**哈尔滨工业大学（深圳）**

Harbin Institute of Technology ,Shenzhen

Interim Assessment of the Thesis

for the Master’s Degree

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| **Thesis Title Research on Assembly Quality** |
| **Detection Algorithm of Atomizer Based on** |
| **Machine Vision** |
| **Discipline Mechanical Engineering** |
| **Supervisor Professor Hu Hong** |
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| 1. Does the thesis progress according to the research objectives and schedule as stated in the primary report? (at least 100 words)   According to the research content of the thesis. I have already constructed the atomizer image dataset, designed the corresponding image processing detection algorithm for different types of assembly failures, carried out research based on deep learning detection algorithm, developed detection software and cloud data management system. I have done some work in advance compared to the schedule as stated in the primary report. But there are still some work that needs further improvement.  In general, the thesis progress does mainly according to the research objectives and schedule as stated in the primary report. And I have finished the research contents on time. |
| 1. The completed work and its related outcomes (at least 1500 words) .   2.1 Building data sets  2.1.1 Data collection  According to the assembly process and actual production experiments, the assembly quality is divided into five categories: normal, missing workpiece, missing cotton core, missing metal sheet and abnormal wire position. We collected image samples on the prototype and collected a total of 382 images. The sample size for each category is shown in Table 2-1.  Table 2-1 Sample size of each assembly failure category   |  |  |  |  |  |  | | --- | --- | --- | --- | --- | --- | | Category | Normal | Missing workpiece | Missing cotton core | missing metal sheet | Abnormal wire | | Sample size | 234 | 78 | 22 | 30 | 18 |   2.1.2 Data enhancement  In order to better adapt to the change of detection environment and provide more data for deep learning algorithm, it is necessary to enhance the data and increase the diversity and quantity of samples.  According to the characteristics of the detection project, the following data enhancement methods are proposed in this paper:  (1) Position migration. Because the relative position of fixtures and cameras will produce slight offset because of the installation accuracy, random slight offset of the image can improve the adaptability of the algorithm to the installation location. An example of the location offset is shown in Figure 2-1b.  (2) Brightness conversion. Different production environments and different light sources will affect the brightness of the image. In order to adapt the algorithm to the change of brightness, it is necessary to enhance the image by appropriate brightness transformation. An example of brightness transformation is shown in Figure 2-1c.  (3) Contrast transformation. Assembling detection is embedded in the pipeline, and there will inevitably be some vibration, resulting in slightly different contrast in imaging. Contrast transformation enhancement of the image can increase the robustness of the algorithm. An example of contrast transformation is shown in Figure 2-1d.    a) original image b) position offset    c) brightness conversion d) contrast conversion  Figure 2-2 Data Enhancement  2.2 Research on Detection Algorithm Based on Image Processing  2.2.1 Detection target location and ROI settings  When testing the assembly, first locate the inspection target. The assembly is fixed inside the fixture. The position of the fixture can be positioned first, and then the ROI can be set according to the relative position of the assembly and the fixture and the items to be tested for poor assembly detection.  For the positioning of the clamp position, since the background of the image is black, the image is binarized by the equation (2-1), and the area of ​​the jig and the fitting is divided. The result of binarization is shown in Figure 2-3 b).   |  |  |  | | --- | --- | --- | |  |  | （2-1） |  |  |  |  |  | | --- | --- | --- | --- | | Where |  | —— | The pixel value at (x, y) after image binarization; | |  |  | —— | The pixel value at the grayscale image (x, y); | |  | *t* | —— | Binarization threshold |   Since the wire of the assembly will extend beyond the scope of the fixture, it should be handled when positioning the fixture. The protruding wire can be eliminated by opening the image, and the opening operation is an operation of first etching and expanding the image to eliminate small objects. Among them, the corrosion is to remove the edge of the white area, and the expansion is the edge of the expanded white area. The result of the open operation is shown in Figure 2-3 c).  The outline of the outer envelope of the fixture can be obtained by contouring the image. The contour search results are shown in Figure 2-3 d).    a) picture to be detected b) for a) binarization    c) for b) open operation d) for c) find outline  Figure 2-3 Target positioning  In industrial inspection, a region of interest (ROI) set for detection is usually used for detection for different detection items. According to the detection requirements and the analysis of bad samples, a total of eight ROIs are set in this paper, as shown in Figure 2-4. According to the order from left to right and top to bottom, 2, 7 are used for metal sheet missing detection, 4, 5 are used for cotton core missing detection, and 1, 3, 6, and 8 are used for wire abnormality detection.    Figure 2-4 ROI settings  2.2.2 Workpiece missing detection  The assembly needs to be clamped several times during the assembly process, and there may be cases where the clamping fails or is lost during the clamping process, so that there is no fixture in the inspection station.  Since the jig is composed of a plurality of parts, a complete outline cannot be obtained when the jig contour search is performed, and a plurality of small outlines are detected. In this paper, according to this feature, the detection of workpiece missing is performed. By setting the contour area threshold for contour screening, the contour of a small area can be filtered. If there is a missing workpiece, the contour can not be found in the contour search, so it can be positioned according to the target. The result of the contour search to determine if the workpiece is missing. The missing workpiece inspection is shown in Figure 2-5.    a) missing workpiece b) Find a profile for a)  Figure 2-5 Workpiece missing detection  2.2.3 Cotton core missing detection  Since the cotton core is wrapped by a metal wire, in order not to deform the metal coil, the clamping force of the feeding material is small, and it is easy to be lost during handling.  For the cotton core missing detection, this topic uses the pixel statistical method, and the cotton core detection ROI sample is shown in Figure 2-6. The cotton core is bright white when imaged, and if there is a cotton core, the cotton core detection ROI should be white pixels. The cotton core is judged to be missing by counting the proportion of the number of white pixels in the ROI. If the ratio is less than the set threshold, it is determined that the cotton core is missing, and vice versa.  The process of counting the number of white pixels is to binarize the picture and set the pixel value threshold. For pixels above the threshold, the pixel is determined to be white, and the pixel value is set to 1, and The entire image is summed to get the white points of the image.    a) cotton core b) no cotton core  Figure 2-6 Cotton core missing detection  2.2.4 Metal sheet missing detection  For the detection of metal sheets, this topic uses template matching. The metal piece has a claw, and it can be determined that the metal piece is present as long as the claw can be detected. Due to imaging reasons, some dark areas may appear on the metal chip jaws, and the picture needs to be pre-processed.  This topic uses a closed operation for preprocessing. The closed operation is an operation of first expanding and then etching the image to eliminate small holes. The results of the closed operation on the metal sheet detection ROI are shown in Figure 2-7 b).    