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The Welding Region Extraction Technology based on HOG and SVM

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Abstract. In order to effectively find the welds in the heating panel welding, we need to detect the weld region accurately. This paper puts forward a method based on HOG features and SVM to establish the regional model of weld image. Firstly, the images generated by the laser irradiation heating panel weld can make a cross-section of training to obtain HOG feature training images with weld portion. As the positive samples of SVM, the image which doesn't contain any weld region are selected as the negative samples of SVM. Therefore, SVM is used to get the classifier of the weld region and the classifier is used to traverse the test image while the weld region is found in the image. Finally, in the regions of these features, the best location of the weld region is obtained by using the non-maximum suppression algorithm.

Introduction

Nowadays welding has a very important role in modern industry, the precise weld positioning is the key to ensure the quality of welding. To overcome the impact of deviation of the welding process, the method resort to the sensor technology on weld location. Now widely used in the two mainstream sensor types of weld positioning system are ARC sensor and Visual sensor[1]. However, due to system based on ARC sensor can only work after the arc light, so in this paper we use the Visual sensor. On the basis of the Visual sensor, this paper proposes the welding region extraction technology based on HOG and SVM that can be reliable and convenient for the best location of welding region.

HOG+SVM

With laser irradiation heating panel, industrial camera capture the weld cross section images、gray processing and extract containing weld section, as shown in Fig.1. After extracting part images size normalization processing (such as 100 x100 pixels). Processed images as the training sample are portion of the weld seam of the HOG feature extraction, after extraction will have images of part of the weld as positive samples in the SVM classifier, select some pictures of non- weld part as negative samples for training and learning with weld model parameters of classifier.

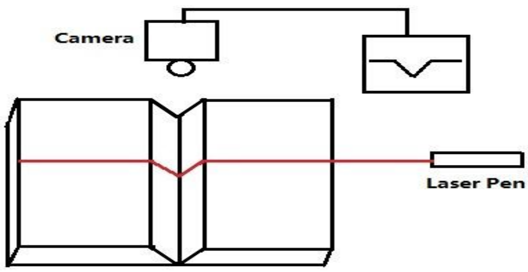


Fig.1 The weld image acquisition of laser irradiation

HOG Feature. The Histogram of Oriented Gradient (HOG), is calculated and statistical local areas of the image gradient orientation Histogram feature. The realization method of weld HOG feature extraction algorithm is as follows[2]:

Containing a weld parts of the image noise reduction, normalization of size and gray scale processing. The normalization of Gamma can effectively reduce the shadow and illumination changes, the formula is as follows:

$$Y(x,y)=\begin{cases}[I(x,y)/0.5]^{gamma}\times 0.5, & I(x,y)\le 0.5\\ \{[I(x,y)-0.5]/0.5\}^{gamma}\times 0.5+0.5, & I(x,y)>0.5\end{cases} \tag{1}$$

The calculation of each pixel in the image gradient (including size and direction):

$$G_x(x,y)=H(x+1,y)-H(x-1,y)\ G_y(x,y)=H(x,y+1)-H(x,y-1) \tag{2}$$

$G_x(x,y)$, $G_y(x,y)$, $H(x,y)$ respectively the image pixel point (x,y) in the direction of the horizontal gradient, vertical gradient and pixel values. Thus, the pixels (x,y) of gradient value and gradient direction respectively

$$G(x,y)=\sqrt{G_x(x,y)^2+G_y(x,y)^2} \tag{3}$$

$$\alpha(x,y)=\tan^{-1}\left(\frac{G_y(x,y)}{G_x(x,y)}\right) \tag{4}$$

The image into small cells (such as cell 5*5 pixel) statistical gradient histogram of each cell, form a HOG feature of each cell; Each of several cell form a block (such as 2*2 cell/block) ,all cell features together is the HOG feature of a block. Also, all the block HOG features set up the image feature vectors.

Compared to other character description and extracting method, HOG operation on each unit in the sample image, makes the relationship between the image local pixels can be well characterized, the geometric and optical image deformation can keep good invariance[3].

The SVM Classifier. Kernel methods (KMs) and support vector machines (SVMs) have become very popular as methods for learning from examples. The basic theory is well understood and applications work successfully in practice. Initially illustrated by their use in classification and regression tasks, recent advanced techniques are presented and key applications are described. Issues of numerical optimization, working set selection, improved generalization, model selection, and parameter tuning are addressed. Application research covering the use of SVMs in text categorization, computer vision, and bioinformatics is discussed.

Support vector machines (SVMs) and kernel methods (KMs) have become in the last few years one of the most popular approaches to learning from examples with many potential applications in science and engineering. Introductory treatment and some advances of this subject matter have been provided in [4]. As a learning method, it is often used to train and design radial basis function (RBF) networks. Learning method for this type of architecture starting with simple training procedures to robust and automatic design methods was presented in [5]. Given a set of examples $\left\{(\vec{x}_i,y_i),\vec{x}_i\in R^n,y_i\in R,i=1,\ldots,N\right\}$, the SVM learning method in its basic form creates an approximation function:

$$f(\vec{x})=b+\sum_{j=1}^{m}y_j\cdot\alpha_j\cdot K(\vec{x}_j,\vec{x}) \tag{5}$$

with $y \approx f(\vec{x})$ for regression and $y \approx \operatorname{sgn} f(\vec{x})$ for dichotomous classification for instance. For that purpose, a subset of support vectors $\left\{\vec{x}_j, j=1,...,m\right\} \subset \left\{\vec{x}_i, i=1,...,N\right\}$ is determined, the kernel function K is chosen, and the parameters $b, \alpha_j, j=1,...,m$ are estimated.

