Adaptive classifier for steel strip surface defects

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Abstract. Surface defects detection system has been receiving increased attention as its precision, speed and less cost. One of the most challenges is reacting to accuracy deterioration with time as aged equipment and changed processes. These variables will make a tiny change to the real world model but a big impact on the classification result. In this paper, we propose a new adaptive classifier with a Bayes kernel (BYEC) which update the model with small sample to it adaptive for accuracy deterioration. Firstly, abundant features were introduced to cover lots of information about the defects. Secondly, we constructed a series of SVMs with the random subspace of the features. Then, a Bayes classifier was trained as an evolutionary kernel to fuse the results from base SVMs. Finally, we proposed the method to update the Bayes evolutionary kernel. The proposed algorithm is experimentally compared with different algorithms, experimental results demonstrate that the proposed method can be updated with small sample and fit the changed model well. Robustness, low requirement for samples and adaptive is presented in the experiment.

1. Introduction

With the growth competition of the steel strip, the quality of the steel strip has become seriously important. In course of time, steel strip quality and surface quality of structural products have assumed significant importance [1]. Importance of surface quality which demands the effective and efficient methods to replace the conventional artificial visual inspection that the expert only inspect about 0.05% of the total steel surface and easily impacted by fatigue and other unfavorable conditions. The artificial inspection cannot satisfy the quality requirements. Therefore, an automatic accurate real-time steel surface inspection system has become an essential section of the production system. Boukouvalas et al. [2] have researched on ceramic tile automatic inspection using computer vision in early 1995. They used Wigner distribution and spatial frequency methods to detect defects. Boukouvalas et al. [3] described an integrated system developed for the detection of defects on color ceramic tiles in early 1997.

The inspection system for surface defect mainly consists of two parts, defect segmentation and defect processing. Defect segmentation mainly used spatial domain. Spatial domain techniques are fast and easy to implement, and they have been used in most of the papers where suitability for real-time operation. Yun et al. [4] has used first order gradient filter followed by an edge pair search and used morphological dilation and erosion to join edge pair. Finally, they used a defect size thresholding to discard pseudo defects. Liu et al. [5] used gradient operators and region growing to identify defects. JM Blackledge et al. [6] first used a Wiener filter for noise reduction to detect six types of defects in cold strip. Then, they extracted rough locations of defects with Sobel edge detector. Finally, defect
locations were identified by a specially developed region growing method. Choi et al. [7] used Laplacian gradient operator for defect detection.

The defect processing contains feature extraction and defect classification. In recent years, abundant researches have been taken by scholars. Different kinds of feature extraction and classification methods have been introduced to classify the surface defect of steel strip. In [8,9], the defects are classified by K-nearest neighbor (KNN) methods with Co-occurrence matrix. Santanu Ghorai et al. [10] described an automated visual inspection system with discrete wavelet transform (DWT) features and support vector machine. Wu et al. [11] described an algorithm with undecimated wavelet transform (UWT) and mathematical morphology to detect geometric defects that achieved a 90.23% accuracy that is hard for real industrial application in 2008. However, in 2013 a noise robust method based on completed local binary proposed by Song [12] has arrived average 98% accuracy and was effective enough applied to real production. From a review of vision-based steel surface inspection system [1], most of systems have achieved higher than 90% accuracy.

To apply to real production, there are still some difficulties for defect detection of steel surface. In real production environment, one product line may produce multiple products, one product may be manufactured in multiple production lines at the same time. As the time gone, the aged equipment and the detection device will change, and the classifier trained by the original database will work with accuracy deterioration. It is hard for the steel company to train every new product with a single database. To train a new model for a new built production line, the production line have to produce without a trained inspection system for a long time until it get enough samples.

Unfortunately, most of the researches focus on the algorithm with enough samples, there are few researches research on train new classifier based on old one. Solly et al. proposed a rapidly evolution system with the expert's feedback. The research describes an adaptive interactive evolution methodology for determining parameters to control segmentation of surface defects on images, but the algorithm do not change the classifier.

Therefore, to solve these issues we proposed an evolutionary classifier with a Bayes kernel (BYEC) evolve with latest batch of samples. To update the classifier, we can concern either modifying the structure of ensemble (weaker components are replaced by base classifiers trained on the most recent data), or updating the aggregation technique (e.g., updating weights).

