Hello everyone, today I want to share an article posted in ICASSP 2022, so-called the "Adaptive Variational Nonlinear Chirp Mode Decomposition". My collaborators are from Xiamen University and Lund University, they are Xinghao Ding, Andreas Jakobsson, Xiaotong Tu, and Yue Huang. So, let's keep into it.

In recent years, nonlinear chirp signals displaying non-stationary structures have drawn increasing attention in a wide set of applications, ranging from speech analysis to fault diagnosis. For such signals, the traditional methods, such as the periodogram, which only provides limited global frequency information, lack the ability to catch the time-varying modes of the nonlinear chirp signals. In order to catch the time-frequency information of such signals, time-frequency methods have been studied, such as short-time Fourier transform, synchrosqueezed transform, and so on. Simultaneously, an important aspect of non-stationary signal analysis is that of signal decomposition, which strives to decompose a complex signal into several modes, yielding a series of decomposition methods, such as empirical mode decomposition, variation mode decomposition, and so on.

However, the existing methods suffer from the following challenges. First, most methods are unsuitable for wide-band signals. And the performance of many methods relies heavily on the setting of the user-selected parameters.

To handle these issues, in this paper, we consider the mode decomposition problem from a Bayesian perspective. Specifically, we propose an adaptive implementation, which can adaptively estimate the instantaneous amplitudes and frequencies, and form the dictionary in a data-driven manner, thereby constructing a high-resolution time-frequency representation. In addition, rather than providing a point estimate for each parameter, a full posterior density function is inferred, which may then be used to give a sense of confidence to the estimator.

We proceed to introduce the proposed method. Consider a multi-component nonlinear chirp signal, which may be well-modeled in the following form. Combined with the trigonometric formula, it also may be expressed as the demodulated form.

The resulting algorithm is formed using a joint optimization framework, striving to minimize the influence of the error factors. Specifically, the signal components may be estimated by solving the following optimization problem. As can be seen, the first term aims to restrict the residual noise energy after the overall signal components are extracted, while the remaining term restricts the smoothness of the instantaneous amplitude. As for the parameter, $\alpha$, is the trade-off between the data fitting term and the level of smoothness. Notably, this parameter will be updated automatically.

Then, by constructing a full rank matrix, D tilde, we can construct an equivalent minimization problem, as follows, which may here be efficiently solved using the Bayesian strategy.

Assuming that the noise is independent zero-mean Gaussian noise, implies that the conditional distribution of y can be written in the following form. Next, consider the principle of conjugate priors, a Gamma prior is assigned to the hyperparameter, w, as follows. Thus, we obtain the marginal likelihood function and the corresponding update procedure by using the expectation-maximum algorithm. This suggests an iterative procedure, which alternately re-estimates the posterior mean and covariance, and then re-estimates the hyperparameters until a suitable convergence criterion is satisfied.

As a supplement, the arctangent demodulation technique may be introduced to update the instantaneous frequency increment, as follows. Typically, the instantaneous frequency is a smooth function. To avoid the numerical errors caused by discrete-time sampling, the increment may be corrected by a low-pass filter.

Finally, let's take a look at the numerical experimental results. In the first experiment, we consider a two-component simulated nonlinear chirp signal, which may be expressed in the following form. The relative errors of the estimated modes and instantaneous frequencies are listed in Table 1. As may be seen, the proposed algorithm provides more accurate results with smaller relative errors. The estimated instantaneous frequencies are shown in Fig.1, clearly showing that the proposed method’s estimates well match the theoretical values.

The proposed approach is also evaluated for a real-life signal from the whistle of a baiji, a Yangtze river dolphin. Fig.2 provides the time-frequency representation results by the discussed methods. As may be seen, our method yields a high-resolution time-frequency representation, being capable of representing the two modes and time-varying features of the signal. The demodulated results by the proposed method are shown in Fig.3. This example indicates the potential of the proposed method in analyzing ocean signals.

Our codes are available at my Github Repositories. Hope you can enjoy our presentation, thank you.