parameters, which are the noise tolerance $\tau$, the convergence error $\varepsilon$, the modal component number $K$, and the quadratic penalty factor $\alpha$, must be prepared firstly before using the VMD method. Since the parameter $K$ represents the number of modes and $\alpha$ represents the bandwidth and the center frequency, they have much more
influence on the result of decomposition; therefore, it is crucial to optimize these two parameters. As for the other two parameters \( r \) and \( \varepsilon \), they can be set according to fixed default values.

### 2.2. Instantaneous Amplitude and Frequency

The next step is to apply the Hilbert transform to all IMFs \( u_j(t) \) which is expressed

\[
H[u_j(t)] = \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{u_j(t)}{t-\tau} \, d\tau,
\]

where \( \tau \) represents time. The complex signal can be expressed as

\[
Z_j(t) = u_j(t) + iH[u_j(t)] = a(t)e^{i\phi(t)}.
\]

In (9), which expresses a signal, the amplitude and phase can be expressed as

\[
a_j(t) = \sqrt{[u_j(t)]^2 + H[u_j(t)]},
\]

\[
\phi_j(t) = \arctan \left\{ \frac{H[u_j(t)]}{u_j(t)} \right\},
\]

where \( a_j(t) \) is the amplitude, and \( \phi_j(t) \) is the phase of the signal. Then, the instantaneous frequency of the signal \( \omega(t) \) can be expressed as

\[
\omega(t) = \frac{d\phi(t)}{dt}.
\]

Then, \( f(t) \) can be expressed as

\[
f(t) = \sum_{j=1}^{n} a_j(t) \exp \left[ i\omega_j(t) \right].
\]

The formula (12) can be extended so that the Hilbert instantaneous frequency \( H(t, \omega) \) can be expressed as

\[
H(t, \omega) = \text{Re} \left\{ \sum_{j=1}^{n} a_j(t) \exp \left[ i \int \omega_j(t) \, dt \right] \right\},
\]

where \( t \) and \( \omega \) represent time and frequency, respectively.

Due to mean zero and the local symmetry property, the IMFs obtained from the equations above are able to assure the physical meanings of the instantaneous frequencies. Instantaneous attributes of GPR data can be extracted from the IMF and its Hilbert transform.

### 2.3. Optimization of VMD

Selecting the suitable parameters, especially the number of decomposed components for VMD is a critical task. GPR signals are vulnerable to be contaminated by interferences such as background noise and electromagnetic factors. These interferences can smear the fault-related features contained in the signals. Therefore, it is crucial and essential to minimize undesirable influences. The optimization of the number of modes for reaching such a purpose has been investigated [16, 17]. Considering the fact that the magnitude of the frequency spectrum of these interferences is often smaller compared to that of valid frequency components, a method based on spectrum envelope has been used to identify the valid frequency components contained in the signal, by which the optimum number of modes of the VMD is determined [12, 17]. This method can be expressed by applying the Fourier transform to the GPR signal.

\[
H(\omega) = \int_{-\infty}^{\infty} f(t)e^{-i\omega t} \, dt,
\]

where \( I \) represents the integer equal to half amount of data. Then, search the local maximum and local minimum magnitudes \( Aax \), and finally, generate the envelope curve of the filtered spectrum by using an interpolation method to calculate appropriate thresholds \( Th \).

\[
Th = Al + r(Ah - Al),
\]

where \( Ah \) and \( Al, l \) respectively, represent the maximum and minimum magnitudes obtained from the spectrum; \( r \) represents the ratio for the control of the level of the threshold; in other words, the variation trend of the value \( r \) is the same as that of the threshold.

Finally, frequency components whose magnitude is smaller than the threshold will be picked out, and the optimum number of modes from the resultant envelope curve for optimized VMD analysis will be identified.