a) picture to be detected b) on a) closed operation    c) for b) binarization d) template matching results    e) Template picture 1 f) Template picture 2  Figure 2-7 Metal sheet inspection  Before performing template matching, the image is binarized so that the area other than the metal piece becomes black, as shown in Figure 2-7 c), which can make the template matching not interfere with the background, and improve the accuracy and stability of the template matching. Sex. The template image we use is also binarized. The template images in two different places are shown in Figure 2-7 e), f).  There are many template matching methods, and the subject chooses the normalized square difference method. The normalized squared difference formula is shown in equation (2-2). This method is simple and fast. The principle of the normalized square difference method is to first calculate the squared difference of the pixel values of the template image and the image to be detected, and then normalize the result, so that the range of the value range is transformed into [0, 1], and the smaller the value The more matching, the template matching results are shown in Figure 2-7 d).   |  |  |  | | --- | --- | --- | |  |  | （2-2） |  |  |  |  |  | | --- | --- | --- | --- | | Where |  | —— | The pixel value of the template graph at; | |  |  | —— | The pixel value to be matched at; |   2.2.5 Wire anomaly detection  There are two cases of abnormal wire, one is that the wire is too short, and the other is the positional deviation caused by the wire being not pressed. For the first case, the pixel statistical method is used to judge, similar to the method of cotton core detection, and will not be described here. The ROI sample of the wire is too short to be shown in Figure 2-8.    a) wire b) no wire  Figure 2-8 Cotton core missing detection  For the second case, this paper determines by measuring the distance between the wire and the vertical side of the metal chip jaw. When the distance deviates from the normal range, it is determined to be abnormal. Analysis of the picture, there will be a lot of bright white areas at the wire and metal chip jaws, most of the other areas are gray, accurately find two bright white areas to measure the distance.  First, the detected image is preprocessed, including closed operation and binarization, closed operation eliminates black holes, and binarization operation splits bright white areas. The pretreatment results are shown in Figure 2-9.    a) Image to be tested b) Pretreatment results  Figure 2-9 Wire distance measurement pretreatment  For the pre-processed image, the number of white points in each column is counted to draw a curve. There are a large number of white points at the vertical edges of the wire and the pole pieces, and two maxima appear. Because the image has other white areas and noise, the curve is not smooth enough to find the correct maximum.  In order to accurately find the maximum value, this paper has some preprocessing on the statistical series. The first step is to filter the values of the series so that the value less than a certain value becomes 0, and the area between the wire and the vertical side of the pole piece is obtained. The second step is to smooth the sequence. Once you find the two maxima, you can measure the distance between the two. The curve of the statistical sequence preprocessing process is shown in Figure 2-10.    a) original curve b) numerical filtering    c) numerical smoothing  Figure 2-10 Curve Processing  2.2.6 Experimental analysis of image processing detection algorithm performance  Two important indicators for evaluating the performance of detection algorithms in industrial inspection are the detection rate and the false detection rate. The detection rate refers to the proportion of the category that is correctly detected. The false detection rate refers to the ratio that is not detected by the category as the category.  The detection performance test of the collected image data set is carried out by using the traditional image processing based detection algorithm proposed in this paper. The number of samples tested is shown in Table 2-1. The detection rate and false detection rate of each bad are shown in Table 2-2.  