



基于半监督学习和分布式光纤的管道安全预警系统

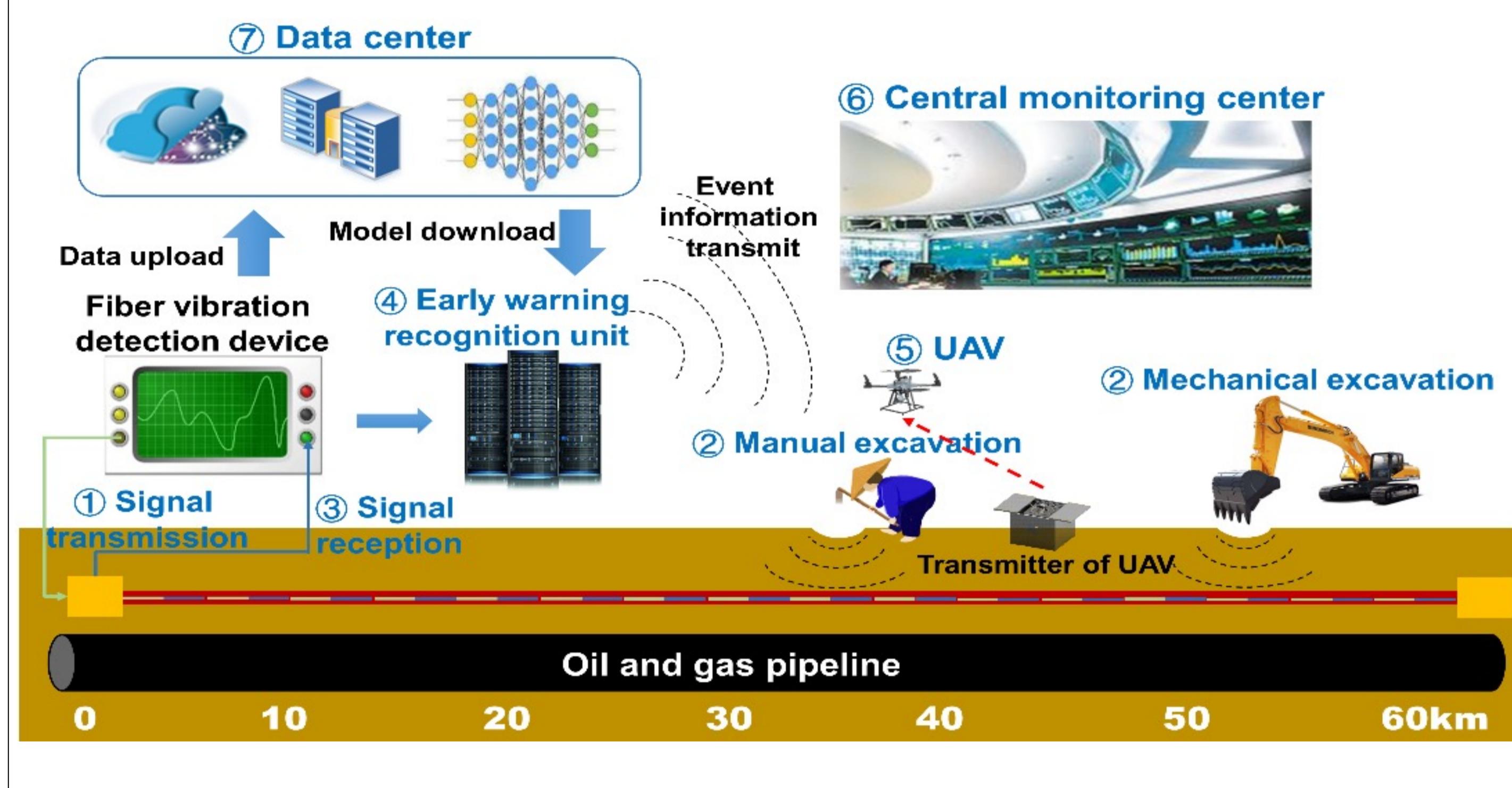
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1 分布式光纤管道安全预警系统介绍