In this paper, we generate n component SVM classifier with different feature sub-space, then we focus on the topic to generate Bayes kernel sequentially from fixed size blocks of training examples (data chunks). In such ensembles, when a new block arrives, the base SVMs are evaluated and their combination weights are updated. This window techniques provide a simple forgetting mechanism by selecting examples introduced to the learning algorithm, thus eliminating those examples that come from an old distribution.

The rest of the paper is organized as follows: Section 2 depicts the procedures of the surface defects inspection system. Section 3 presents the features we used in this paper. The method to build SVM sub-classifiers on random subspace of features is provided in Section 4. The method to build Bayes kernel and evolve the kernel are discussed in Section 5. Section 6 gives comparative experimental results of this algorithm and research some factors that affect the results. Finally, we conclude this paper in section 7 and give some suggestions for future work.

2. Structure of the evolutionary classifier for steel surface defects

For this evolutionary inspection system for surface defects, it would be trained as the classic classifier. We can update the classifier based on old one with latest samples. The structure of the inspection system is presented in Fig. 1. Our system mechanism mainly contains three processes: defect acquisition, feature extraction and defect classification.

The image acquisition system has been discussed in many literature [2,3,4,5,6,7,13,14,15], it has been a mature field and we will not discuss it in this paper again.

As it illustrated in the Fig. 1, five kinds of features were introduced in this system. We integrated the uniform local binary patterns (ULBP) [16], Gray-level co-occurrence matrix (GLCM) features [17],
and Histogram of Oriented Gradient (HOG) feature, Gray level histogram and Gabor filter features. These abundant features guarantee enough information for the classifier. Multiple classifier system was imported to utilize these features.

The classification part has two components described in Fig. 1: base SVM classifiers and Bayes kernel classifier. The fuser Bayes kernel is the key contribution of this system compared with the classic steel surface inspection system. It fuses the result from the base classifiers and update the aggregation parameters.

Support vector machine (SVM) [18] is a popular small sample set learning method, which has a very good performance for pattern classification problems by minimizing the Vapnik-Chervonenkis (VC) dimension and achieving a minimal structural risk. In light of the small sample set requirement, fast learning and good performance, SVM is a good choice for this method. Every SVM classifiers are trained by a subspace of the feature space, and we can change the weights of the base SVM classifiers.

Multiple classifier system (MCS) offers many alternatives for unorthodox handing for realistic increasing complex problems [19], it allows us to exploit the potential of the individual classifiers and get an enhanced performance by the combination. It can perform the best individual classifier and easily implemented on parallel, multithreaded and distributed architecture, which is very important for the real time production environment. It is well suited to deal with concept drift that means the statistical dependencies between object features and its classification may change in time that leads accuracy deterioration. A dynamic weighted majority algorithm were described in [20]. We also use an evolvable weighted method to change our classifier with time.

The method we aggregate the base classifiers must be adjusted with small sample. The Bayes classifier is a good candidate as it build a reference from prior probability to posterior probability. We can score the performance of the classifiers on the latest sample. With a small sample, we can get the approximate posterior of the base classifiers and use it to re-weight the integrated classifier to get new one. A Bayes kernel was built as these reasons.

**Figure 1.** Structure of the evolutionary classifier for steel surface defects with Bayes kernel
3. Features extraction

The feature extraction is one of the important tasks of surface inspection system, which is mainly to describe the defect characteristics. To avoid the lack of information after integration, we introduce superfluous features to overcome this weakness. Five different kinds of features are extracted in the inspection system, they dedicate to describe the property of texture, color and shape respectively. The feature space consists of Gray-level co-occurrence matrix, uniform local binary pattern, Histogram of Oriented Gradient, Gray level histogram and Gabor filter.

Gray level co-occurrence matrix $N_p \times N_B$ is a matrix where $N_p$ is the number of gray levels in the image, this matrix reflects the direction, adjacent distance and change range of the image. We used the GLCM feature to cover the texture feature of the defect.

The histogram is a key tool in image processing, it is one of the most useful techniques in gathering information about a matrix. Dalal Navneet and Triggs Bill proposed the Histogram of oriented gradient (HOG) in 2005 [21], this feature is used in computer vision and image processing for object detection, which counts the occurrences of the oriented gradient in an image which have been used in .

Local binary pattern is one of the most successful statistical approaches for texture classification due to its gray-scale and rotation invariance, this feature reflects the local texture of the image.

The Gabor filter is used for edge detection in image processing, the frequency and orientation representations of Gabor filters are similar to those of the human visual system and efficient to describe the texture and shape.