Table 2-2 Traditional image processing algorithm detection performance table   |  |  |  | | --- | --- | --- | | Bad category | Right detection rate | False detection rate | | Missing artifact | 100% | 0% | | Missing cotton core | 72.72% | 0% | | Missing metal piece | 100% | 0.85% / 2/234 | | Abnormal wire | 100% | 2.99% / 7/234 |   Algorithms based on traditional image processing have a large number of parameters that need to be set, and different parameter settings will result in different results. Since the detection rate is usually strict in industrial inspection, the principle of determining the parameters in this paper is to reduce the false detection rate as much as possible under the condition of ensuring high detection rate, and to obtain the optimal result after continuous adjustment and optimization.  Causes of cotton core miss detection: Missing samples are detected as missing workpieces. Because the picture without individual cotton core is dark, the contour search fails. Causes of misdetection of metal pieces: ROI is inaccurate (the area of the metal jaws is incomplete). Due to the different imaging dimensions of the different station fixtures, the position of the assembly in the fixture will rotate, resulting in the relative orientation of the assembly in the fixture. There are some deviations in the position. Reasons for wire misdetection: On the one hand, the ROI is inaccurate, and on the other hand, because the ROI may include some interferences, resulting in inaccurate ranging.    a) Missile inspection sample b) Metal chip misdetection sample    c) Wire misdetection sample  Figure 2-11 Sample of missed detection and false detection 2.3 基于卷积神经网络的检测算法研究2.3.1 卷积神经网络 卷积神经网络（CNN）是一种深度学习算法，主要应用于图像识别。卷积神经网络的重要组成部分有卷积、激活函数和分类函数。  （1）卷积 卷积的作用是提取图像特征。对图像进行卷积运算的原理是，让卷积核在图像上以一定的步长进行滑动，计算每个窗口区域的卷积值。不同的卷积核大小、卷积核个数和滑动步长可以得到不同的图像特征。卷积分为二维卷积和三维卷积，计算公式分别见式（2-5）和式（2-6）。   |  |  |  | | --- | --- | --- | |  |  | （2-5） | |  |  | （2-6） |   卷积神经网络通常由多层卷积组成，需要大量的运算，往往很难用于实时检测。为了减少算法的运算量，学者们提出了深度分离卷积，在保证模型准确性偏差不大的情况下大幅降低算法的运算量。深度分离卷积是将正常的卷积拆分成深度卷积和逐点卷积，拆分原理如图2-11所示。    a) 标准卷积    b) 深度卷积    c) 逐点卷积  图 2-11 深度可分离卷积  假设有一个的特征图。标准的卷积层包括N个三维卷积核，每一个卷积核需要对输入特征图的所有通道进行卷积运算得到输出特征图的一个通道，N个卷积核需要的计算量。深度可分离卷积把标准的卷积层拆分为两步，第一步使用M个的二维卷积核对输入的特征图进行卷积运算，每个二维卷积核分别和对应的输入通道进行卷积运算，计算量为；第二步使用N个的二维卷积对第一步的输出特征图进行卷积运算，计算量为。这两种方法都能得到相同尺寸的输出。根据公式2-7计算二者计算量的比率，其中卷积神经网络中的卷积核个数通常较多。   |  |  | | --- | --- | |  | （2-7） |   由上式可见，如果使用的卷积核，深度分离卷积的计数量约为标准卷积层计算量的九分之一。  （2）激活函数 激活函数（Activation Function）通常是作用在卷积运算之后的，负责将卷积的输出按照激活函数关系进行映射。通过使用激活函数，使得卷积神经网络具有了非线性，进而使得卷积神经网络可以逼近更复杂的非线性函数，增加了网络的学习能力。目前卷积神经网络常用的激活函数有Sigmoid见式（2-7）和ReLu见式（2-8）。   |  |  |  | | --- | --- | --- | |  |  | （2-7） | |  |  | （2-8） |   （3）分类函数 分类函数是作用在整个卷积神经网络的最后面，对计算的结果进行归一化得到每个类别的概率。分类任务可以分为二分类和多分类。二分类通常使用Sigmoid函数进行分类，得到其中一个类别的概率，通过概率和为1的关系可以求得另一类别的概率。多分类通常使用softmax函数进行分类，得到每个类别的概率，softmax函数见式（2-9）。   |  |  |  | | --- | --- | --- | |  |  | （2-9） |  |  |  |  |  | | --- | --- | --- | --- | | 式中 |  | —— | 上一层第i个类别的计算结果； | |  |  | —— | 总类别数； |  2.3.2 模型选择 根据工业检测的特点，本课题选择了MobileNet 卷积神经网络模型。MobileNet是一个基于深度可分离卷积的模型，跟其它模型相比，在准确率相差不大的情况下它的计算量远远少于其它模型。MobileNet的具体网络结构参数见表 2-1。  表 2-1 MobileNet网络结构   |  |  |  | | --- | --- | --- | | 网络层/步长 | 卷积核形状 | 输入尺寸 | | Conv / s2 | 3 × 3 × 3 × 32 | 224 × 224 × 3 | | Conv dw / s1 | 3 × 3 × 32 dw | 112 × 112 × 32 | | Conv / s1 | 1 × 1 × 32 × 64 | 112 × 112 × 32 | | Conv dw / s2 | 3 × 3 × 64 dw | 112 × 112 × 64 | | Conv / s1 | 1 × 1 × 64 × 128 | 56 × 56 × 64 | | Conv dw / s1 | 3 × 3 × 128 dw | 56 × 56 × 128 | | Conv / s1 | 1 × 1 × 128 × 128 | 56 × 56 × 128 | | Conv dw / s2 | 3 × 3 × 128 dw | 56 × 56 × 128 | | Conv / s1 | 1 × 1 × 128 × 256 | 28 × 28 × 128 | | Conv dw / s1 | 3 × 3 × 256 dw | 28 × 28 × 256 | | Conv / s1 | 1 × 1 × 256 × 256 | 28 × 28 × 256 | | Conv dw / s2 | 3 × 3 × 256 dw | 28 × 28 × 256 | | Conv / s1 | 1 × 1 × 256 × 512 | 14 × 14 × 256 | | 5 × Conv dw / s1  Conv / s1 | 3 × 3 × 512 dw  1 × 1 × 512 × 512 | 14 × 14 × 512  14 × 14 × 512 | | Conv dw / s2 | 3 × 3 × 512 dw | 14 × 14 × 512 | | Conv / s1 | 1 × 1 × 512 × 1024 | 7 × 7 × 512 | | Conv dw / s2 | 3 × 3 × 1024 dw | 7 × 7 × 1024 | | Conv / s1 | 1 × 1 × 1024 × 1024 | 7 × 7 × 1024 | | Avg Pool / s1 | Pool 7 × 7 | 7 × 7 × 1024 | | FC / s1 | 1024 × 5 | 1 × 1 × 1024 | | Softmax / s1 | Classifier | 1 × 1 × 5 |   模型参数中的Conv表示标准的卷积，Conv dw表示深度分离卷积。