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SOURCE PULSE ESTIMATION OF MINE SHOCK BY BLIND DECONVOLUTION

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ABSTRACT. The deconvolution of a seismic signal is to separate information – both about the rockmass and about the signal in the shock source. In prospecting seismology use is made of a variety of deconvoluting methods, but none of them was found to be effective in the analysis of shock–induced signals gathered in the mines of the Lubin Copper Mining District (referred to as LGOM). This lack of effectiveness stems from the inadequacy of the model involved. Each of the methods dealt with in blind deconvolution is based upon certain assumptions describing the signal model, and unless these assumptions are satisfied – reliable results cannot be expected. Neither can we simply transfer the methods of deconvolution from prospecting seismology to mining seismology.

For the signals gathered in the LGOM copper mines we formulated a different model which involved the following assumptions: (1) The signal in the shock source is a short–term signal. (2) The signal–transmitting system (rockmass) forms a parallel connection of elementary systems. (3) The elementary systems are of resonant vibration type. The adoption of such a model was justified by the seismic wave propagation conditions inherent in the geological structure, as well as in the location of shock focus and seismometers. The resonant nature of vibration was indicated by physical premise, signal trajectories, time–frequency transformations of signals, and – finally – by the results obtained via classical deconvolution. While reflections from rockmass layer boundaries are undoubtedly present in the signals, we believe that the contribution of resonant–type vibration is decisive.

The adequacy of the new model, as well as the efficiency of the blind deconvolution method proposed, was corroborated by the results from the approximation of the signal (high approximation accuracy with the use of a small number of elements; relations between the parameters describing the signal), and by the results of blind deconvolution (estimators obtained for the signal in the shock source).

1. INTRODUCTION

To model the travel of the seismic signal from the source to the seismometer it is conventional to make use of a causal and stable linear system. Let $x(t)$ denote the signal emitted by the vibrating source (input signal of the system), and let $h(t)$ be the impulse response (IR) of the rockmass between the vibration source and the vibration receiver. Then the signal $y(t)$ received by the seismometer (output signal of the system) is given by the following relation

$$y(t) = \int_{-\infty}^{t} x(\tau)h(t, t-\tau)\, d\tau + n(t) = x(t) * h(t) + n(t) \tag{1}$$

In (1) the term $n(t)$ represents the additive noise, and the asterisk * is a common abbreviation for convolution.

Two terms on the right-hand side of (1) are interesting for a geophysicist: $x(t)$ and $h(t)$. The operation by which the two quantities, or one of them, are determined is known as deconvolution. Leaving out, temporarily, the $n(t)$, we can say that there exist two major types of deconvolution – the deterministic one and the blind one. For the seismic signals gathered in mines, $x(t)$ and $h(t)$ are unknowns (the observed signal $y(t)$ being the only known quantity). Thus, the separation of $x(t)$ and $h(t)$ becomes a blind deconvolution problem. In a general case, i.e. when a priori information on the phenomenon model is lacking, the blind deconvolution problem is unsolvable. The well-known methods of blind deconvolution make use of certain assumptions pertaining to the IR of the system and/or input signal. And it is only on the basis of these assumptions that effective deconvolution methods can be developed.

The principal group of blind deconvolution methods dealt with in prospecting seismology is of utility when the system IR can be modelled as the sum of Dirac impulses shifted on the time axis and occurring at various amplitudes e.g. [Stone 1984; Ziolkowski 1984]. The best known methods designed on the basis of such assumptions are spiking deconvolution and predictive deconvolution. Unfortunately, both methods failed to be applicable to the signals gathered in the LGOM copper mines (these signals will be referred to as LGOM signals). And this failure should be attributed to the inadequacy of the model on which the methods have been based. It became obvious that the deconvolution of the LGOM signals required a new approach. The new LGOM signal model proposed differs from the classical model only in one assumption.

This paper also includes a scheme instructing how to solve the blind deconvolution problem for the class of finite-energy non-minimum phase signals, and such are undoubtedly the seismic signals considered. A detailed description of the method as a whole can be found in [Makowski 1994a]. Some elements of the method are reported in [Makowski 1986; Makowski 1988; Makowski 1990; Makowski 1991; Makowski 1992; Makowski 1994b]. The present paper provides an example of the results obtained from the deconvolution of the signals gathered in the Rudna copper mine.

2. Models of Signals and System

The seismic signal model under consideration is based on the following assumptions:

1. The signal emitted by the source is a single short-term impulse.

2. The system is a parallel connection of a small number of elementary systems.
3. The elementary systems are of resonant type.
4. The signal/noise ratio is high.

Ad 1. It is generally agreed that the signal $x(t)$ emitted by the source is a single random impulse or a series of such impulses. In the case of low-energy shocks it may be expected that $x(t)$ is a single short-term impulse. Its randomness is associated not only with the randomness of the shock focus location, but also with the randomness of the phenomenon itself and the time of its occurrence. Hence we can write

$$x(t) = \eta(t - t_x)\,, \tag{2}$$

where η denotes the impulse and t_x is a random variable. If the duration of the impulse $\eta(t)$ is comparatively small (with respect to the duration of the IR of each elementary system), the signal is regarded as a short-term one.

