Sparse Bayesian Learning with Generalized Double Pareto Prior for Bearing Fault Diagnosis

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Introduction

As the most important driving equipment, the motor plays an irreplaceable role in industrial and agricultural production and daily life. In addition, they are limited by the level of designers, as well as the imperfection of production and manufacturing technology, which makes the motors have many hidden troubles. Research proves that motor bearing fault which is one of the most common motor faults accounts for up to 40% of all kinds of faults. Therefore, effective fault diagnosis of bearing is of great significance.

Although the sparse representation (SR) methods can achieve state-of-the-art performance, most of these methods rely on manually tuning several hyper-parameters, and performance may be degraded due to approximate regularization and/or heuristic sparse models. To overcome these shortcomings and extract the fault impulse more accurately, in the paper, we present a sparse Bayesian learning (SBL) framework as well as exploit the group-sparsity structure for bearing fault diagnosis. This method avoids the manual adjustment of parameters. However, in this conventional SBL framework, the sparsity of extracted fault impulses is determined by the traditional prior model. When the noise is too large or the sampling time is short, this method also has performance loss. In order to reduce the performance loss of this method, we further introduce Generalized Double Pareto (GDP) prior which promotes the sparsity more significantly than conventional priors like Gamma and Laplace, thus improving the performance of the proposed method.

Finally, through several groups of experiments, the effectiveness and superiority of the proposed method are proved.

Our Method

The observed vibration signal is composed of fault impulse and background noise. So, it is defined as:y=x+n,where y denotes the observed vibration signals, x denotes the fault impluse which has a periodic group-sparsity structure, and n denotes the i.i.d. Gaussian noise with mean zero and the variance z. In bearing fault diagnosis, what we need to do is extract the fault impulse x from the original signal y under background noise. According to the data model, we can give the sparse Bayesian formulation to extract the fault impulse. The following is the modeling and formula derivation:

$$p(\mathbf{y}|\mathbf{x},\alpha)=\mathbb{N}\left(\mathbf{y}|\mathbf{x},\mathbf{I}_R\alpha^{-1}\right)=\prod_{r=1}^{R}\mathbb{N}\left(y_r|x_r,\alpha^{-1}\right)$$

$$p(\alpha)=\Gamma\left(\alpha|a,b\right)$$

$$p(\mathbf{x}|\boldsymbol{\gamma},\mathbf{z})=\prod_{r=1}^{R}\prod_{m=1}^{3}\left\{\mathbb{N}\left(x_r|0,\gamma_{r+m-2}\right)\right\}^{z_{r,m}}$$

$$p(\boldsymbol{\gamma}|\boldsymbol{\xi})=\prod_{r=1}^{R} gamma\left(\gamma_r;1,\frac{\xi_r^2}{4}\right)$$

$$p(\boldsymbol{\xi})=\prod_{r=1}^{R} gamma(h,h)$$

$$p(\mathbf{z})=\prod_{r=1}^{R}p(\mathbf{z}_r)=\prod_{r=1}^{R}\prod_{m=1}^{3}\left(\frac{1}{3}\right)^{z_{r,m}}$$

$$p(\mathbf{y},\mathbf{x},\alpha,\boldsymbol{\xi},\boldsymbol{\gamma},\mathbf{z})=p(\mathbf{y}|\mathbf{x},\alpha)p(\alpha)p(\mathbf{x}|\boldsymbol{\gamma},\mathbf{z})p(\boldsymbol{\gamma}|\boldsymbol{\xi})q(\boldsymbol{\xi})p(\mathbf{z})$$

update : $\boldsymbol{\xi}$

$$Q(\boldsymbol{\xi})=\ln\xi_r^2-\frac{\xi_r^2}{4}\gamma_r+(h-1)\ln\xi_r-h\xi_r$$

$$令\ \frac{\partial Q(\boldsymbol{\xi})}{\partial\xi_r}=0$$

$$\frac{2}{\xi_r}-\frac{\gamma_r}{2}\xi_r+\frac{h-1}{\xi_r}-h=0$$

$$解得:\quad \hat{\xi}_r=\frac{-h+\sqrt{h^2+2\gamma_r(h+1)}}{\gamma_r}$$

$$\ln q(\mathbf{x})=\left\langle \ln p(\mathbf{y}|\mathbf{x},\alpha)p(\mathbf{x}|\boldsymbol{\gamma},\mathbf{z})\right\rangle_{q(\alpha)q(\boldsymbol{\xi})q(\gamma)q(\mathbf{z})}$$