4. The SVM sub-classifiers on random subspace of features

After the feature extraction, we get a feature vector of 212 dimensions. In general, the feature dimensions are too large compared with the scale of the sample that may lead to over-fitting problems. So instead of training one classifier to cover all the feature space, we separate the features with random sampling scheme without replacement and keep almost equal dimensions for every subspace.

In order to overcome the small sample, we introduce support vector machine, which has been widely used in many areas, such as computer vision, natural language processing and Neuroimaging, for the good performance, fast training and the small requirements for labeled samples.

There are six kinds of defects in the database which we used for experiment, as SVM is a binary classifier, we implemented the multiclass classification with the "one-against-one" scheme which is usually applied for binary classifier [22,23]. For every base SVM classifier in this paper, the number of binary SVM classifiers we need is defined as Eq. 1, $k$ is the number of classes exists in data set.

$$n_{\text{SVM}} = k(k-1)/2, \text{ where } k \geq 1.$$  

We combine the results from the binary classifier with voting scheme: every binary classifier has a vote and a data point is classified to the class with the maximum number of votes. To solve the clash of same votes, we simply choose the class with greater sequence number. Besides this, we circle increase the sequence number for the classes with every multiclass SVM to avoid the accumulation deviation, a simple example indicates the risks without this strategy, assume we have three classes, $A$, $B$ and $C$, they all have the same accuracy and scale, finally samples classified to $A$ are least.

5. Combination of sub-classifiers by the Bayes kernel

5.1. Bayes aggregation kernel

The combination of the sub-classifiers is very important to this evolutionary classifier because it not only response for improving the performance of the final integrated classifier but also for the ability to update itself to fit the new changed model. Many ensemble methods have been presented [24,25,26], nevertheless, these methods do not suite for this adaptive inspection system. This is because: (1) these methods are sensitive to the size of the training sample set, however, even in a mature production line there are not too many labeled samples, (2) the fusion of classifier may be biased as the combination of samples from changed model.
As these reasons, a new fusion strategy is proposed, native Bayes classifier, which is a highly practical Bayesian learning method which deduce from the Bayesian theorem (Eq. 2), this theorem has been proposed for about three hundred years by Thomas Bayes and developed into a great branch of machine learning, in some domains, it has presented comparable to neural network and the other machine learning methods. The naive Bayes classifier $f(x)$ is described by a conjunction of attribute values when $f(x)$ is limited to a finite set $v$.

In Bayes learning, the training examples are described by a feature vector $(a_1, a_2, a_3 ... a_m)^T$, the Bayes classifier make decision based on the probability for every possible value and select the most portable target.

In this model, we assign every base classifier as a feature and described them as a probability matrix. The feature vector of the Bayes vector is defined as $=(D_1, D_2, D_3 ... D_m)^T$, the $D_i$ is the decision made by the $i$th classifier, and the decision of the Bayes classifier is taken from a finite set $V(v_1, v_2, ... v_n)$. The prior probability that the $i$th classifier make decision $v_{i_k}$ and the real class is $v_j$ is defined as Eq. 3.

$$P(R = v_j | D_i = v_k) = \begin{cases} 1 & \text{if } D_i = v_k \text{ and } r_j = v_j \\ 0 & \text{otherwise} \end{cases}$$

We can deduce the post probability of the decision $v_j$, that the $i$th classifier make decision $v_j$, defined by Eq. 4.

$$PM(D_i = v_k | R = v_j) = \frac{P(R = v_j | D_i = v_k)}{\sum_{j=1}^{n} P(R = v_j | D_i = v_j)}$$

The advisable decision number the classifier can make is defined by variable $n$. With post probability for every individual classifier, the Bayes classifier can take decision based on multinomial model[27]. The naive Bayes classifier simplify assumption that the attribute values are conditionally independent, individual classifiers are independent in this model. The probability of observing the conjunction of classifiers $D_1, D_2, D_3 ... D_m$ is just the product of the post probability of the individual classifier.

For every class, the probability is calculated with Eq. (5):

$$PV(R = v_j) = \frac{1}{c} \sum_{i=1}^{c} \begin{cases} 1 & r_i = v_j \\ 0 & \text{otherwise} \end{cases}$$

The $r_i$ is the instance of the sample set and the size of sample set is defined as $c$. For every decision $v_i$ belongs to $V$, the post probability that $v_i$ is the current answer when the decision vector of sub-classifiers is $d_1d_2 ... d_m$ defined as Eq. 6.

$$P(v_i | d_1d_2 ... d_m) = PV(R = v_i) \prod_{i=1}^{m} PM (d_i | v_j)$$

The $v_j$ is one possible label of the finite result set $V$. We calculate the probability of every $v_i \in V$ when the decision vector of sub-classifiers is $d_1d_2 ... d_m$. The result $v$ of the classifier is the most portable $v_i$. The Bayes classifier not only takes advantage of the true positive result but also the true negative result from base classifiers.