光纤被认为是目前最好的工业信号载体，它支持低成本和长距离的铺设。特别地，相干瑞利散射分布式光纤传感器具有更高的灵敏度和更大的检测范围，并且只需要使用一条额外的普通通信光缆，这使得其更符合国际上对建设分布式长距离运输管道的硬件要求。下图是一种新型的基于光纤的能源管道安全预警系统，它可以识别危险行为、发出实时警告、进行现场检查并实时记录数据。

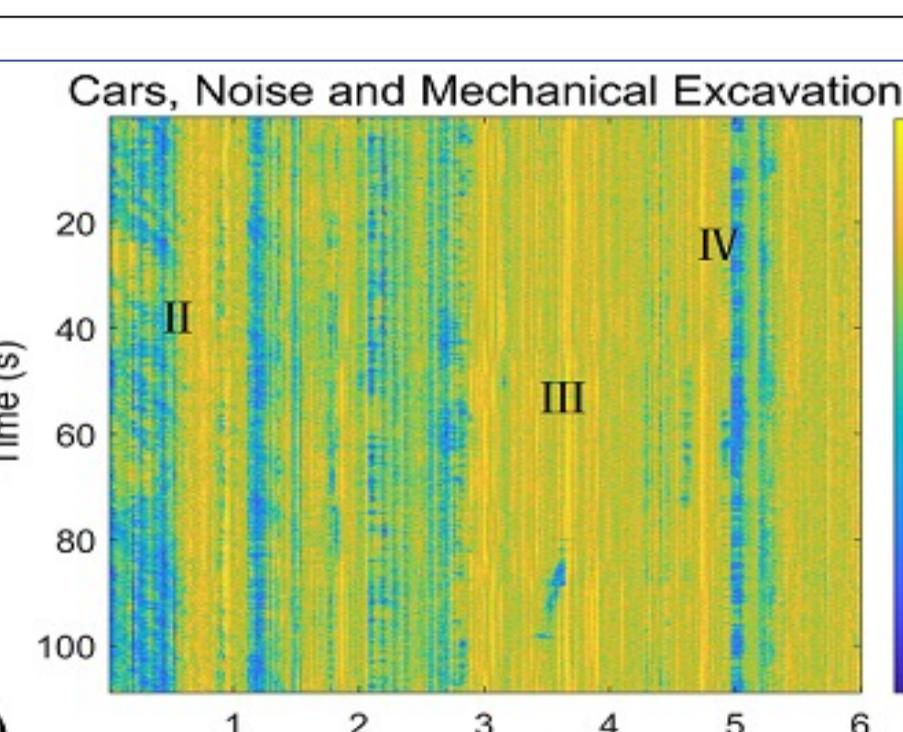
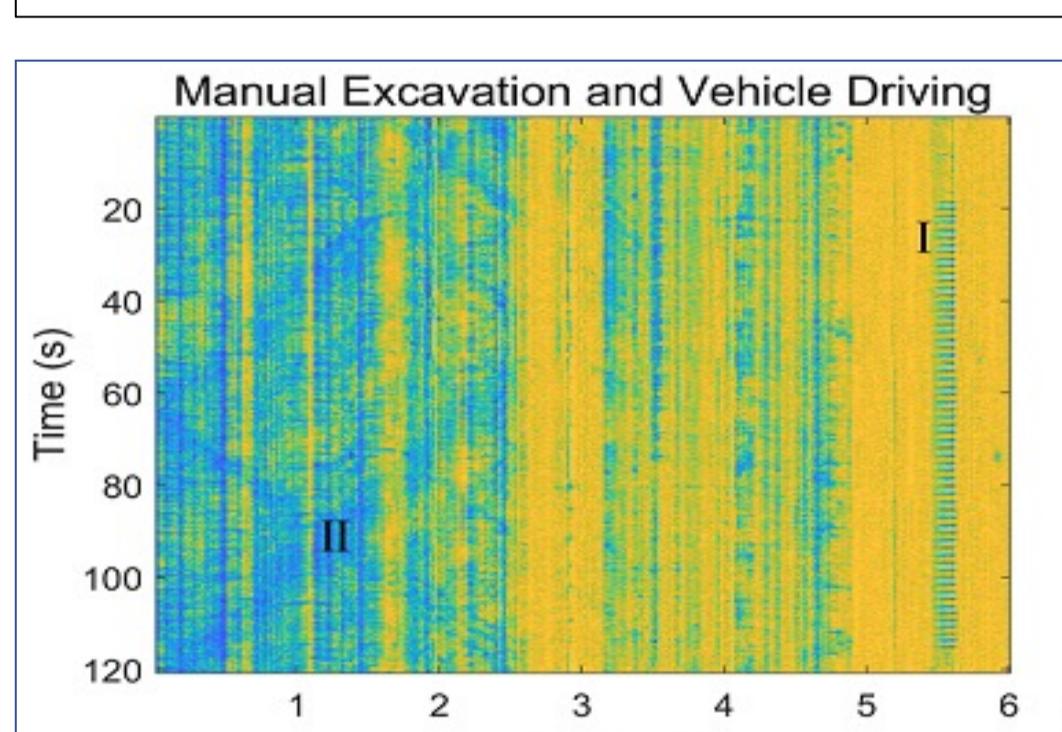
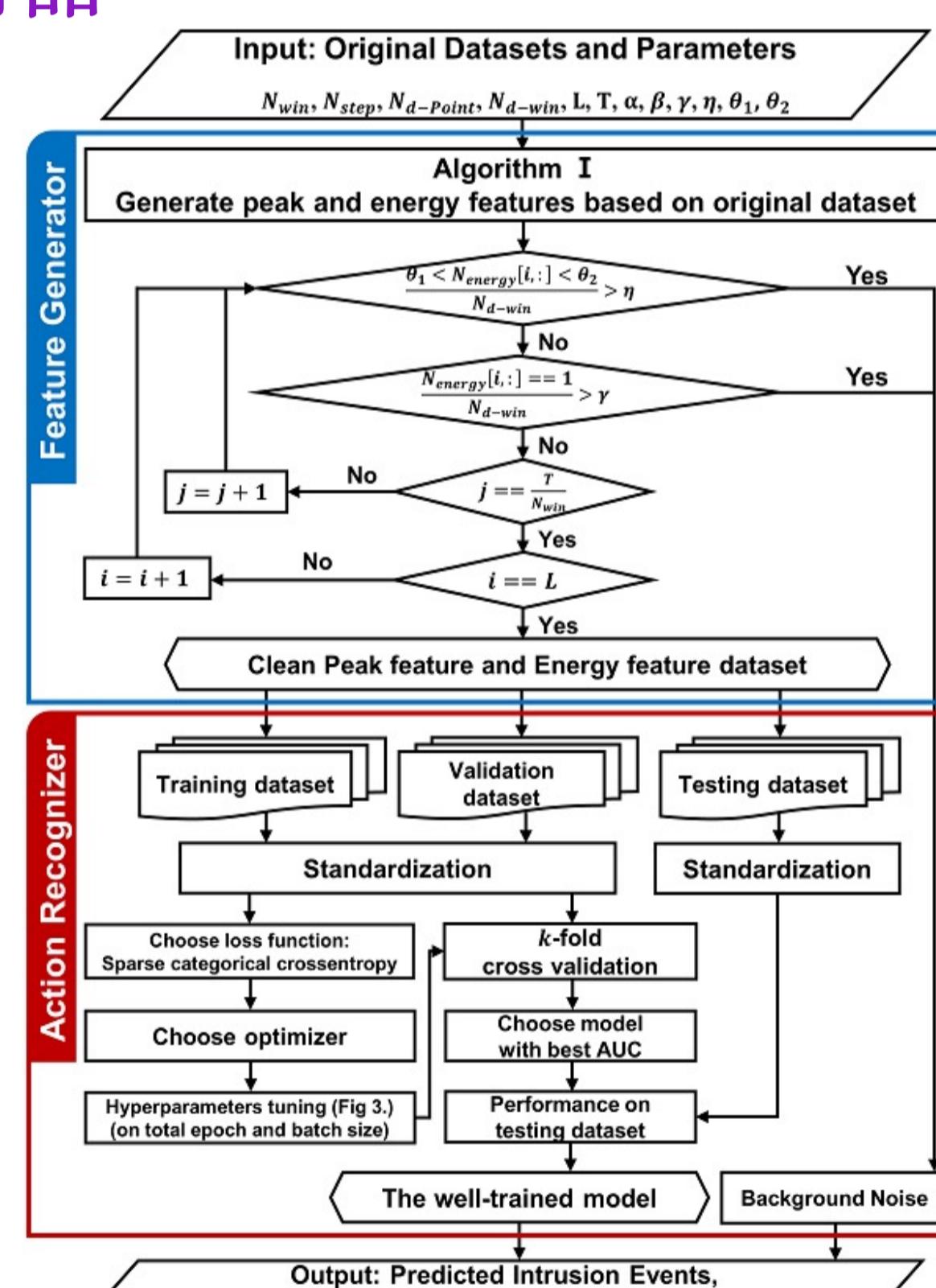