KMs are methods that use kernels of the form:

$$K(\vec{x}_1, \vec{x}_2) = \vec{\phi}(\vec{x}_1) \cdot \vec{\phi}(\vec{x}_2) \tag{6}$$

is an inner product and $\vec{\phi}$ is in general a nonlinear mapping from input space X onto feature space Z .KMs are used among others, in SVMs kernel principal component analysis (PCA), kernel Gram–Schmidt, Gaussian processes, and Bayes point machines. The symmetry of the inner product determines the symmetry of the kernel. The necessary and sufficient condition for a symmetric function to be a kernel is to be positive definite, thus statistically seen, kernels are covariances. In practice, the kernel function K is directly defined. $\vec{\phi}$ and the feature space Z are implicitly derived from its definition. Kernel substitution of the inner product can be applied for generating SVMs for classification based on margin maximization to improve generalization, or to diminish the number of support vectors in hypothesis construction.

Like with other neural network architectures and associated learning methods, historically, the treatment of classification and regression tasks has helped to illustrate their use, but at the same time, to point to key differences. That procedural knowledge is applied in this paper to illustrate the use of SVMs and KMs on classification.

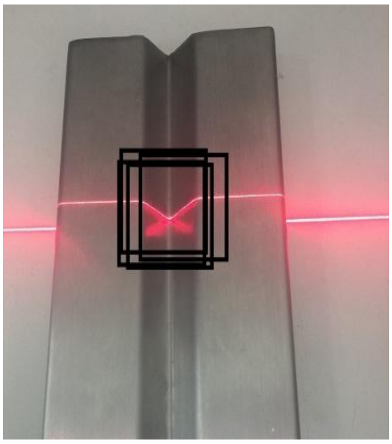
Given a data set $\left\{(\vec{x}_i, y_i), \vec{x}_i \in R^n, y_i \in \{-1,+1\}, i=1,...,N\right\}$.The binary classification problem can be posed as stated in expression (7):

$$\begin{aligned} &\min_{w,b,\varepsilon} \quad F = \frac{1}{2} w^T w + C\sum_{i=1}^{N} \varepsilon_i \\ \text{s.t.} \quad & y_i\left[w^T \phi(x_i) + b\right] \geq 1 - \varepsilon_i \quad i=1,...,N \\ & \varepsilon_i \geq 0 \qquad\qquad\qquad\quad i=1,...,N \end{aligned} \tag{7}$$

where $y_i\left[w^T \phi(x_i) + b\right] \geq 1$ comprises first the given constraint $w^T \phi(x_i) + b \geq +1$ if $y_i = +1$, $w^T \phi(x_i) + b \leq -1$ if $y_i = -1$ and ε_i are the slack variables that allow misclassifications in the set of inequalities. A comparison of approaches to handle the multiclass case as opposed to the binary case.

Putting containing portion of the weld images as positive training samples, the rest of such size and non-weld images as the negative training samples, when the sample output is 0, negative sample output is 1[4]and after getting the characteristics of the positive and negative samples for training, that we can obtain the training model parameters[5].

After SVM training, we can get the image contains the part of the weld through the new test images to traverse. The weld region model identification of test samples we created by SVM, will get many sliding windows' characteristics in accordance with the weld region model, as shown in Fig.2. In order to get the best detection position, we use non-maximum suppression (NMS) algorithm to search local maximum, eliminating redundant (overlapping) windows[6], as shown in Fig.3.



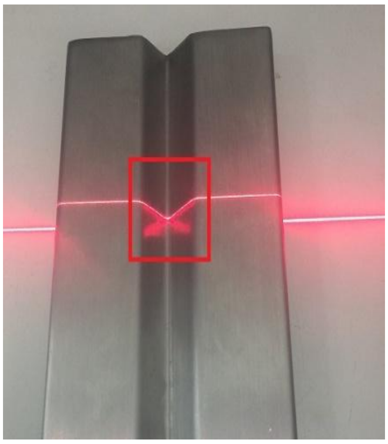


Figure 2. SVM detection result Figure 3. After NMS detection result

Conclusion

Accurate welding seam positioning is the key factor to ensure the welding quality. This paper proposes a method based on HOG features and SVM to establish the regional model of weld image. Using the laser pen and the visual sensor to get the welding seam images. After that we are able to obtain the HOG characteristic of the weld part and training that by SVM. Through the SVM classifier, the weld region can be found in the traverse test image. Finally, using NMS algorithm, we can get the best weld region detection result. Through experiments, we can accurately detect the region of the welding seam. Compared to other methods, SVM can get much better results than other algorithms in the small sample training set through a series of experiments.

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