人工知能－基礎と応用

システム知能学講座
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- 学部:10人
- 研究生:１人

会津大学

A Panel Code Suitable for Long Distance Meter Reading

Kaito Suzuki and Jumpei Kanno Supervisor: Qiangfu Zhao

Background

In many Japanese factories, there is still a need to read analog meters manually. To replace thousands of analog meters with digital ones is too expensive. Therefore, in a joint research with a private company, we try to automate the meter reading process to reduce both human labor and human errors. Here, we introduce a panel code that can be used to encode thousands of meters and to identify the meters from long distance.

The proposed method

The panel code is a 2D-Code consisting of four colored markers (i.e. the finder markers) and multiple code sections. The four colored markers are used to correct the image, and the code sections are used to identify the meter by embedding the meter information (e.g. the meter ID).

The panel code can be adjusted according to the shape of the meter, such as rectangular, triangular, or circular. The color and shape of the colored markers will also be adjusted to match the environment for easy recognition.

Compared with QR code, the panel code is has an advantage in reading distance and is suitable for "normalizing" the meter images to improve the reading accuracy.

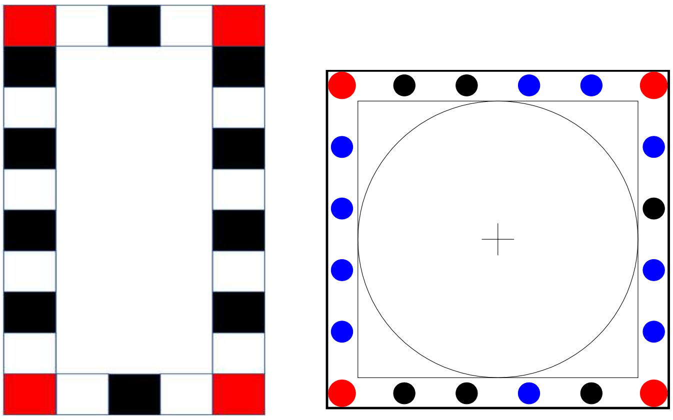
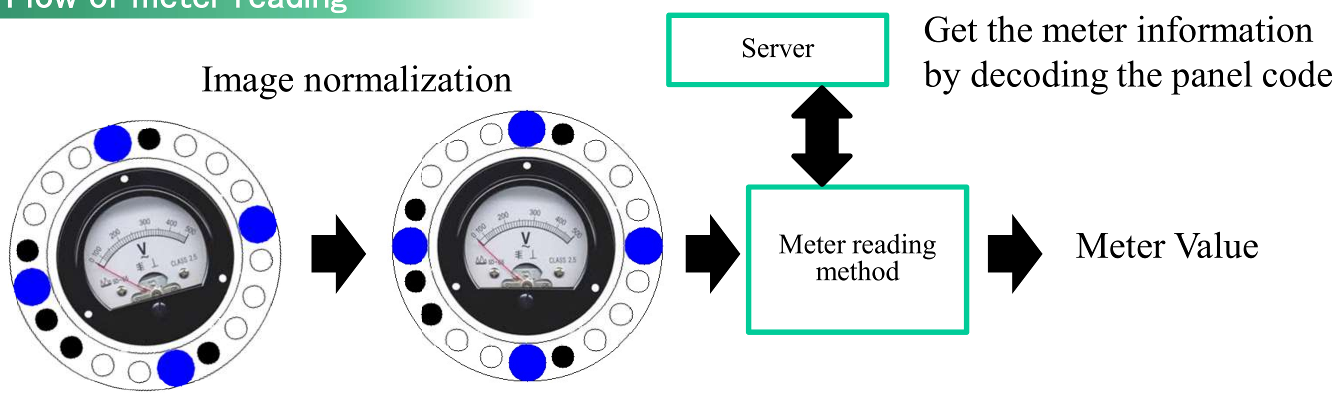


Figure 1: Examples of panel codes

Encode and Decode

The colored markers and meter identification numbers converted to binary codes are placed around the meter. The markers can be detected using color detection or object detection methods such as SSD. A single type of panel code (e.g. the squared one) can be used to encode various meters. Therefore, it is not necessary to design many models for detecting various meters. In addition, using homographic transformation based on the colored markers, we can normalize the meter images and make meter reading easier and more accurate.

