Railway Fastener Defects Detection Using Gaussian Mixture Deformable Part Model

Biao He, Yun Hou, Ying Xiong and Bailin Li
School of Mechanical Engineering, Southwest Jiaotong University, Chengdu 610031, China.
Email: hebiao_swjtu@163.com

Abstract. This paper addressed the problem of detecting the completely missing and partly missing railway fasteners in the collected images. A Gaussian mixture deformable part model (GMDPM) algorithm was proposed using histogram of oriented gradient (HOG) features. The fastener template was divided into four parts considering the shape of the fastener, and seed points were uniformly sampled along the fastener’s shape contour. The part and the seed point deformation were defined to fit the deformation of the fastener. Each seed point template in the part model was solved iteratively by using Gaussian mixture model (GMM) with an expectation-maximization algorithm. The results reveal that the proposed method achieves good performance, especially when the illumination difference is large and the fastener is partially occluded or has slight shape deformation.

1. Introduction
By the end of 2018, China's railway business mileage reached 131,000 km, of which the total length of high-speed railway was 29,000 km. Railway defects detection based on computer vision is needed. In this paper, we consider the problem of detecting completely missing and partially worn fastener in tens of thousands of static images taken by monocular camera. Many researchers [1–8] are interested in proposing a suitable vision-based algorithm for railway fastener detection. Liu et al. [1] propose a symmetrical method for fastener samples and use improved sparse representation and classification (SRC) algorithm to detect both partly worn and completely missing fasteners. Marino et al. [2] using two multilayer perceptron neural classifiers (MLPNC) to reveal the presence or absence of the fastening bolts. Dou et al. [3] using fast template matching-based algorithm (FTM) to locate the bolts with constrains of the railway geometric structure and a nearest neighbor classifier to determine whether a bolt is in position or not. Fan et al. [5] proposed the line local binary pattern (LLBP) for high-speed railway fastener detection. Deformable Part Model (DPM) is one of the most effective template-based approaches used in object detection [6-7]. Felzenszwalb et al. [7] described an object detection system that represents highly variable objects using mixtures of multiscale deformable part models and trained with latent SVM. Gaussian mixture models have already been applied to point set registration problems [8-10]. Jian et al. [8] presented a unified framework for the rigid and nonrigid point set registration problem using the L2 distance between two Gaussian mixtures. Inspired by the work of deformable part models [7] and Gaussian mixture models [8], we proposed a Gaussian mixture deformable part model (GMDPM) algorithm, which using histogram of oriented gradient (HOG) [11] feature as low-level feature.

The rest of this paper is organized as follows. In section 2, the fastener defects and detection difficulties are discussed; In section 3, the Gaussian mixture deformable part model (GMDPM) algorithm is briefly introduced; experiment results and comparison of the fastener defects detection
using the proposed GMDPM algorithm are introduced in section 4; Finally, we conclude this paper in section 5.

2. Fastener Defects and Detection Difficulties
By analyzing thousands of captured fastener images, we found that the fastener defects mainly include partially worn and completely missing fasteners, as shown in Figure 1b and Figure 1c.

![Fastener defects](image)

(a) intact fastener (b) partially worn fastener (c) completely missing fastener

Figure 1. Fastener defects

The fastener images are captured in the wild, as shown in the Figure 2. It can be seen that the fastener images have the following characteristics:

1. There is a large illumination difference in the fastener image;
2. The fastener is partially obscured by the track ballast;
3. The fastener has a slight deformation.

These problems have not been fully studied in previous literature. In order to solve these problems, we developed a Gaussian mixture deformable part model algorithm, which was trained by Gaussian mixture models that will use a large number of positive examples, while only a few negative examples. The proposed GMDPM algorithm is suitable for fastener detection, because the defective fasteners are very few in practice.

![Captured fastener images](image)

Figure 2. captured fastener images

3. Gaussian Mixture Deformable Part Model Algorithm
The proposed GMDPM algorithm can be expressed in the form of graph model $G = (P, E)$, in which vertices $P = \{p_1, p_2, \ldots, p_n\}$ corresponding to the $n$ individual parts and edges $(p_i, p_j) \in E$ representing the connection between part $p_i$ and $p_j$. In GMDPM, $p_i$ is the appearance feature descriptions of the object’s part, and $p_i = \Phi(q_1, q_2, \ldots, q_m)$. $q_m$ represents a series of seed feature template points; $\phi_{i,j}$ is the spatial connection relationship between $p_i$ and $p_j$, where $\phi_{i,j} \in \Omega$, and $\Omega = \{\phi_{i,j} | (p_i, p_j) \in E\}$. 