$$\propto\left\langle -\frac{1}{2}\sum_{r=1}^{R}(y_r-x_r)^{\mathrm{H}}(\alpha)(y_r-x_r)-\frac{1}{2}\sum_{r=1}^{R}\sum_{m=1}^{3}z_{r,m}(x_r)^{\mathrm{H}}\gamma_{r+m-2}^{-1}x_r\right\rangle_{q(\alpha)q(\boldsymbol{\xi})q(\gamma)q(\mathbf{z})}$$

$$\propto\sum_{r=1}^{R}\left(-\frac{1}{2}\left(-\hat{\alpha}y_r^{\mathrm{H}}x_r-\hat{\alpha}(x_r)^{\mathrm{H}}y_r+(x_r)^{\mathrm{H}}\left(\sum_{m=1}^{3}\hat{z}_{r,m}\hat{\gamma}_{r+m-2}^{-1}+\hat{\alpha}\right)x_r\right)\right)$$

$$\Sigma_r=\left(\sum_{m=1}^{3}\hat{z}_{r,m}\hat{\gamma}_{r+m-2}^{-1}+\hat{\alpha}\right)^{-1}$$

$$\mu_r=\hat{\alpha}\Sigma_r y_r$$

$$\ln q(\alpha)=\left\langle \ln p(\mathbf{y}|\mathbf{x},\alpha)p(\alpha)\right\rangle_{q(\mathbf{x})}$$

$$\propto\left\langle \sum_{r=1}^{R}\left(\frac{1}{2}\ln\alpha-\frac{1}{2}\alpha(y_r-x_r)^{\mathrm{H}}(y_r-x_r)\right)+(a-1)\ln\alpha-b\alpha\right\rangle_{q(\mathbf{x})}$$

$$\propto\left(a+\frac{R}{2}-1\right)\ln\alpha-\left(b+\frac{1}{2}\sum_{r=1}^{R}\left((y_r-\mu_r)^2+\Sigma_r\right)\right)\alpha$$

$$\hat{\alpha}=2a+R\Big/\left(2b+\sum_{r=1}^{R}\left((y_r-\mu_r)^2+\Sigma_r\right)\right)$$

update : $\boldsymbol{\gamma}$

$$Q(\boldsymbol{\gamma})=\sum_{r=1}^{R}\left(-\frac{1}{2}\sum_{m=1}^{3}\hat{z}_{r-m+2,m}\ln\gamma_r-\left(\frac{1}{2}\sum_{m=1}^{3}\hat{z}_{r-m+2,m}\left(\mu_{r-m+2}^2+\Sigma_{r-m+2}\right)\right)\gamma_r^{-1}-\frac{\xi_r^2}{4}\gamma_r\right)$$

$$令\ \frac{\partial Q(\boldsymbol{\gamma})}{\partial\gamma_r}=0$$

$$\frac{-\frac{1}{2}}{\gamma_r}+\frac{\frac{1}{2}\sum_{m=1}^{3}\hat{z}_{r-m+2,m}\left(\mu_{r-m+2}^2+\Sigma_{r-m+2}\right)}{\gamma_r^2}-\frac{\xi_r^2}{4}=0$$

$$\hat{\gamma}_r=\left(-1+\sqrt{1+2\xi_r^2\sum_{m=1}^{3}\hat{z}_{r-m+2,m}\left(\mu_{r-m+2}^2+\Sigma_{r-m+2}\right)}\right)\Big/\xi_r^2$$

Experiment

In this simulation experiment, we perform a series of numerical simulations to illustrate the performance of the proposed method. Morever, In real experiment , we apply the VALENIAN PT100 test rig to obtain fault nformation of outer race fault bearing for examining the effectiveness of the proposed method. The theoretical fault frequency of outer race fault bearing of the motor is 59.6Hz. the length of the signal L is 16384.

Fig. 1 shows the NMSE performance of all methods at different noise levels. Fig. 2 shows our experimental platform and device. Fig. 3 showst he extracted result and envelope spectra for outer race failure.

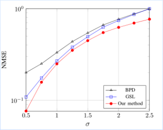

Fig. 1

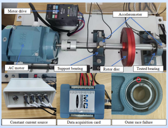

Fig. 2

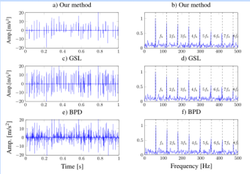

Fig. 3

Conclusion

In order to avoid manual parameter adjustment and performance degradation of the algorithm, in the paper, we present a SBL-based method .To reduce the performance loss of the algorithm, we further introduce the GDP prior. Moreover, we use a novel three-level hierarchical prior model, which can make the marginal distribution of real signals follow the GDP distribution.Finally, through the simulation and practical application of bearing fault diagnosis, the superiority of the algorithm is well verified.

References

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