2 特征提取器与事件定位识别器

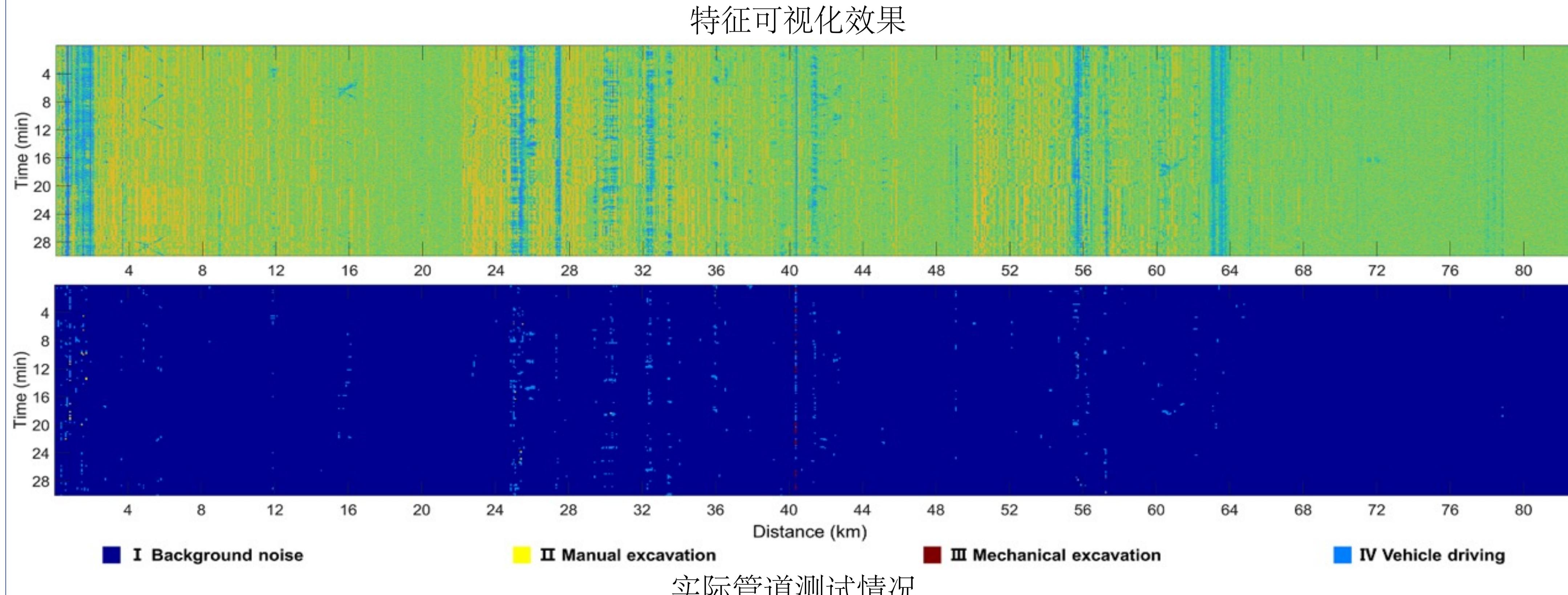
Algorithm 1 Matrix of Peak and Energy Features M_{peak}, M_{energy}

Input: Origin data X , Background noise data X_{base} .
Output: Matrix of Peak and Energy Features M_{peak}, M_{energy}
variable: Length of window and step N_{win}, N_{step} , Number of observation points L , Number of data in time dimension T , Number of observation points and windows to be considered $N_{d-point}, N_{d-win}$, Threshold α and β .