### 3. Field Validation

The above technique is validated for the GPR signal of ballasts using field data collected in a railway depot in Huntington WV in Feb 2022. The experiment contains two different fouling cases, which are dry and wet, respectively, for the ballast. The test site was investigated using a 400 MHz frequency GPR horn antenna system which was towed along the rail sections through a dedicated cart that allowed the antenna works. Specifically, a 100 feet-long railway section was used. The GPR data collected were analyzed to validate the aforementioned method. For comparison, we also conduct JTFA and wavelet transforms of the tested GPR signal, with the corresponding calculated frequency spectra for the case of dry and wet fouled ballast conditions.

#### 3.1. Test Site

The test item is a 100 feet-long section of the railway. The location and schematic characteristics of the test site are shown in Figures 1(a) and 1(b). The superstructures are composed of steel rails with the distance between the rails on a running line being 4’ 8.5”. The railway fastened to wood sleepers with the crosstie spacing of mainline railroad 19’’.
3.2. Equipment of the Test. Different EM responses from different configurations were investigated by towing a pulsed GPR system equipped with high-frequency horn antennas manufactured by RT Clark Company along the test site. The central frequency of the antennas is 400 MHz. The surveys were conducted through a hand-towed cart shown in Figure 1(c). The GPR antennas were suspended in the air at a height of 1 cm beyond the ballast surface through a plastic support laying on a hand-towed cart for railway track study.

3.3. Materials. Based on the inspection, the existing ballast in the site is attributed to be a kind of highly fouled type. Two types of ballasts were arranged in the test samples, namely, the existing railway dry ballasts and then the wet ballasts that were generated by applying 3-gallon water into existing dry ballasts enclosed by two rails and two sleepers in the test site. Data collection was carried out two times when the ballasts are dry and wet, respectively. All the collections are operated by towing the GPR system along the full test-site area.

4. Results and Discussion

The raw data of GPR signal are processed through Fourier transform, short-time Fourier transform method, and discrete wavelet transform method. Figure 2 illustrates the GPR signal of dry ballast and the FFT spectrum.

Figure 3 shows the spectrogram of the GPR signal of dry ballast and the wavelet spectrum.

In Figure 2(b), FFT spectrum of GPR signal of dry ballast, there exists wideband, multiple peaks of coupled modes (four peaks which could be assumed to be four coupled modes). This indicates the heavily fouling condition.

It is noted that based on existing research, the clean fresh ballast usually exhibits a spectrum with one peak with a relatively much wider band than fouled one [18]. The existing research also demonstrated that the highly fouled ballast or ballast with highly different-sized aggregates usually exhibits a spectrum with multiple peaks [10].

The time-frequency analysis, which is depicted in Figure 3, demonstrates that most of the energy is focused on a short arrival time, approximately 5 ns, followed by a gradual attenuation ending up around 20 ns.

The influence of wet condition on the spectrum of the ballast is shown in the following figures.

Figure 4 shows the GPR signal of wet ballast and the FFT spectrum. Figure 5 shows the spectrogram of the GPR signal of wet ballast and the wavelet spectrum.

For comparison, the following figure puts the GPR signal and FFT spectra of dry and wet ballast together, respectively. Figure 6 shows GPR signals of dry ballast vs wet ballast and the FFT spectra of GPR of dry ballast vs wet ballast.

From the GPR signals recorded over the dry and wet cases in Figure 6(a), it is clear that the wet condition influences the overall responses. On the other hand, it is noticed that wet condition causes big differences in the signals in the frequency domains in Figure 6(b), as reported in previous studies in the literature.

In Figure 6(b), there exist the complex features of wet ballast spectrum compared with dry ballast spectrum: a. peak frequency shift of specific frequency component or specific mode; b. attenuation of the peak of a specific mode; c. the area changes of the spectrum of a specific mode. It is noted that the above changes in the peak shift/attenuation/area are not consistent for different four modes.

Comparison of the peak shifts of the modes in the spectrum, the peaks of the first three modes of the wet ballast shift to a lower frequency end, whereas the peak of the last mode of the wet ballast is identical to its dry case.

