Multi-Class Object Classification and Location of Thermal Imagery in Electric Substation

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Abstract

We present a algorithm based on chamfer matching for classification and location of thermal imagery in electric substation. We first refine chamfer algorithm, then we present a new object class classification and location algorithm based on chamfer distance, also we analyze the object class recognition issue in thermal imagery and introduce a new solution scheme. At last we use a thermal image data set for evaluation.

Keywords: object classification, object location, thermal imagery, chamfer distance, electric substation

1. Introduction

Recently, the research on specific objects has been more matured than before. The focus of object recognition research has been shifted to object class recognition[1][2][3]. Although some development has been made on object class recognition, its performance is still not as good as the specific one. Currently the research on object class recognition is primarily focus on images under nature light; there is little research on thermal imagery, which has a lot of advantage over images under nature light. For example, it can be used in monitor system which can worked under day and night; it does not has shadow; it does not volunteer to light change.

There are many high voltage equipments in the electric substation. It is dangerous to inspect these equipments by man. Also it is not possible to inspect these equipments day and night. We can use patrol robots instead of human to inspect these equipments. The defects of these equipments often behave as high temperature, if we find their temperature, we can easily conclude if it has defect. Fortunately, thermal images can give us such information. The difficult is that there are so many kinds of equipments, and their defect temperature is different, so we must localize equipments accurately.

There are so many kinds of equipments in the electric substation, and it is difficult to recognize and localize them in real time, so we must use the prior information which the patrol robots offer to improve the accurate rates and recognize speed. The patrol robot can be set stop points using RFID, and it can remember its pose (angle, position, etc). Although some error may occur, it is small enough to accept. So we can avoid thinking about rotation, translation or scale, directly make a template using edge points of object of each pose of each stop point.

The attributes of this paper is the following:

1) Refinement of chamfer algorithm.
2) We analyze the object class recognition issue in thermal imagery and introduce a new solution scheme.
3) We present a new object class classification and location algorithm based on chamfer distance.

2. Refinement of chamfer algorithm

In order to match two binary images, we must calculate the distance between these images. The distance is the minimums between the features of them. The requirement for this distance is that it must represent accurately the difference of the two images. In this paper, one image is called pre-distance image and the other is called pre-polygon image.

2.1. Distance Transformation

Distance transformation (DT) is a operation which transform the feature points to 0 and non-feature points to the minimum distance to the feature points. We perform distance transform to pre-distance image and result in a distance image. It is important that the DT must a good approximation of Euclidian distance; otherwise the discriminate ability will be bad. Of course, the best one is Euclidian distance, but for the reason of high complexity measure, it is good idea that we use an approximation DT which has low complexity measure.

Borgefors[4] propose a chamfer DT which uses iterated local operations. In this paper we use 3-4 DT, which in the 3×3 neighborhood the distance between horizontal/vertical neighbors and diagonal is 3 and 4. The maximum difference between 3-4 DT and Euclidean distance is 8%, which is much good than the 2-3 DT of 13% and city block of 59%.

The basic of Borgefors' algorithm is the follows:

```
Initialize:
for i=1,……, M do
for j=1,……, N do
if (i,j) is edge point then
  D(i,j)=0
else
  D(i,j)=∞

Forward:
for i=2,……, M do
for j=2,……, N do
D(i,j)=minimus(D(i-1,j-1)+4,
        D(i-1, j)+3,D(i,j-1)+3,D(i,j))
Backward:
for i=M-1,……, 1 do
for j=N-1,……, 1 do
 D(i,j)=minimus(D(i+1,j+1)+4,D(i+1,j)
        +3,D(i,j+1)+3,D(i,j))
```

The Borgefors' algorithm has a defect that it is not specific deal with the first and last of row and column, and sometimes get the error result. For example, for the binary image of

$$\begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \end{pmatrix},$$

Follow Borgefors' algorithm, the result is

$$\begin{pmatrix} 9 & 8 & \infty \\ 8 & 5 & \infty \\ \infty & \infty & 1 \end{pmatrix},$$

which is not the right answer.

Against these defects, we refine Borgefors' algorithm as follows.

```
Initialize:
for i=1,……, M do
for j=1,……, N do
if (i,j) is edge point then
  D(i,j)=0
else
  D(i,j)=∞

Forward:
for i=2,……, M do
```

D(i,1)=minimus(D(i-1,1)+3,D(i,1))
for j=2,……, N do
D(1,j)=minimus(D(1,j-1)+3,D(1,j))
for i=2,……, M do
for j=2,……, N do
D(i,j)=minimus(D(i-1,j-1)+4,
D(i-1, j)+3,D(i,j-1)+3,D(i,j))
Backward:
for i=M-1,……, 1 do
D(i,N)=minimus(D(i+1,N)+3,D(i,N))
for j=N-1,……, 1 do
D(M,j)=minimus(D(M,j+1)+3,D(M,j))
for i=M-1,……, 1 do
for j=N-1,……, 1 do
D(i,j)=minimus(D(i+1,j+1)+4,D(i+1,j)
+3,D(i,j+1)+3,D(i,j))

Applying this refined one to the previous binary image, we get the correct answer:

$$\begin{pmatrix} 9 & 8 & 7 \\ 8 & 5 & 4 \\ 7 & 4 & 1 \end{pmatrix}$$

2.2. Chamfer Matching Algorithm

In the pre-polygon image the feature points are extracted and converted into a list of coordinate pair, which called polygon. We superimpose the polygon on the distance image which we get from 2.1. We use root mean square average of the pixel values that the polygon hits as the matching measures:

$$\frac{1}{3}\sqrt{\frac{1}{n}\sum_{i=1}^{n} d_i^2} \qquad (1)$$

In (1), d_i is the distance of the ith point and n is the number of the polygon.