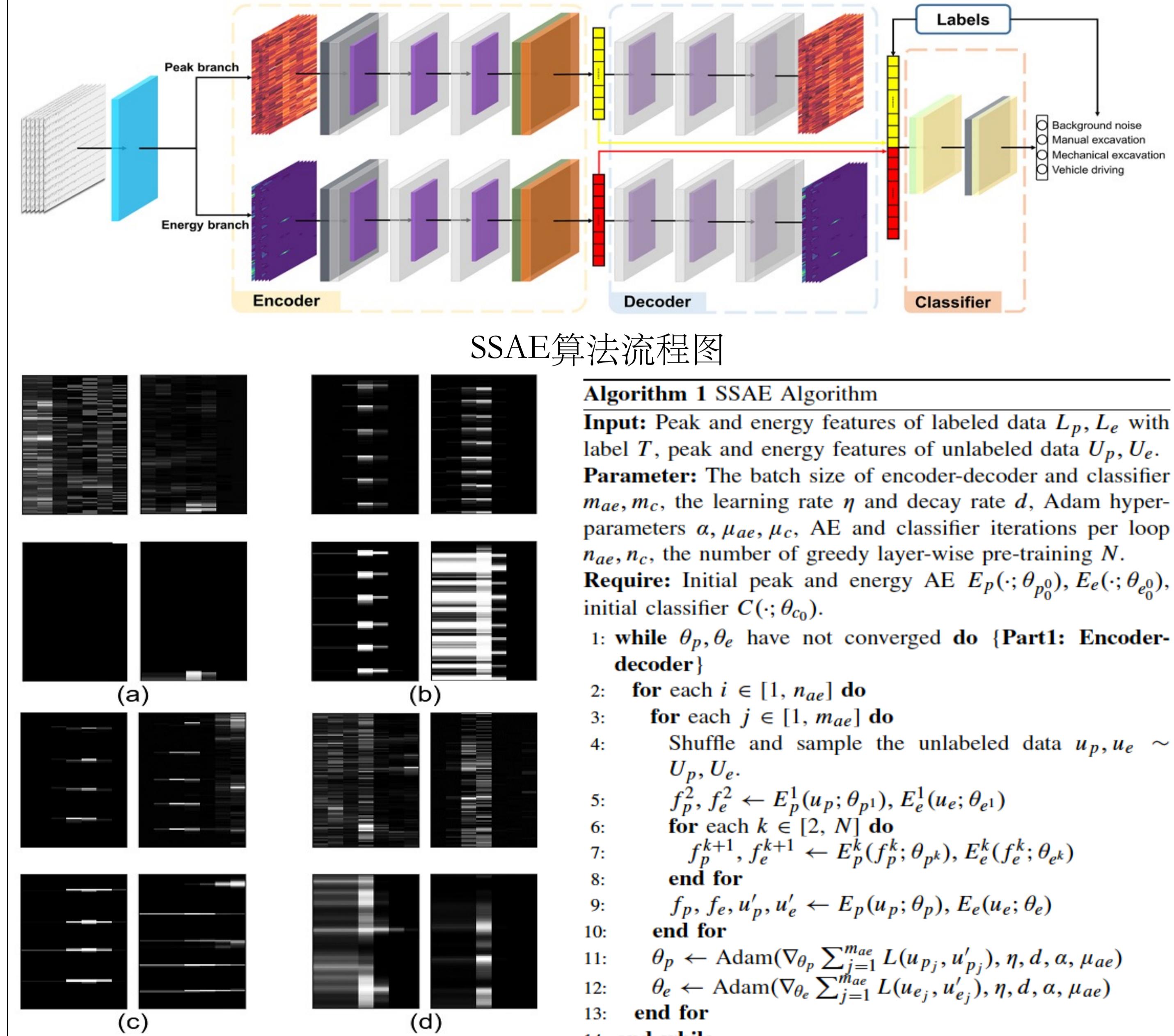
- Attenuation compensation and standardization of X and X_{base} .
- for each $i = 1, \dots, L$ do
- for each $j = 1, \dots, \frac{T}{N_{win}}$ do
- $F_{peak}[i, j] \leftarrow \text{Count peak}(X[i, j * N_{step}:j * N_{step} + N_{win}])$
- for each $k = 1, \dots, N_{win} - 2$ do
- $F_{energy}[i, j] \leftarrow \frac{\sum_{k=1}^{N_{win}-2} |data[k] - data[k]|^2}{T * X_{base}}$
- end for
- Set $F_{energy}[i, j] \leftarrow 1$ if $F_{peak}[i, j] > \beta$
- end for
- end for
- for each $m = \frac{N_{d-point}}{2}, \dots, L - \frac{N_{d-point}}{2}$ do
- for each $n = 1, \dots, \frac{N_{win} * N_{d-win}}{2}$ do
- $M_{peak}, M_{energy} \leftarrow F_{peak}, F_{energy}[m - \frac{N_{d-point}}{2}, \frac{N_{d-point}}{2} + m + 1, n * \frac{N_{d-win}}{2}; n * \frac{N_{d-win}}{2} + N_{d-win}]$
- end for
- end for