最后一层的分类类别数根据具体任务确定。 2.3.3 模型训练 卷积神经网络模型的参数需要通过数据训练确定，模型训练的两个主要部分是损失函数和优化算法。  （1）损失函数 损失函数是用来衡量预测值与真实值的差别。损失函数值越小说明预测值与真实值之间的差别越小，模型学习的结果越好。损失函数对模型的学习效果有很大的影响，选择合适的损失函数可以得到较好的效果。在图像识别领域通常使用交叉熵损失函数，见公式2-9。从公式中可以看出，当预测值越接近于真实值时损失函数值就会越小，反之。   |  |  |  | | --- | --- | --- | |  |  | （2-10） |  |  |  |  |  | | --- | --- | --- | --- | | 式中 |  | —— | 真实值； | |  |  | —— | 预测值； |   （2）优化算法 优化算法是根据损失函数值和一定规则进行网络参数更新的算法，网络参数的更新公式见式（2-10）。优化算法的选择决定着模型的训练时间和收敛效果。常用的优化算法有梯度下降、动量梯度下降、RMSprop、Adam等。本文选着的是Adam优化器，它结合了动量梯度下降和RMSprop，是一个已经被广泛的应用并证明有效的优化器。   |  |  |  | | --- | --- | --- | |  |  | （2-10） |  |  |  |  |  | | --- | --- | --- | --- | | 式中 |  | —— | 参数； | |  |  | —— | 学习率； | |  |  | —— | 损失函数 |   学习率也是一个重要的参数，分为固定和动态两种方式。动态学习率的好处是在训练模型的前期可以设置较大的学习率加快训练的速度，在后期学习率会不断的衰减可以稳定的收敛到更优解。动态学习率有多种，本文使用的是阶梯下降，即每隔一定的迭代次数减小一次学习率。  前向传播  计算损失函数值  到最大迭代次数  ？  是否满足终  止条件？  批量样本  开始  结束  训练算法更新参数  权重初始化  否  是  图 2-12模型训练流程图  （3）模型训练 模型的训练是一个不断迭代的过程，可以通过设置损失函数阈值或训练的最大迭代次数来结束。训练流程图见图2-12。 2.3.4 卷积神经网络检测算法性能实验分析 深度学习算法的预测结果通常被划分为四类：真正例（TP）、假正例（FP）、真反例（TN）、假反例（FN）。正例被预测为正例是真正例，反例被预测为正例是假正例，反例被预测为反例是真反例，正例被预测为反例是假反例。常用的评估指标有准确率（Accuracy）、精确率（Precision）、召回率（Recall）、F1系数，公式分别见式（2-7）、式（2-8）、式（2-9）和式（2-10）。   |  |  |  | | --- | --- | --- | |  |  | （2-11） | |  |  | （2-12） | |  |  | （2-13） | |  |  | （2-14） |   使用卷积神经网络检测算法对我们数据集进行检测，算法的检测性能如表2-3所示。  表 2-3 卷积神经网络算法检测性能表   |  |  |  |  |  | | --- | --- | --- | --- | --- | | 不良类别 | 精确率 | 召回率/检出率 | F1 | 误检率 | | 工件缺失 | 100% | 100% | 100% | 0% | | 棉芯缺失 | 100% | 100% | 100% | 1.71% | | 金属片缺失 | 100% | 100% | 100% | 3.85% | | 金属丝异常 | 100% | 100% | 100% | 5.13% |   可以看出，对比基于传统的图像处理检测算法，卷积神经网络算法的分类准确率和误检率得到了提升，但是检出率会有一点降低。主要原因是卷积神经网络算法是平等的对待每一种类别。后续将对检出率做一些优化。  2.4 Detection software and cloud data management system design  2.4.1 Detection software design  The detection software needs to implement a combination of detection algorithms, detection information management, and graphical interfaces. According to the functions implemented by the software, the detection software can be divided into four parts: image processing detection algorithm, convolutional neural network detection algorithm, graphical user interface, database.  (1) Image processing detection algorithm. This topic uses OpenCV image processing library to design image processing detection algorithm. Due to various types of assembly defects, the detection sequence of this subject is: workpiece missing detection, cotton core missing detection, metal sheet missing detection, wire anomaly detection.  (2) Convolutional neural network detection algorithm. This topic uses the TensorFlow deep learning framework to design a convolutional neural network algorithm. TensorFlow is an open source framework developed by Google Inc. and is currently the most popular development framework for deep learning. When using the convolutional neural network algorithm for detection, the network weight file initialization model needs to be loaded first. In order to make the operation of the software more convenient, it is selected to perform related initialization when the software is started.  (3) Database. This topic uses the MySQL database management system to store and manage misassembly detection information. The MySQL database management system is a relational database management system (RDBMS) that uses a structured query language SQL for database management. Simple, compact and free, it is ideal for the needs of this topic. At the end of each test, the detection software generates a test record to be saved in the database, including the detected image path, test result and detection time.    Figure 2-13 Detection software main interface  (4) Graphical user interface. This topic uses the QT software interface design framework to develop a graphical user interface. The main functions include detection algorithm selection, detection object selection, detection result display, software operation information prompt, detection record query and export. The main interface of the detection software is shown in Figure 2-13. The test record query and export interface is shown in Figure 2-14.    