3. Object class classification and location algorithm based on chamfer distance.

We represent object class as a template and use the similar measure between the object and template to recognize object. The similar measure is defined as the distance between them. If the distance is less than a threshold, then we say the object is belongs to this class, otherwise not. Then an issue arises, if the distance between a region of an image and two templates are all less than their threshold, does this region belongs to one class or both? If it is only belong to one, what class do this region belongs to? In order to solute such issue, we added two limit condition: first, there is no overlapped region between two objects, the object belongs to the larger one if two distance are all less than their threshold; second, the object should close to the template of the same stop points. According to the second condition, we propose a template weighted image.

3.1. Calculate the template weighted image

For each class of objects, the template weighted image is the result of the operator of the distance between template and the image which contains it. The weight is in proportion to the distance. Remember the matching measure is inverse proposition to the distance, so the template weighted image is an analogy to following prior knowledge: the less the distance between object and template, the more likely this object belongs to this template.

$$w_{ij} = f(dist(ij, x)) \qquad (2)$$

In (2), f must be a incremental function.

3.2. Calculate the matching distance image

Given template edge and template weighted image and DT image of the image which we want to recognize, the matching distance image is acquired by the following method. Get the sub image D_{ij} from left to right, from top to down

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and using the method of section 2.2, calculate the distance between m and D_{ij}, then multiplying the weight w_{ij}, thus we get the matching distance.

$$M_{ij} = D_{ij} \otimes m \cdot w_{ij} \tag{3}$$

3.3. Recognize and localize objects using matching distance image

Whether the object O_i in the image I depends on two terms: first there must have a number in the matching distance image which less than the threshold; second, the place which the object occupy must not overlapped with other object. Assumes that we have n object templates, $O_1, O_2, \ldots, O_n$, the matching distance image between I and these templates are $D_1, D_2, \ldots, D_n$, followed the above two requirements, for the jth templates O_j we using the following method to recognize and locate the object: first find all the non-overlapped position which value less than the threshold. If this place is occupied by another object template O_k, then compare the two values, the position is belong to the less one. Finally we pick out the n least place as the position of this object class, where n is the number of this object class.

4. Experiments

We applied our method to five object class of electric substation. In each of these classes, we calculate and save the template edge and template weighted image in advance. When we recognize and locate these objects, we can read them in advance, thus improve the speed of this method.

The requirement for the template edge is that it must resist to the noise. This is because that thermal imagery is easily affected by climate, temperature etc. Through experiments, we find that sobel do better than canny, prewitt etc. So we use it.

We use 81 images for test and result in 3 errors in locating. On our machine (which has intel CPU of core duo 4400 and 1G memory), the average speed is 1.046 seconds per image with our machine. The error is mainly due to the translation, rotation of view points and similarity of regions.

Figure 1,2,3 show the six sample of the test result.

5. References

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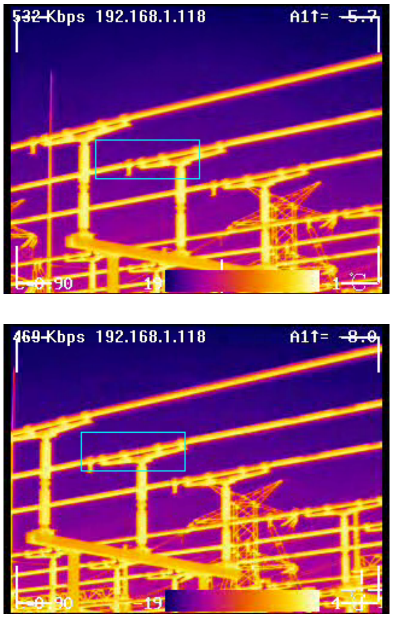

Fig. 1: Top: error location of a generating line.
Bottom: a correct one of the same class.

Fig. 2: Two example of CT equipments.

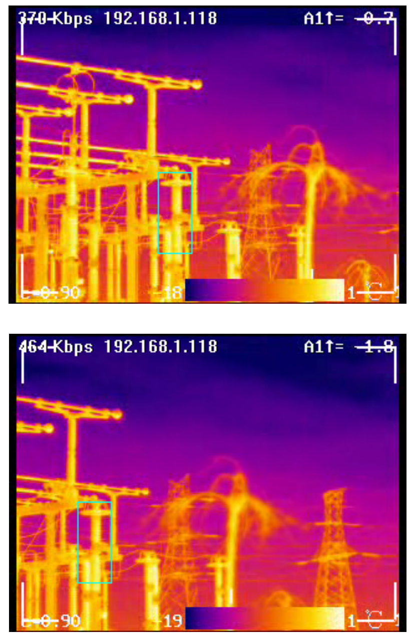

Fig.3 Two examples of PT equipments