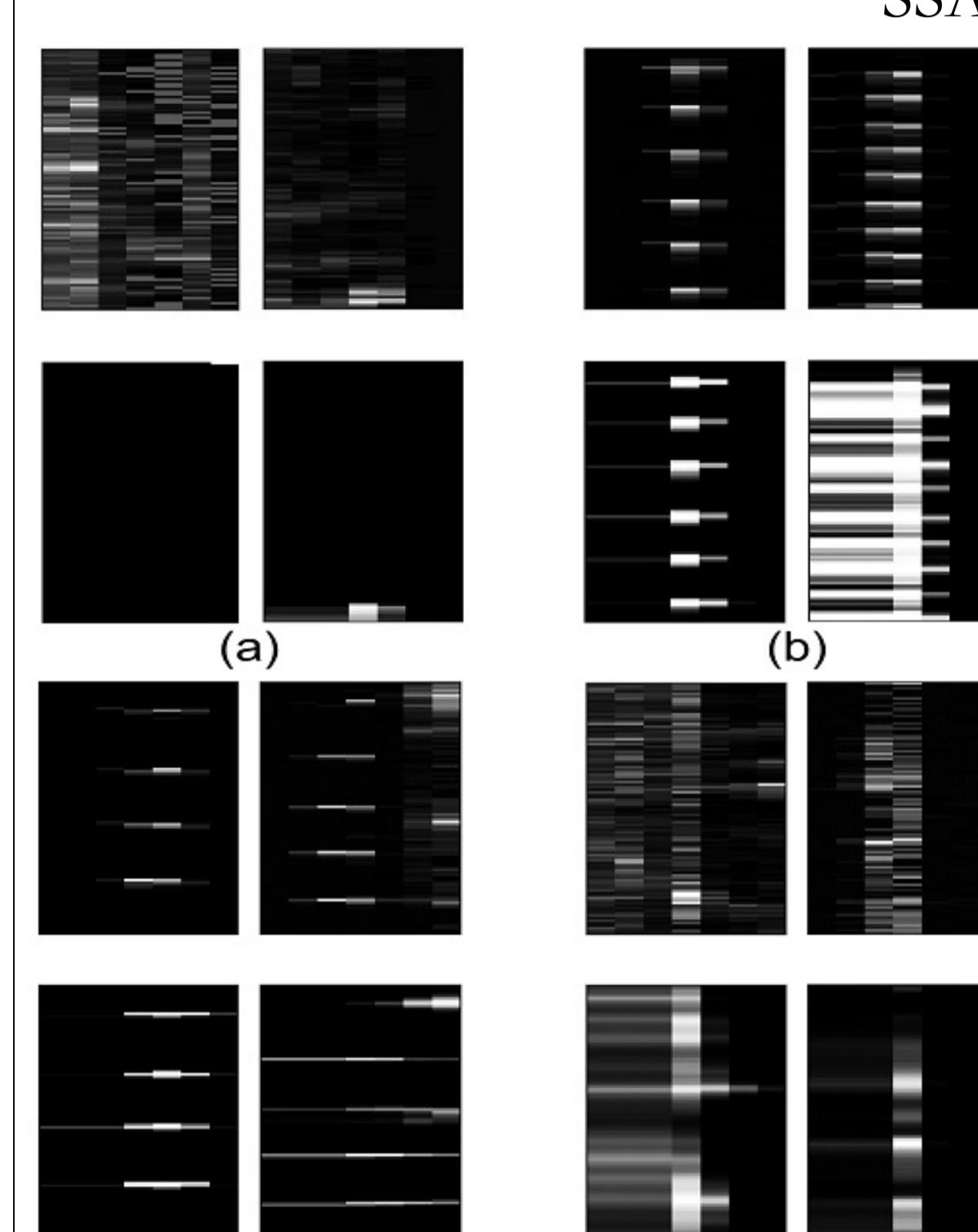
特征可视化效果



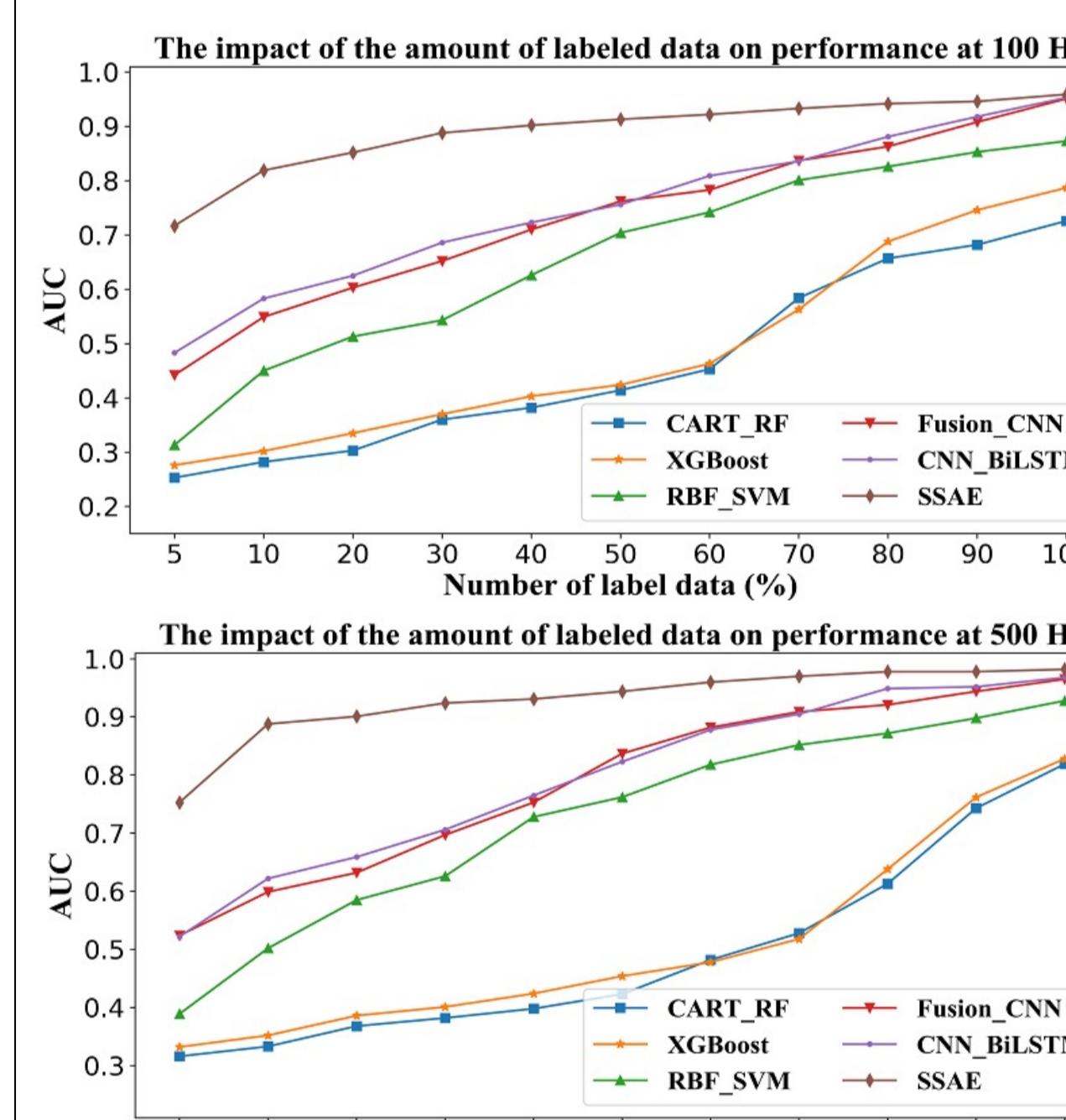
3 SSAE算法及识别定位效果



SSAE算法流程图



解码器输出可视化效果



标记数据量对性能的影响

Algorithm 1 SSAE Algorithm

Input: Peak and energy features of labeled data L_p, L_e with label T , peak and energy features of unlabeled data U_p, U_e .

Parameter: The batch size of encoder-decoder and classifier m_{ae}, m_c , the learning rate η and decay rate d , Adam hyperparameters α, μ_{ae}, μ_c , AE and classifier iterations per loop n_{ae}, n_c , the number of greedy layer-wise pre-training N .

Require: Initial peak and energy AE $E_p(\cdot; \theta_{p0}), E_e(\cdot; \theta_{e0})$, initial classifier $C(\cdot; \theta_{c0})$.

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1: while  $\theta_p, \theta_e$  have not converged do [Part1: Encoder-decoder]