Figure 2-14 Detection record interface  2.4.2 Cloud Data Management System Design  With the advent of the industrial intelligence era, inspection data and data mining in industrial production are becoming more and more important, and it is necessary to design a corresponding cloud data management system.  This topic uses the Django framework to develop cloud systems. Django is an open source web application framework written in Python. Django is a framework based on the MVC structure. But in Django, the part of the controller that accepts user input is handled by the framework itself, so Django is more concerned with models, templates, and views, called MTV patterns.  (1) Model. That is the data access layer. Handle all transactions related to the data, including how to access it, how to verify validity, the behavior to include, and the relationship between the data. The connection between the model and the database uses Object Relational Mapping (ORM), which defines the data model in the form of a Python class. It can manipulate the database using object-oriented ideas and also supports raw SQL statements.  (2) Template. That is, the presentation layer. Handling performance-related operations, how to display them in pages or other types of documents, templates are inheritable.  (3) View. That is the business logic layer. Access the model and retrieve the relevant logic for the corresponding template. A view is a bridge between a model and a template.  The cloud data management system designed in this topic consists of two modules. One is the detection record query module, and the other is the bad picture query module. The detection record query module can query the detection record according to the time period and can view the corresponding picture. Figure 2-15 shows the interface of the test record query module. The bad picture query module can query the corresponding bad pictures according to the time period and the bad type, which is convenient for observation and summary. Figure 2-16 shows the interface of the test record query module.    Figure 2-15 Test record query    Figure 2-16 Bad image query |
| 1. The work to be completed and its schedule .   The work that needs to be completed in the future is to improve and optimize the convolutional neural network algorithm, improve the detection software and the cloud data management system.  The specific schedule is as follows:   |  |  | | --- | --- | | Time | Schedule | | 2019.03—2019.05 | Improve the convolutional neural network algorithm, try to modify the loss function, use the Siamese network, and optimize the training strategy. | | 2019.06—2019.07 | Improve the database and cloud management system for detecting data. | | 2019.08—2019.09 | Optimize the corresponding detection algorithm and debug related detection software. | | 2019.10—2019.12 | Organize research results, write master's thesis, and prepare a defense. | |
| 1. The existing or expected difficulties and problems.   The existing problem is that the convolutional neural network algorithm has improved the overall accuracy of the classification, and the robustness of the algorithm is better, but the missed detection rate cannot meet the requirements of industrial detection.  The expected difficulty is that there is no relevant research based on the Siamese network in industrial detection, which makes the research more difficult. |
| 1. The considerations on the possibility of completing the thesis on-time (at least 100 words).   Up to now, the atomizer image dataset has been constructed, the corresponding image processing detection algorithm for different types of assembly failures has also been designed, the deep learning detection algorithm have been researched, the detection software and cloud data management system has been basically formed. In the following time, image processing detection algorithm and detection software were modified and optimized and deep learning detection algorithm will be design.  In general, most of the work of the thesis has been completed, and there are still some challenges. With the guide of teacher and the help of my colleagues and classmates, I believe that I can finish the graduated thesis on time. |