Flow of meter reading



特願2020-189720

Automatic Reading of Flow Meters Based on Object Detection

Jumpei Kanno and Kaito Suzuki Supervisor: Qiangfu Zhao

Background

Various types of analog meters are installed in Japanese factories to monitor conditions and detect abnormalities in the manufacturing process. Therefore, human inspectors have to go around the factory and visually read the values of the meters, record the data, and take proper actions if needed. This work is done manually, which puts a heavy burden on the inspector and is prone to human error. The purpose of this study is to automate the manual process by using deep learning models of object detection and image processing.

The Proposed Method

Our proposed method consists of six steps using the object detection method SSD (Single Shot Multi-Box Detector) and image processing. SSD is trained to detect flow and float. Image processing is used to normalize the image and improve the reading accuracy.

Below are the basic steps for automatic reading (see Fig. 1):

1. Detect the flow meter using SSD
2. Image normalization
3. Detection of flow meter scale range by image processing
4. Detect the float using SSD
5. Estimate the coordinate of the float by image processing
6. Estimate the value of the flow meter

Experimental Results

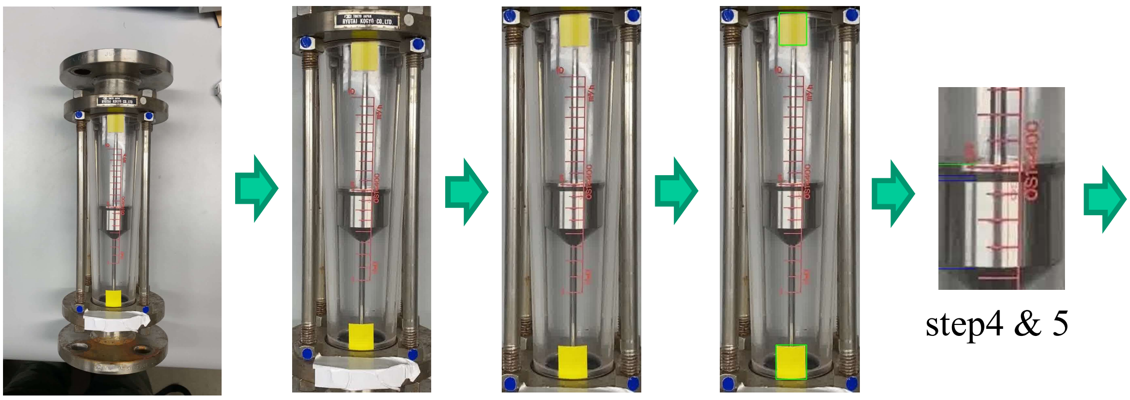
We performed experiments to measure the accuracy of our reading method. We performed the reading process on 100 images of each scale (1～10) and the results are shown in Table 1.

The error for each value is basically within the range [-0.2, 0.2], which is within the tolerance for practical application. The brightness in the image could cause image processing to fail and errors to increase. Therefore, it is better to use the average or median value as the reading result in multiple frames.

Table 1: Reading experiment result

True Value	Average	Max error	MeanAE	MedianAE	MeanSE
1	0.99509	0.09689	0.02392	0.00589	0.00096
2	2.09011	0.15242	0.09252	0.10631	0.01020
3	3.04961	0.14007	0.06852	0.06596	0.00593
4	4.03442	0.13864	0.05850	0.05069	0.00453
5	5.00306	0.16627	0.04311	0.01757	0.00313
6	5.93219	0.19298	0.07418	0.05133	0.00871
7	6.98281	0.21068	0.04376	0.00362	0.00395
8	7.92566	0.28974	0.08971	0.07806	0.01168
9	8.98525	0.22726	0.06038	0.01034	0.00525
10	10.0087	0.17091	0.09072	0.04698	0.00942

Schematic diagram of the proposal



6. Calculate the scale value and output the result

Fig.1.Reading flow

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Generative Model-Based Anomaly Detection for Symmetric Industrial Products

Shota Nakada and Takumi Meguro Supervisor: Qiangfu Zhao

Background

At factories or manufacturing sites, visual inspections are conducted to ensure the quality of industrial products. In recent years, various deep learning-based methods have been investigated for anomaly detection. In this research, we study anomaly detection for symmetric products. Using the symmetric property of the product images, we propose several image " normalization" methods that are useful to reduce the diversity of the data and obtain more effective generative deep learning models for anomaly detection.

The Proposed Method

Our proposed anomaly detection method consists of five steps using generative models such as variational auto-encoder (VAE) and generative adversarial network (GAN). Below are the basic steps for our anomaly detection method.

1. Image rotation. Rotate the images to make them “orientation invariant”.
2. Image translation. Shift the images parallel to the x-axis and/or y-axis to make them “position invariant”.
3. Creating models. Train the models only for “edges” and “corners”.
4. Binarization. Create black-white image from the difference image.
5. Connected component extraction. Calculate the size of “defect”.

