MAXIMUM–LIKELIHOOD IMPULSE RESPONSE ESTIMATION WITH IMPULSIVE–GAUSSIAN NOISE CORRUPTED DATA

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EXTENDED SUMMARY

Estimation of the impulse response of a linear time–invariant system is a very important issue in various signal processing applications. A good estimate of the impulse response of an electromagnetic scatter is an important tool for designing systems to resist EMP, the electromagnetic pulse caused by a nuclear explosion. A reflectivity sequence $\mu(k)$ in seismology is distorted by the source wavelet which must be estimated and removed from seismic data for the recovery of $\mu(k)$.

Although there exist many methods for impulse response estimation, most of them are based on the assumption that the measurement noise n(k) is white Gaussian. However, there are cases that n(k) is not Gaussian but a mixture of a dominant Gaussian noise and an impulsive noise, such as speckle–type noise in imaging process and other patchy disturbance. The probability distribution of n(k) is expressed by

$$p[n(k)] \sim (1-\lambda)\ G(0,R) + \lambda\ G(0, \alpha R) \qquad (1)$$

where G(0,R) denotes a Gaussian distribution with zero mean and variance R, λ indicates the impulsive spike density and $\alpha \gg 1$. For the same signal–to–noise ratio (SNR), the performance of most existing methods when data were contaminated by this mixture of noises is worse than that when data were contaminated by a Gaussian noise (λ=0). Bhargava and Kashyap [1] recently proposed a robust approach based on Huber's function against this mixture of noises. By simulation, their method has been shown to be robust for $0 \lesssim \lambda \lesssim 0.22$.

In this paper, we model this mixture noise by a Bernoulli–Gaussian model [2], which has a probability distribution given by (1), as follows:

$$n(k) = w_1(k) + q(k)\ w_2(k)$$

where q(k) is a Bernoulli sequence defined as $P_r[q(k)=1]=\lambda$ and $P_r[q(k)=0]=1-\lambda$, $w_1(k)$ and $w_2(k)$ are uncorrelated white Gaussian noises with zero mean and varainces R and $(\alpha-1)R$, respectively. Given a set of input measurements u(k) and a set of output measurements x(k)

$$x(k) = u(k) * h(k) + n(k)$$

of a linear time–invariant system h(k), we simultaneously estimate the impulse response h(k), statistical parameters R, α and λ, and detect q(k) by maximizing the likelihood function defined as:

$$S\{\underline{\theta},R,\lambda,\alpha,\underline{q}\,|\,\underline{x}\}=p(\underline{x}\,|\,\underline{\theta},R,\alpha,\underline{q})\cdot P_r(\underline{q}\,|\,\lambda)$$

where $\underline{\theta}$ includes all the autoregressive moving average (ARMA) parameters associated with h(k), $\underline{x}=(x(0), x(1), ..., x(N-1))'$ and $\underline{q}=(q(0), q(1), ...,q(N-1))'$. The obtained maximum–likelihood (ML) estimator, which is nonlinear in nature and implemented by an iterative block component method (BCM) [2] shown in Figure 1. Whenever the parameters asscoiated with each block are updated during the operation of the iterative BCM, S is guaranteed to increase. When the BCM converges, the desired $\underline{\theta}$ is obtained and thus the associated estimated impulse response is also obtained. We also performed some computer simulations for SNR ranging from 8.2 db to 34.2 db using this BCM to indicate the performance of the proposed ML estimator.

The normalized mean square error (NMSE) was used as the performance index for each estimated impulse response. The performance improvement Δ is defined to be

$$\Delta = (NMSE)_2 \,/\, (NMSE)_1$$

where $(NMSE)_1$ is associated with the proposed ML estimator and $(NMSE)_2$ is associated with the ML estimator with x(k) treated as a Gaussian signal. The simulation results show that $(NMSE)_1$ increases as λ increases and SNR decreases; $\Delta \gtrsim 1$ for all $0 \lesssim \lambda \lesssim 1$; Δ increases as λ increases when $\lambda<T$ where $T \simeq 0.4$; Δ decreases as λ increases when $\lambda>T$; $\Delta \simeq 16$ when λ=T. We conclude, from the performed simulations, that the proposed ML estimator is robust against the mixture noise n(k) for a wider range of λ than Bhargava and Kashyap's method. The reason for this is that our ML estimator actually treats the impulsive noise sequence $q(k)w_2(k)$ as a "signal" which is detected during the estimation of the impulse response. Therefore, its effect on the estimation of h(k) can be removed by the ML estimator.

REFERENCES

[1] U. K. Bhargava and R. L. Kashyap, "Robust Parametric Approach for Impulse Response Estimation," IEEE Trans. Acoustics, Speech, and Signal Processing, vol. 36, no. 10, pp. 1592–1601, Oct. 1988.

[2] Chong–Yung Chi, Jerry M. Mendel and Dan Hampson, "A Computationally Fast Approach to Maximum–likelihood Deconvolution," Geophysics, vol. 49, no. 5, pp. 550–565, May 1984.

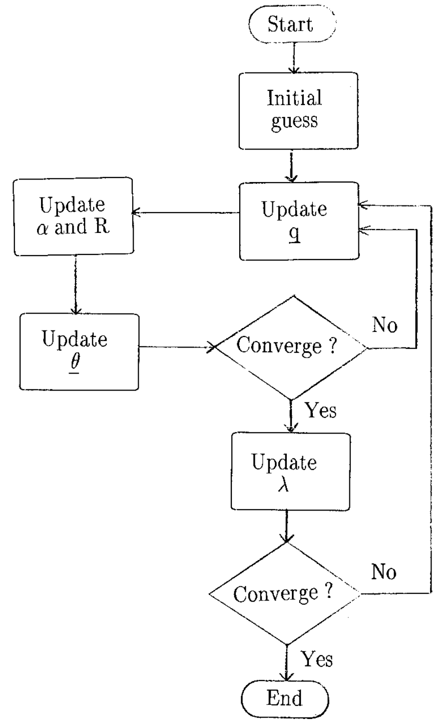

Figure 1. A block component method for implementing the ML estimator

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