2:   for each  $i \in [1, n_{ae}]$  do
3:     for each  $j \in [1, m_{ae}]$  do
4:       Shuffle and sample the unlabeled data  $u_p, u_e \sim U_p, U_e$ .
5:        $f_p^j, f_e^j \leftarrow E_p^j(u_p; \theta_{p1}), E_e^j(u_e; \theta_{e1})$ 
6:       for each  $k \in [2, N]$  do
7:          $f_p^{j+1}, f_e^{j+1} \leftarrow E_p^k(f_p^j; \theta_{p^k}), E_e^k(f_e^j; \theta_{e^k})$ 
8:       end for
9:        $f_p, f_e, u'_p, u'_e \leftarrow E_p(u_p; \theta_p), E_e(u_e; \theta_e)$ 
10:    end for
11:     $\theta_p \leftarrow \text{Adam}(\nabla_{\theta_p} \sum_{j=1}^{m_{ae}} L(u_p, u'_p), \eta, d, \alpha, \mu_{ae})$ 
12:     $\theta_e \leftarrow \text{Adam}(\nabla_{\theta_e} \sum_{j=1}^{m_{ae}} L(u_e, u'_e), \eta, d, \alpha, \mu_{ae})$ 
13:  end for
14: end while
15: while  $\theta_c$  has not converged do [Part2: Classifier]
16:   for each  $i \in [1, n_c]$  do
17:     for each  $j \in [1, m_c]$  do
18:       Shuffle and sample the labeled data  $l_p, l_e \sim L_p, L_e$  and their label  $t \sim T$ , correspondingly.
19:        $\hat{f}_p, \hat{f}_e \leftarrow E_p(l_p; \theta_p), E_e(l_e; \theta_e)$ 
20:        $\hat{f} \leftarrow C(\hat{f}_p, \hat{f}_e; \theta_c)$ 
21:     end for
22:      $\theta_c \leftarrow \text{Adam}(\nabla_{\theta_c} \sum_{j=1}^{m_c} L(t, \hat{t}), \eta, d, \alpha, \mu_c)$ 
23:   end for
24: end while

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SSAE算法

4 总结

本文提出了一种基于半监督学习和分布式光纤的方法，用于监测管道安全状况。根据多个管道的实验结果，提出的特征提取器可以表达多种复杂条件下事件的信息，半监督模型能够准确识别并及时定位入侵事件。本方法满足了实时性、硬件适应性等工业需求，并优化了样本利用率，降低了实验成本。该方法已部署于中石油某管道，并入内部智慧管道系统，已稳定运行超过1年。

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