Experimental Results

We trained VAE and GAN using 3000 normal images. Then we tested our anomaly detection method using 64 abnormal images and 500 normal images. Table 1 shows the results of the proposed method. Compared with existing method, these results are much better. However, in product anomaly detection, It is important to get Recall close to 100%. From Table 1 we can see that the proposed method is still not good enough for practical use. We are investigating methods to improve the performance.

Table 1: Anomaly detection results. Threshold means the size of defect.

threshold	3	4	5	6
TP	56	56	53	52
FN	8	8	11	12
FP	19	15	8	3
TN	481	485	492	497
Precision	74.7	78.9	86.9	94.5
Recall	87.5	87.5	82.8	81.2

Schematic diagram of the proposal

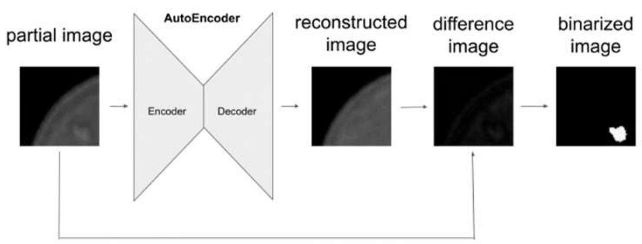


Fig.1.Binarization

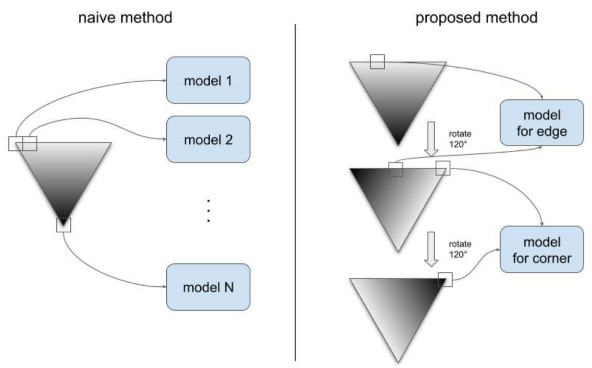


Fig.2.Creating models

Learn what is good, and know what is bad!

Product Defect Detection Based on Multi-Class Classification

Takumi Meguro and Shota Nakada Supervisor: Qiangfu Zhao

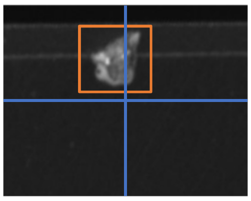
Background

In anomaly detection tasks, missing anomalies is a problem that must be avoided as far as possible. It has very serious consequences for companies that manufacture products if products with anomalies are delivered to the users. On the other hand, we should also minimize the over-detection rate while keeping the number of missed anomalies to zero or almost zero. To achieve these objectives, we propose an image-based multi-class classification method that can not only detect but also localize the anomalies.

The Proposed Method

The proposed method can pay more attention to the anomalies, images of the normal parts will provide a less negative effect on the performance. Interestingly, by setting a proper threshold for one of the outputs, we can separate normal and abnormal data more clearly compared with the straightforward two-class approach.

Fig. 1. How to label



Label：1100

Experimental Results

The following table shows the results of the existing and proposed methods, where FN indicates a missed anomaly and a threshold value should be used to set FN to 0.

Comparing the two results, the proposed method is able to reduce FN to zero while suppressing over-detection. In addition, the number of rejections is very small. It can be said that the proposed method clearly distinguishes abnormal data from normal data.

Table 1: Prior method result

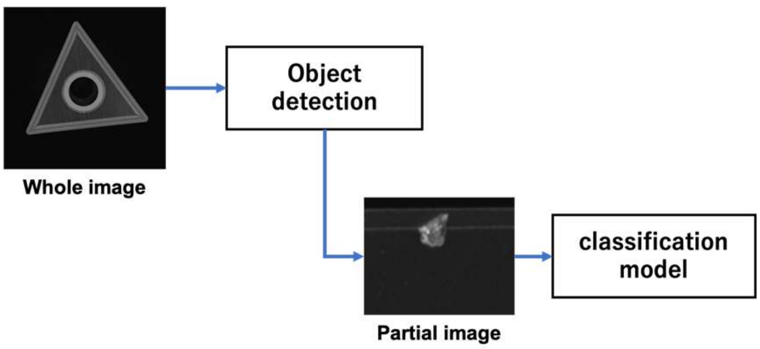
		0.9	0.99	0.999
TP	135	135	135	135
TN	1096	1076	956	586
FP	4	4	4	4
FN	12	7	2	0
Reject	----	25	150	522
Accuracy	0.987	0.990	0.994	0.994
Precision	0.971	0.971	0.971	0.971
Recall	0.986	0.950	0.985	1.0