5.2. Kernel update method

The key structure in this model is the post probability matrix for base classifiers that we trained on labeled samples. To adjust our model, we changed the post probability matrix.

For the application enviroment, the accuracy loss are categorized into sudden and gradual loss. The sudden lose happens as the technological updating, equipments updating or new production line...
applied, and the gradual loss happens along the time. For these two scenes, we have different updating schemes.

Let $\mathcal{S}$ be the sample set labeled by expert, this BYEC algorithm maintains a slide window and a pool of base SVM classifiers. The $\mathcal{S}_0$ is the origin sample set, and the pool of base SVMs is trained with the origin sample set $\mathcal{S}_0$. After each data chunk of samples labeled, the size of the sample set $\mathcal{S}$ increases and the slide window slide to cover the latest samples contain $c$ examples described as Fig. 2. We let $\mathcal{B}_i$ to describe the sample set contained by the $i$th moved slide window, $\mathcal{B}_1, \mathcal{B}_2, ..., \mathcal{B}_n$ each containing $c$ examples. For each sample set $\mathcal{B}_i$, the post matrix $PM_i$ is calculated with Eq. 4 and class probability matrix $PV_i$ is calculated with Eq. 5.

$$PM_i(D = v_k | R = v_j)$$ denotes the probability that defect instance $x$ is an instance of $v_j$ and classifier $D_i$ predicts its class label $v_k$. The result of BYEC classifier is generated by Eq. 6 with $PM_i$ and $PV_i$.

As the $\mathcal{B}_i$ is the latest chunk of sample at the slide time, the $PM_i$ most reflect the possibility between the base classifiers and the real instance of the defect. For the gradual accuracy lose scene, every time, a chunk of labeled defects inputed to adjust the classifier, the BYEC slide the slide window and generate the new $PM$ and $PV$ and substitutes the old one. For the sudden accuracy lose scene, we clear the slide window and only take the inputed chunk of samples to generate the new $PM$ and $PV$.

The base classifiers predicts the class of instance $x$ and output the prediction vector $(D_{x1}, D_{x2}, D_{x3} ... D_{xm})^T$, the Bayes aggregation kernel predict with Eq. 6 to get the most possible result.

6. Experimental results

To evaluate the effectiveness of the inspection system for surface defects, a surface defect data set was used and described in the subsection. Meanwhile we compared this approach with some other classification methods. In addition, some factors were examined to present how they affect the classification accuracy.

6.1. Experiment implementation details

The accuracy of this evolutionary classifier has been compared with other classifiers such as SVM [28], NN-BP [29] and KNN [9]. To reveal the fairness of the classifier, a surface defect database, NEU surface defect database [30] was used. There are six kinds of typical defects of the hot-rolled steel strip surface in the database and 1800 grayscale images, 300 samples for every defect: rolled in scale(RS), crazing(CR), inclusion(IN), patches(PA), scratches(SC) and pitted surface(PS).

As Fig. 3 present, the defect image is collected and sampled as $200 \times 200$ resolution. The bias between different production lines are mainly caused by electronic circuit noise and sensor noise due to poor illumination and/or high temperature and these factors often lead to Gaussian noise in image acquisition [31], so we add Gaussian noise to the NEU database with different variance to simulate the defect images from different changed production lines. Fourteen contrasting data sets are used with standard deviations $(0 - 13)$, the data with 0 deviation is the original data set, the paired photographs are indicated in Fig. 4.

6.2. Adaptive of the classifier

To evaluate the adaptive of this classifier, one original NEU defect data set and thirteen defect data sets were used. The standard deviations of the noise added to the NEU defect set were $(0 - 13)$, with an equal mean of 0. 212 features were extracted from every defect image.
The BYEC classifier that composed by 25 SVM sub-classifiers were trained by 70% of the original NEU defect data set and the remaining 30% data were used to evaluate the accuracy of the BYEC on the original data set. Then we randomly sampled 10% of the processed data sets to adjust our BYEC classifier. Finally, the accuracy of the adjusted BYEC classifier and the original classifier on the processed data set were tested by the reminder 90% of the processed data. Same as the BYEC, 70% of the original data set were used to train the KNN, BPNN and SVM classifier and 30% were used to evaluate the accuracy on the original data set, then the accuracy of these classifiers on processed data set were test by 90% of the processed data set. The parameters of BPNN and KNN are determined by cross-validation testing. The average accuracy of the classifiers on every data set were run 100 times and the data set were sampled individually.