Ad 2. The assumption that the system is a parallel connection of elementary systems is a formalization of the fact that the signal travels from the source to the receiver via many paths. Using such a model, we can also take into account various types of wave propagation. The assumption indicates that the system IR is the sum of elementary system IRs. Hence, we obtain

$$h(t,\tau) = \sum_{n=1}^{N} h_n(t,\tau)\,, \tag{3}$$

where N is the number of elementary systems and, consequently

$$y(t) = \sum_{n=1}^{N} x(t) * h_n(t) + n(t)\,. \tag{4}$$

Ad 3. Since the shock source and the seismometers are located at a similar depth (the distance between the source and the seismometers being generally long), wave propagation in the LGOM copper mines is predominantly horizontal. This is concomitant with the dominating occurrence of vibrations in the rock forming plates, and such vibrations are of resonant type. The correctness of this argumentation has been corroborated by the results reported elsewhere [Makowski 1986; Makowski 1988; Makowski 1992; Makowski 1994a; Makowski 1994b], particularly by those obtained in terms of time-frequency transformation, approximation and blind deconvolution. The anticipated resonant nature of vibrations must be clearly defined at the stage of implementation. For the LGOM signals it has been assumed that the elementary system IR is given by the following relation

$$h_n(t) = \beta_n 1(t - t_n)\,[(t - t_n)\triangle]^{m_n}\, e^{-\gamma_n (t - t_n)\triangle} \sin(2\pi f_n (t - t_n)\triangle)\,, \tag{5}$$

where β_n is a multiplier, t_n denotes time delay, m_n is a model index, γ_n and f_n describe attenuation and frequency of vibration, respectively, and $\triangle$ represents sampling period.

3. Concise Description of the Blind Deconvolution Method

The method proposed for the blind deconvolution of the signals satisfying the aforementioned assumptions involves two basic steps – estimation of system IR and inverse filtering with optimization.

The description of particular steps by which the algorithm for the estimation of the system IR was constructed is found elsewhere (e.g. in [Makowski 1988; Makowski 1992; Makowski 1994b]). The algorithm involves the approximation of the signal, and its characteristic feature is the determination of the approximation basis for each signal separately (a basis matched to the signal). For the LGOM signals such approximation was found to be highly effective. The elements of the basis $\{w_n(t) : n = 1, \ldots , N\}$ for the approximation were selected functions of the form (5), for $m_n = 1$, normalized to unity ($\| \bullet \| = 1$).

The first step of the blind deconvolution method yields the estimator of the system IR which takes the form of

$$\hat{h}(t) = \sum_{n=1}^{N} \alpha_{n,N} w_n(t) , \tag{6}$$

where $\alpha_{n,N}$ is the representation of the signal $y(t)$ in the basis $\{w_n(t)\}$.

If the terms $y(t)$ and $h(t)$ of the convolution $y(t) = x(t) * h(t)$ are known, and we want to find $x(t)$, we can achieve that by inverse filtering

$$x(t) = y(t) * h^{-1}(t) , \tag{7}$$

where $h^{-1}(t)$ is the IR of inverse filter such that fulfils the relation

$$h(t) * h^{-1}(t) = \delta(t) , \tag{8}$$

where $\delta(t)$ is the Kronecker impulse.

It should be noted, however, that inverse filtering makes us face the problem of inverse filter unstability [Makowski 1990; Makowski 1994a]. Another problem concomitant with the presence of the noise $n(t)$ in the gathered signal (by virtue of (1)) is the ill–conditioning of inverse filtering. Thus, to obtain satisfactory results it is necessary to make use of an appropriate regularization [Makowski 1994a].

As already mentioned, the other step of the blind deconvolution method involves inverse filtering. On determining the estimator of the system IR by virtue of (5) and (6), we can establish the estimator of the inverse filter. Since we know the inverse filter estimator only, we shall obtain the estimator of the input signal as the result of the inverse filtering procedure. But it should be remembered that even small errors of the system IR estimation deteriorate the quantity of the estimator $\hat{x}(t)$. Calculated results have shown that the system IR estimation errors are responsible for the input signal echoes in the signal after inverse filtering. And this means that the signal after inverse filtering includes information about these errors, so they can be eliminated by optimization.

Optimization is an important part of the method, which allows to obtain a good quality of both estimators, $x(t)$ and $h(t)$. The optimization procedure requires definition of the cost function, the minimum of which is to be found. In order to maintain the phase relations occurring in the signal, the cost function M has been defined in terms of higher order statistics. Hence we have

$$M = \sum_{k_1=p}^{P} \sum_{k_2=p}^{P} \frac{\hat{m}_{4,\nu}(k_1, k_2, 0)}{\hat{m}_{4,\nu}(0,0,0)}, \tag{10}$$

where $\hat{m}_{4,\nu}(k_1, k_2, 0)$ is the section of the forth moment of the signal, defined by the relation

$$\hat{m}_{4,\nu}(k_1, k_2, 0) = \sum_t \nu^2(t)\nu(t+k_1)\nu(t+k_2), \tag{11}$$

where $\nu(t)$ denotes the signal after inverse filtering.