3.1. Deformation Between Parts
In deformable part model, parts are not independent of each other, but have spatial connections. Star connection is often adopted, taken $p_1$ as the connection center, and the rest $n-1$ parts $\{p_2, ..., p_n\}$ need to meet a certain spatial constraint.

$$\phi_{i,j} = (x_{i,j}, y_{i,j}) + (\Delta x_{i,j}, \Delta y_{i,j})$$

(1)

Where, $\phi_{i,j}$ indicates the range of locations in which $p_i$ can vary with respect to $p_1$, $i = 2, 3, ..., n$, and $(x_{i,j}, y_{i,j})$ is the anchor locations of $p_i$, $(\Delta x_{i,j}, \Delta y_{i,j})$ represents the variable range of $p_i$ relative to $p_1$. During test time, $p_1$ using global or local search in the test image feature space according to the task requirements.

3.2. Local Deformation of Seed Points
In the classic deformable part model, each part is a rectangular area, HOG features are uniformly distributed throughout each rectangular part, while the parts of real object in the image do not fill the entire rectangular area and usually have specific shape. Therefore, the part template using the entire rectangular area cannot accurately establish the real object part. In this letter, the part template is improved based on the above discussion. Several points are sampled at a certain distance along the contour of the object as seed points. These seed points describe the shape feature of the object, which can be regarded as shape constraints. Each seed point will extract the corresponding HOG feature, and GMM is used to get the typical HOG features as mixture feature template of the seed point. In order to increase the shape robustness of the part template, the seed points in the part are not completely fixed, but allow local deformation near its standard position.

$$S_{i,j} = S_{0,j} + \Delta S_{i,j}$$

$$S_{0,j} = (x_1, y_1, ..., x_m, y_m)$$

$$\Delta S_{i,j} = (dx_1, dy_1, ..., dx_m, dy_m)$$

(2)

In the formula, $S_{0,j}$ represents the standard shape of $p_j$, $\Delta S_{i,j}$ is the shape variable range of $p_i$ relative to its standard shape $S_{0,j}$, and the shape of $p_j$ consists of $m$ seed points. Figure 3 shows the fastener parts and the seed points in fastener shape contour.

![Figure 3. Seed points in fastener parts](image)

(a) The number of fastener parts (b) Seed points of fastener part 1

3.3. Part Score
During the test, part $p_i$ searches all possible locations, each part of the rest has several possible locations, and the final similarity of these parts take the maximum value,

$$\varphi_i = \max_{\phi_{i,j}} (p_i(x, y)) \quad (i = 2, 3, ..., n)$$

(3)

The score of $p_i$ is obtained by summing scores of all the seed points,
The score of each seed point is the maximum matching value in all variable locations with the local feature templates.

$$p_i(x,y) = \sum_{j=1}^{N} q_j(x,y)$$

Where, $$S_i(x_j,y_j)$$ is the variable locations of the seed point at $$(x,y)$$, $$\lambda_k(x,y)$$ is the matching score of the $$k$$-th template at $$(x,y)$$. Each seed point template in $$p_i$$ is a mixture of $$K$$ vectors, and each vector's dimension is $$L$$. Let $$t_k(x,y,z)$$ represent the $$k$$-th template vector at the seed point $$(x,y)$$ in part model $$p_i$$, $$t_k(x,y,z)$$ corresponding to $$\mu_k$$ in GMM, and $$z \in \{1,2,...,L\}, \ k \in \{1,2,...,K\}$$. In the feature space of the test image, let $$h(x,y,z)$$ represent the feature vector with the same size as $$p_i$$, and using cosine similarity[12] to get the seed point score at $$(x,y)$$ with the $$k$$-th template vector,

$$\lambda_k(x,y) = \frac{\sum_{z=1}^{L} h(x,y,z)t_k(x,y,z)}{\sqrt{\sum_{z=1}^{L} h(x,y,z)^2} \sqrt{\sum_{z=1}^{L} t_k(x,y,z)^2}}$$