Fig. 5 depicts the accuracy obtained by KNN, BPNN, SVM, Original BYEC and BYEC classifier. The standard deviation of the defect samples ranges from 0 to 13 and increases by 1 at each iteration, so the first data set is the original data set, the second is added Gaussian noise with standard deviation 1, and so on. The accuracy associated with the SVM is higher than the corresponding values for the KNN, original BYEC and BYEC classifier for the original data set, but the accuracy of the SVM, KNN, BPNN and Original BYEC classifier decline as the standard deviation increases. The accuracy of KNN, SVM and BPNN decline with a nearly 30 degree and the Original BYEC decline a little slower than them.

However, the increase of stand deviation has a little impact on our BYEC classifier. It can be observed that this proposed method performs more adaptive to different standard deviations in comparison with other classifiers. The accuracy of BYEC classifier on the original data is lower than the SVM, the possible reason of this may be that information loss are leaded by the combination of SVM classifiers. The Original BYEC without adjustment process also suggests a relatively high adaptive compared with other classifiers.

Figure 3. Each row is one of the six typical surface defect on the NEU database that sampling from 300 samples for one class

Figure 4. Each row if one defect image
6.3. Number of the sub SVM classifiers

The number of the SVM sub-classifiers is a key parameter for our BYEC classifier which is defined as $k$, it decides the particle size that our system can be adjusted. The purpose of this section is to examine how the $k$ affects the accuracy.

We trained five BYEC classifier with $k(5, 15, 25, 35, 45)$, these classifiers were trained as described in Section 6.2 with original defect set, adjusted with 10% data and test with 90% data. The experimental result is presented in Fig. 6, the highest accuracy on the original defect set is acquired by the classifier with $k = 5$, but it reduces fast compared with the other classifiers that perform lowest accuracy on the defect set with highest noise. The classifier, that parameter $k$ equals 25, presents 3th higher accuracy on the original data set but acquires the highest accuracy on the defect set with highest bias to original data set. This figure suggests that the BYEC is more adaptive with larger $k$ value but lower accuracy will be presented with the BYEC classifier on the original data set.

As the result indicated in Fig. 6, $k$ should be set with the real production environment. The BYEC classifier should be set with larger $k$ value when higher adaptive performance was needed. However, to avoid information loss, we should set the BYEC with a smaller $k$ value when the changed model has a small bias with the old one.
6.4. Set size of the sub SVM classifiers
An important characteristic of classifiers is the size of sample set that used for train. The more samples supplied, more information the classifier machine can learn. To our BYEC classifier, the accuracy of the base classifiers are evaluated more precise with more samples.

The Fig. 7 depicts the accuracy of BYEC classifiers updated by different sizes of samples. All the classifier were performed on the data set described at Section 6.2. We can see that the classifiers trained by 10% reached a lowest accuracy and has least adaptive, but the classifiers trained by 30% reached fairly good performance that the classifiers with more samples have little advantage over this classifier. Even in the defect set with standard deviation 13, the gap between the BYEC classifier trained by 10% and 50% is 1.01%. This illustrated that our BYEC converged very fast and the low requirement for the sample size.

![Figure 7. The accuracy of BYEC classifiers adjusted by different](image)

7. Conclusion
Since the accuracy deterioration issue in steel surface inspection system, this research proposes an evolutionary method that can be adjusted with small sample. Firstly, to overcome the information loss, we proposed five kinds of features that cover texture, color and shape respectively. Secondly, random subspace SVM classifiers are proposed to conquer the over-fitting problem. Then, we introduced a Naive Bayes to fuse the results from base SVMs. Finally, we introduced a method to evolve the classifier. The experimental result in Section 6.2 indicates that the BYEC algorithm is adaptive with changed steel surface defect data set compared with other algorithms. Research at Section 6.3 suggests that the adaptive of the classifier is highly relative to parameter $k$, with the growth of the $k$, the BYEC shows a higher adaptive, but with some accuracy loss. Small sample set requirement was showed in Section 6.4.

We can apply a original BYEC algorithm without any labeled samples to changed model. A new classifier can be trained based on old one with a small sample set and achieve accuracy improvement. The future work is to increase the accuracy both on large sample set and changed production model.

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