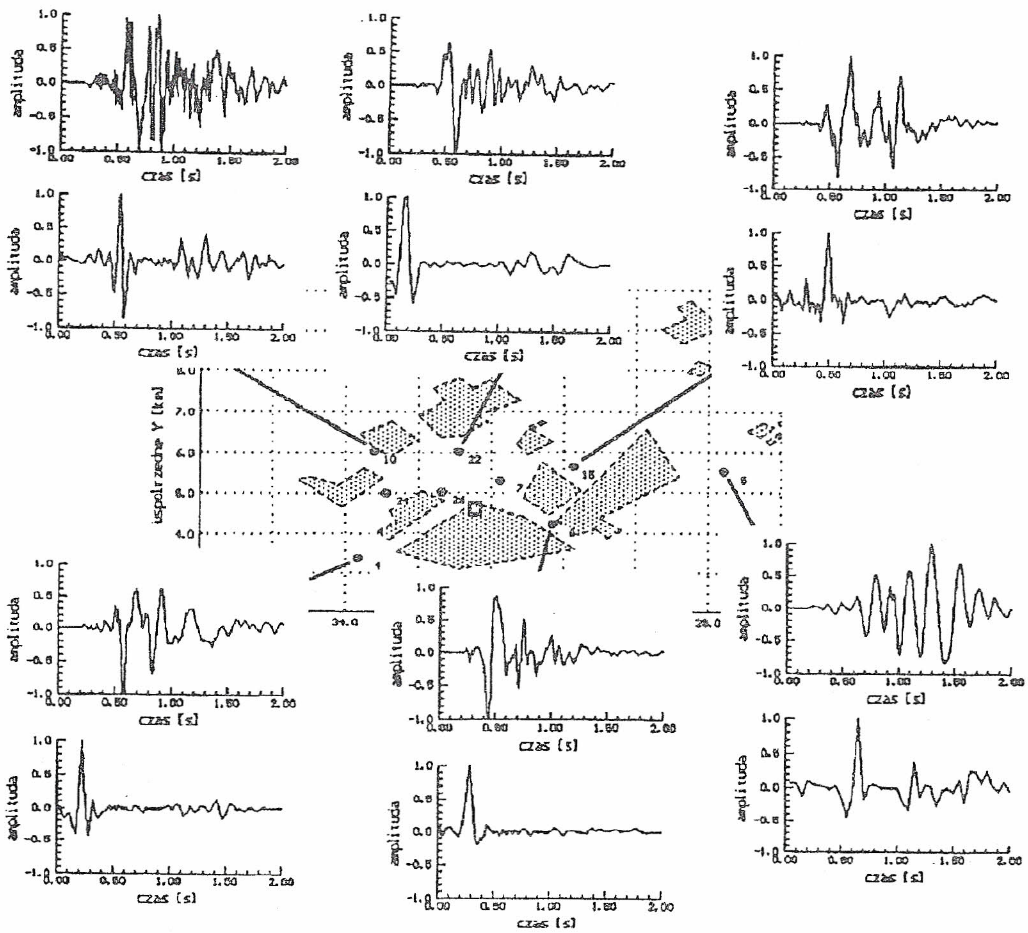

FIG. 1 Example of the results obtained by deconvolution of a seismic signal

4. Examples of Results

Figure 1 shows an example of the results obtained by the deconvolution of the seismic signal gathered in the Rudna copper mine. The central part of the diagram includes a schematic map of the mine with the projection of the shock focus (rectangle) and positions of the seismometers (filled ellipses). The diagram also comprises pairs of signals plots. The upper plot shows the signal gathered by each seismometer, and the lower plot indicates the estimator of the source signal obtained by blind deconvolution.

The source signal estimators (corresponding with relevant seismometers) differ from one another. These differences can be attributed not only to the inadequacy of the model or estimation errors, but also to the directionality of the source. However, in the majority of instances, the short duration of the signal in the source is quite clearly indicated and the differences mentioned are not such that preclude, e.g., the possibility of determining the duration of the phenomenon.

5. Conclusion

The promising results of the deconvolution of the seismic signal recorded in the LGOM mines, as well as the high approximation accuracy obtained in a previous study of these signals, seem to corroborate the adequacy of the proposed model which is to describe the travel of the signal from the source to the receiver. If the model is adequate, the description of the signal by the parameters $\{\beta_n, t_n, m_n, \gamma_n, f_n \,:\, n = 1, \ldots, N\}$ of the approximating elements is adequate with respect to the nature of the phenomenon. Consequently, the parameters should enable observation of mining–induced changes in the rockmass.

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