Comparison of the peak attenuations of the modes in the spectrum, the peaks of the first two modes of the dry ballast are higher than their wet cases, respectively, whereas the peaks of the last two modes of the dry ballast are lower than their wet cases, respectively.

Comparison of the area changes in the spectrum of the modes, the areas of the first two modes of the wet ballast are smaller than that of the dry ballast, respectively, whereas the areas of the last two modes of the wet ballast are larger than that of the dry cases, respectively.
Figure 2: (a) GPR signal of dry ballast. (b) FFT spectrum of GPR signal of dry ballast.

Figure 3: (a) Spectrogram of GPR signal of dry ballast. (b), (c) Wavelet spectrum of GPR signal of dry ballast.

Figure 4: (a) GPR signal of wet ballast. (b) FFT spectrum of GPR signal of wet ballast.
It is noted that many existing research used the spectrum area change or peak shift of GPR signal as criteria for ballast analysis. In the existing research, the spectrum of GPR signal exhibits a single wide mode for clean ballasts that were well prepared in the lab, and the spectrum changes toward a lower frequency end and smaller area for fouled ballast. However, the real fouled ballast exhibits diversified trends due to multiple mode interactions. This renders the difficulty to select criteria to setup the evaluation index in the real application.

Many existing research used spectrogram and wavelet spectrum of GPA such as in Figures 3 and 5 to distinguish the attribute changes of ballast under different conditions. It should be noticed that the energy attenuation can only be observed qualitatively in the spectrogram and wavelet spectrum by comparing the color change rate from the hot color that represents high energy to cool color that represents low energy. Al-Qadi et al. [9] proposed to use the spectrogram to analyze the levels of the fouling conditions for ballast by comparing different speeds among the energy attenuations [9]. They also illustrated that it is possible to make use of the wavelet coefficient of wavelet transform to reconstruct the original signal to distinguish fouling levels, but reliable criteria need to be established.

Figure 7 shows the Hilbert spectrum of the decoupled modes GPR with optimized VMD of dry ballast and wet ballast.

Based on Figure 7, the comparison of the Hilbert spectrum of optimized VMD GPR from dry and wet ballast, we can see that there exists a very clear difference between specific mode frequency of dry and wet ballast. As such, it is very clear and easy to use specific mode frequency to form an assessment index and use its shift as reliable and robust criteria to assess the changes in the properties of ballast, which obviously overperform that of...
the conventional methods as illustrated in Figures 2–6. This method can also be extended for quantifying the water contents in other materials such as sand, soil, and concrete which had been assessed by using conventional spectra of GPR signals [22–26]. Moreover, this method can be further improved by incorporating the advanced optimization and artificial intelligence methods [19–21, 26, 27]. It is noted that several advanced approaches such as EMD, EEMD, CEEMDAN, LMD, and ITD have been developed and used to process complicated signals, some of which could be competitive to VMD in specific applications. However, compared with EMD, EEMD, CEEMDAN, LMD, and ITD, VMD has a strong mathematical theory basis [28–30].

5. Conclusion

This paper uses the optimized variational mode decomposition method to decouple the complex nonlinear modes of the GPR signal of ballast for condition assessment. The proposed advanced time-frequency analysis overperforms the conventional spectrum and time-frequency analysis of GPR signal by giving quantitative evaluation to the assessment of ballast conditions.

The results of the water content effect on ballast GPR signal spectrum changes in both peaks and areas are consistent with all published research. The decoupled nonlinear modes of GPR signal from optimized VMD are much easier to be used to establish a new condition assessment index for quantifying railway ballast fouling conditions, which is better than all the previously used spectrum methods. The works can be further improved by incorporating advanced optimization algorithms and artificial intelligence algorithms into the VMD for accurate assessment of fouling ballast in the future.

Data Availability

The data used to support the findings of this study will be made available on request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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