Table 2: Proposed method result

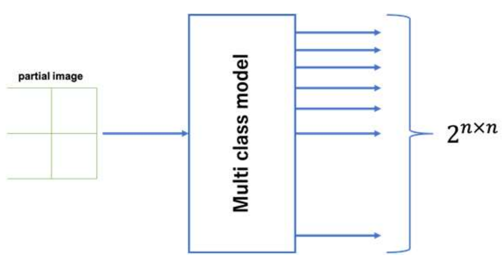
		23	24	25
TP	131	131	131	131
TN	1098	1088	1080	1066
FP	2	2	2	2
FN	16	2	1	0
Reject	----	24	33	48
Accuracy	0.985	0.996	0.997	0.998
Precision	0.984	0.984	0.984	0.984
Recall	0.891	0.984	0.992	1.0

We speculate that two factors contributed to the above results. The first is that the rise in the relevant class caused a large difference in the output of the normal class between normal and abnormal data. The second is that the training was conducted using multi-class classification, which resulted in a large difference between normal and abnormal data in the feature space. This was confirmed when dimensionality reduction was performed.

Schematic diagram of the proposal



Classification Model



Look closer and we can gain more!

You Only Look at Interested Cells – An Efficient Way for Detecting On-road Risks

Kai Su Supervisors: Yoichi Tomioka and Qiangfu ZHAO

Background

On-road risk detection is one of the prevailing applications in object detection and recognition, and it is also a crucial part of the driving assistance system. Only a tiny amount of research has recently been conducted to create a lightweight road risk detection system for low-cost vehicles such as mobility scooters. However, road risk detection tasks require strict requirements for real-time and high detection accuracy. Furthermore, most of the detection methods in use today need expensive computational power. Therefore, this is necessary to find a more efficient and effective way to solve the above problems.

Our proposal

Our proposed approach is called You Only Look at Interested Cell (YOLIC). The detection model leverages both bounding box and semantic segmentation methods. In this way, a detected object can be represented by one or more small cells (or blocks) instead of one big bounding box or pixel area where each cell will focus on the different parts of the object. Fig. 1 illustrates interested cells for on-road risk detection. The main idea is to focus on road and traffic signal cells. The cell sizes can be different depending on the distances and other factors.

On-road risk detection

In our on-road risk detection system, a depth camera is used and mounted on a mobility scooter. Based on the scooter speed and the human response time, we regard the road within 6 meters from the mobility scooter as the detection area. As shown in Fig. 1, the first three rows (i.e., cells 1 to 32) are the notification area. The danger area is the last four rows (i.e., cells 33 to 96). The white tapes on the floor are the reference lines. We set 96 cells to detect on-road risks and eight to detect traffic signs.

Experimental Results

In our experiment, we have defined 11 types of objects. The following results can be obtained if we use MobileNet v2 as the backbone network for detection. To know the detection performance more directly. Please scan the QR code to see an actual test demo.

categories	MobileNet v2		
	Precision	Recall	F1-score
Bump	0.9267	0.9487	0.9376
Column	0.8750	0.8645	0.869
Dent	0.8817	0.8887	0.8852
Fence	0.9227	0.9465	0.9345
Creature	0.8772	0.9199	0.8980
Vehicle	0.8960	0.9496	0.9220
Wall	0.9440	0.9567	0.9503
Weed	0.9342	0.9615	0.9476
Zebra Crossing	0.9695	0.9819	0.9756
Traffic Cone	0.8762	0.8752	0.8757
Traffic Sign	0.8415	0.7464	0.7911
Normal	0.9922	0.9875	0.9898
All Risks	0.9420	0.9633	0.9526

Figures to illustrate the proposed method

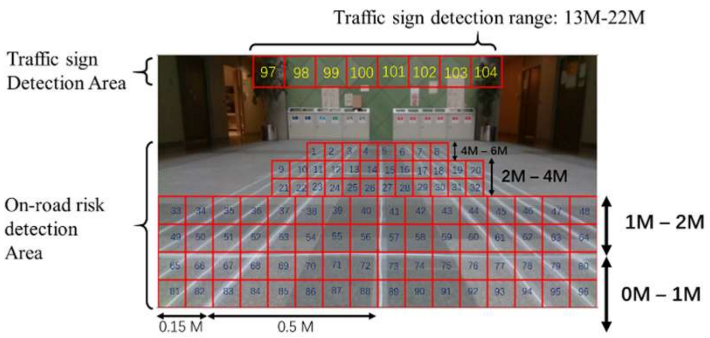


Fig. 1: Interested cells for on-road risk detection

Road risk detection demo

Pay attention to important things!

