BEAM DETECTION BASED ON MACHINE LEARNING ALGORITHMS

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ABSTRACT

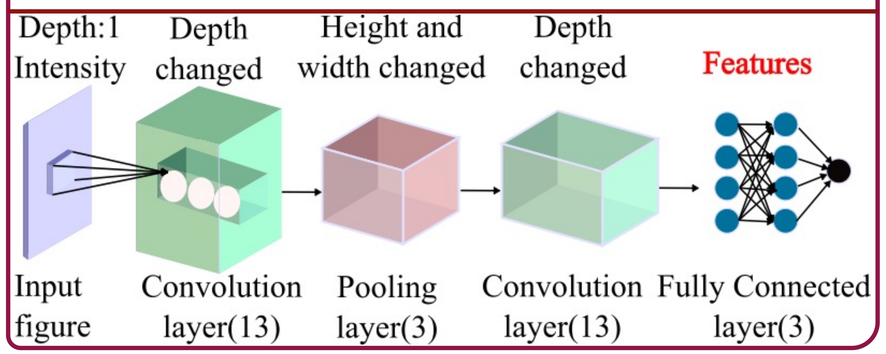
The positions of electron beams and laser beams are of fundamental importance in the control and maintenance of the free electron laser at Stanford Linear Accelerator Center (SLAC). Thus, we hope to have an algorithm capable of locating the projected beams' positions on virtual cathode camera (VCC) screen quickly and automatically. To achieve this goal, we first construct a convolutional neural network (CNN) and train preprocessed pictures. The purpose of this step is extracting codewords in certain layers. Next we use these codewords as features and apply supportive vector machine (SVM) to regress and predict the positions of beam spots.

DATASET

The dataset in this project consists of 16362 VCC screen figures on which the ground truth of beam positions are well marked. Each figure contains only one beam spot. Only 162 of them originate from the SLAC database and are preprocessed by Gaussian blur and background subtraction. The rest 16200 figures are artificially generated by applying three methods on original ones: cutting and refilling, shifting and adding white noises.

CNN FOR FEATURE EXTRACTION

We construct a convolutional neural network based on VGG16 and extract features of the figures from transitive training of VGG16 outputs. This CNN is composed of 13 convolutional layers, 3 pooling layers and 3 fully connected layers as shown in the following figure. The output of penultimate and antepenultimate layers are connected end to end to form the feature vectors. The feature for the ith figure is denoted by $q^{(i)} \in \mathbb{R}^{8192}$. To avoid overfitting, we use principle components analysis (PCA) to extract the most influential features.



SMV FOR LINEAR REGRESSION

We use supportive vector regression (SVR) with Gaussian kernel to model the situation. The position of the beam in each figure is represented by the coordinates of two diagonal vertices: $z^{(i)} = (y^{(i)}_{\min}, y^{(i)}_{\max}, x^{(i)}_{\min}, x^{(i)}_{\max})^T$. The four parameters of the position are independent. So we train a SVR model for each of the four labels by maximizing the following dual function:

$$\mathcal{L}_s = \sum_{i=1}^{m} \alpha_i^s z_s^{(i)} - \frac{1}{2} \sum_{i,j=1}^{m} \alpha_i^s \alpha_j^s K(q^{(i)}, q^{(j)})$$

Here, l^2 regularization is implemented and $\alpha_i \in [-t, t]$, where t is the penalty ratio of the difference between the predicted label and the real label, $i \in \{1, 2, \cdots, m\}$, $s = 1, 2, 3, 4$. m is the number of training samples.

RESULTS AND DISCUSSIONS

The codewords-based SVM obtains superior performance. Figure 1 demonstrates typical performance on test sets in a nine-fold cross validation. Red and white boxes are predictions and ground truth respectively. Colors in the subfigures represent relative intensity of beam. Figure 2 shows the influence of PCA dimension on the average ratio of overlapping to true spot area. Figure 3 demonstrates the training error.

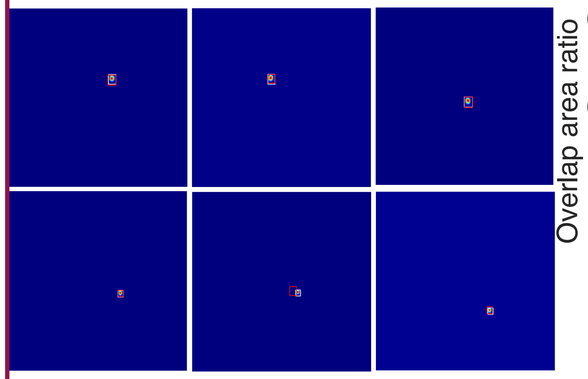


Figure 1 Test results for cross validation

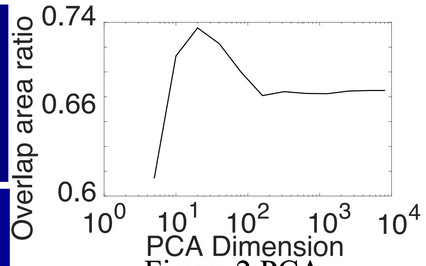


Figure 2 PCA

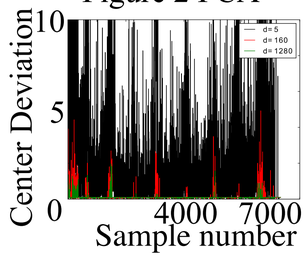


Figure 3 Training error for different PCA dimensions

FUTURE WORKS

1. Combine linear regression and classification for the loss function.
2. Normalize figure intensity before training.
3. Optimize learning rates for each layer in CNN.

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