### 3.4. Gaussian Mixture Model

For a feature point $$v$$ in $$p_i$$, we can extract the feature point(such as HOG feature descriptors, etc) at specific location from the training image set to form a feature vector set $$V = \{v_a, a = 1, ..., A\}$$, the dimensionality of $$v_a$$ is $$L$$, $$A$$ is the number of training image set. Assuming that $$V$$ follows Gaussian mixture distribution, there is

$$u(v) = \sum_{k=1}^{K} w_k u_k(v | \mu_k, \Sigma_k)$$

Where, $$w_k \geq 0$$ and $$\sum_{k=1}^{K} w_k = 1$$, $$K$$ is the number of mixed Gaussian distributions, $$u_k(v | \mu_k, \Sigma_k)$$ indicates the $$k$$-th Gaussian distribution in GMM,

$$u_k(v | \mu_k, \Sigma_k) = \frac{1}{(2\pi)^{L/2} |\Sigma_k|^{1/2}} \exp\left(-\frac{1}{2} (v-\mu_k)^T \Sigma_k^{-1} (v-\mu_k) \right)$$

Among them, $$\mu_k$$ and $$\Sigma_k$$ represent the mean value and covariance matrix of the $$k$$-th Gaussian distribution respectively. The parameters in GMM are iteratively solved by expectation-maximization algorithm to optimize the maximum likelihood function according to the local feature vector set $$V$$ which extracted from the training images.

### 3.5. Cascade Detection of Railway Fastener

Classic deformable part model sums all the part scores and subtracts the part deformation cost to obtain the detection score, and determines the detected target according to the training threshold and non-maximum suppression algorithm. The experimental object in this paper is railway fastener, which requires to detect the defective fasteners from the normal fasteners. The defective fasteners include completely missing and partly missing fasteners. Therefore, the idea of cascade classifier is adopted to judge whether the corresponding part exists according to the score of each part, that is $$\phi_i \geq T_i$$, and the part threshold $$T_i$$ indicates the minimum requirement for detecting the part, which is obtained...
according to the training. If all parts of the fastener are present, the current test fastener is determined to be intact fastener, otherwise it is determined to be a defective fastener.

![Cascade detection of railway fastener](image)

**Figure 4.** Cascade detection of railway fastener

### 4. Experiment Results

#### 4.1. Results of Fastener Detection

Table 1 shows the experimental results of GMDPM algorithm in fastener detection. It can be seen that the proposed GMDPM algorithm has achieved lower false negatives rate and higher accuracy rate while satisfying lower false positives rate. Although FTM algorithm proposed in document [3] has also achieved lower false positives rate, but the false negatives rate is higher. The false negatives rate of document [2] is also higher, which will increase the workload of later manual review. The results of fastener detection under different lighting conditions are shown in Figure 5, which shows that GMDPM is robustness to large illumination difference. As shown in Figure 6, the fasteners in the three images have shape deformation due to slightly changes in shooting angles. The fasteners in Figure 7 have crushed stone interference, and the detection results show that GMDPM algorithm can effectively avoid such interference. The proposed GMDPM algorithm can both detect completely missing and partly missing fasteners as shown in Figure 8.

| Method     | Total | Positive | Negative | TP  | FP  | FN  | TN  | FPR\(^a\) | FNR\(^b\) | Accuracy |
|------------|-------|----------|----------|-----|-----|-----|-----|-----------|-----------|----------|
| Ours       | 4811  | 4716     | 95       | 4256| 0   | 460 | 95  | 0         | 0         | 0.904    |
| FTM[3]     | 4204  | 4185     | 19       | 3425| 0   | 760 | 19  | 0         | 0.182     | 0.819    |
| FTM[3]     | 3738  | 3651     | 87       | 3012| 8   | 639 | 79  | 0.092     | 0.175     | 0.827    |
| MLPNC[2]   | 3391  | 3370     | 21       | 2647| 1   | 723 | 20  | 0.048     | 0.215     | 0.786    |
| SRC[1]     | 1500  | 500      | 1000     | –   | –   | –   | –   | –         | –         | 0.971    |
| LLBP[5]    | 6000  | 4000     | 2000     | –   | –   | –   | –   | –         | –         | 0.998    |

\(^{a}\)FPR : false positives rate.

\(^{b}\)FNR : false negatives rate.