他の研究テーマ

- Modular selective neural network (Takahashi)
- Image annotation based on unsupervised learning (Ogata)
- Deep learning-based Automatic documentation (Hasegawa)
- Attention recognition (Liao)
- Deep learning-based Chinese painting generation (Wang)
- Deep learning-based X-recognition (Hamauzu)

My research

- **Conditional computation**:
  - NNTree: Neural network trees (combination of specialist neural networks using a tree structure)
  - MS-Net: Modular selective neural networks (combination of specialist neural networks using a generalist network)
- **Awareness computation:**
  - Sensor array-based situation awareness -> senior-care
  - Three-value logic-based awareness -> sparse computing.

No. F-17

会津大学

理解可能な多変数決定木による データ分類と解析 ～全体像を見れば隠されている規則が よくわかる～

教授　趙 強福

概要

○機械学習のモデルには、ニューラルネットのような非記号的モデルと決定木のような記号的モデルがある。前者は、データに含まれる情報を効率よく取り入れることができるが、学習結果はブラックボックスであり、人間も機械も理解できない。後者は理解しやすいモデルとされている。しかし、記号的モデルの学習結果は、機械的に形式的には解釈できるが、人間が理解できないものが多い。

○様々な応用において、コンピュータは補助的に使用され、人間が最終決断を行う。故に、学習結果を「人間に理解しやすく」する必要がある。多変数決定木技術は前記二つのモデルを融合したもので、一つのソリューションを提供する。本技術には以下の特徴がある。

- 類似度を基にした多変数決定木を利用しているので、人間にも理解可能なルールを学習結果として提供することができる。
- 忘却学習、注意学習、次元圧縮などいくつかの技術を採用しているので、コンパクトな多変数決定木を効率よく構築することができる。
- データ間の位相関係を階層的に可視化し、学習結果が直感的に理解できる。

実用化の可能性

○情報化社会において、データはモノであり、資産である。データの価値を高めるために、様々なデータマイニング技術が開発されている。その中で最も重要視されているのが機械学習に基づく技術である。

○本技術は、我々によって確立された新しい機械学習技術である。その有効性は様々な公開データベースで実証されている。本講座では、この技術を基に、文書解析システム、画像認識システムなどを開発している。商品化を視野に企業との共同研究も進めている。

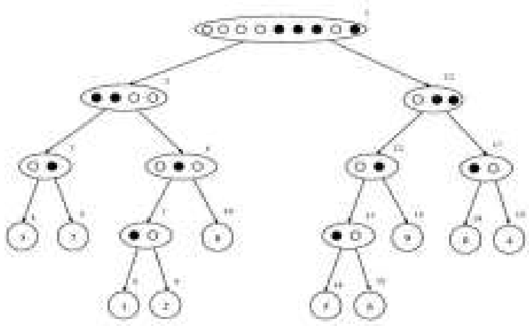
UBICからのメッセージ

○多変数決定木とは、中間ノードに多変数判別関数を利用した決定木の一種である。複雑なデータを効率よく分類できるのがこのモデルの特徴である。

○本技術に採用している多変数決定木はデータ間の類似度を基にしたものであり、学習結果を可視化して見ることもできれば、ルールに直して読むこともできる。

○本技術は、データを分類し、その結果を人間にわかる形で提供できるので、情報検索、セキュリティシステムなどの分野への応用が期待できる。

研究概要図



左図は手書き数字認識のための多変数決定木の例である。白丸は左子ノードに割り当てたデータの代表点、黒丸は右子ノードに割り当てたデータの代表点である。代表点はデータの典型的なパターンであり、データの内部表現である。これらの代表点との類似度を測ることによって、入力データの分類を行う。代表点を可視化すれば、典型的なデータパターンが一目でわかる。また、決定木をルールの形にも直せるので、興味のあるデータだけを分析することもできる。

生のデータを見えるように、読めるようにしましょう

関連特許：多変数決定木構築システム、多変数決定木構築方法および多変数決定木を構築するためのプログラム
（特願第2006－034343、2006－034344【特許第4997524号、4997525号】）