![Fastener detection results using different illumination](image)

**Figure 5.** Fastener detection results using different illumination

![Fastener detection results using different shooting angle](image)

**Figure 6.** Fastener detection results using different shooting angle
4.2. Comparison of Different Methods
Table 2 shows the performance comparison of the related algorithms. Compared with FTM algorithm in document [3], GMDPM algorithm’s false positives rate and false negatives rate decrease by 7.55 % and 8.1 % respectively, while its accuracy increases by 8.14 %. Compared with MLPNC algorithm in document [2], GMDPM algorithm’s false positives rate and false negatives rate decrease by 4.80 % and 11.75 % respectively, while its accuracy increases by 11.84 %. Although the accuracy in document [1] and [5] are as high as 97.10 % and 99.80% respectively, it did not give the corresponding false positives rate and false negatives rate.

| Method      | FPR  | FNR   | Accuracy |
|-------------|------|-------|----------|
| Ours        | 0    | 9.75 %| 90.44 %  |
| FTM[3]      | 7.55 %| 17.85 %| 82.30 %  |
| MLPNC[2]    | 4.80 %| 21.50 %| 78.60 %  |
| SRC [1]     | –    | –     | 97.10 %  |
| LLBP[5]     | –    | –     | 99.80%   |

5. Conclusions
The detection of defective fasteners is an essential task in railway maintenance. We present a Gaussian mixture deformable part model algorithm for fastener detection in this paper. Within the GMDPM framework, an improved HOG feature was used as low-level feature descriptor, a set of seed points were defined and parts were divided according to the shape of the fastener, the part and the seed point deformation allows the GMDPM algorithm to fit the deformation of the fastener. The experimental results demonstrate the advantage of our method in robustness to large illumination difference and slightly shape deformation of the fastener images. Future work may further use GMDPM algorithm for common object detection.

6. Acknowledgments
This work was supported in part by the Sichuan Province Science and Technology Support Program Project under Grant 2018GZ0361 and in part by the Sichuan Province Major Science and Technology Project under Grant 2018GZDZX0031.
7. References

[1] Liu J J, Li B L, Xiong Y, He Biao and Li L 2015 Integrating the symmetry image and improved sparse representation for railway fastener classification and defect recognition Mathematical Problems in Engineering 50(2) pp 256-263

[2] Marino F, Distante A and Mazzeo P L 2007 A real-time visual inspection system for railway maintenance: automatic hexagonal-headed bolts detection IEEE Trans. on Systems, Man and Cybernetics, Part C (Applications and Reviews) 37(3) pp 418-428

[3] Dou Y, Huang Y, Li Q 2014 A fast template matching-based algorithm for railway bolts detection International Journal of Machine Learning & Cybernetics 5(6) pp 835-844

[4] Wang Q, Li B L, Chen X Y 2017 Random sampling local binary pattern encoding based on gaussian distribution IEEE Signal Processing Letters 24(9) pp 1358 - 1362

[5] Fan H, Cosman PC, Hou Y 2018 High speed railway fastener detection based on line local binary pattern IEEE Signal Processing Letters 25(6) pp 788 - 792

[6] Felzenszwalb P F, Girshick R B, McAllester D and Ramanan D 2008 A discriminatively trained, multiscale, deformable part model IEEE Computer Society Conference on Computer Vision and Pattern Recognition pp 24-26.

[7] Felzenszwalb P F, Girshick R B, McAllester D and Ramanan D 2010 Object detection with discriminatively trained part-based models. IEEE Transactions on Pattern Analysis and Machine Intelligence 32(9) pp 1627-1645

[8] Jian B, Vemuri B C 2011 Robust point set registration using gaussian mixture models IEEE transactions on pattern analysis and machine intelligence 33(8) pp 1633-1645

[9] Myronenko A, Song X B 2010 Point set registration: Coherent point drift IEEE transactions on pattern analysis and machine intelligence 32(12) pp 2262-2275

[10] Sánchez J, Perronnin F, Mensink T, Verbeek J 2013 Image classification with the fisher vector: Theory and practice International journal of computer vision 105(3) pp 222-245.

[11] Dalal N, Triggs B 2005 Histograms of oriented gradients for human detection Computer Vision and Pattern Recognition pp 886-893

[12] Seo H J, Milanfar P 2010 Training-free, generic object detection using locally adaptive regression kernels IEEE Transactions on Pattern Analysis and Machine Intelligence 32(9) pp 1688-704