2D/3D Multi-Modality Image Registration in Non-Destructive Evaluation

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Abstract

Non-destructive evaluation(NDE) is a group of analysis techniques used in industry to evaluate the property of a material, component or product without causing damage. Among all the techniques, radiology and thermography are two most common methods that are used to inspect the property of the interior of product and combining the knowledge contained in images of two modalites requires the space alignment. In this article, a 2D/3D multi-modality image registration scheme is presented to find the alignment between thermal infrared(IR) image and CT image of a engine blade.

Contents

Multi-modality image registration is widely used in image guided surgory, it can in principle remove the uncertainty in the mind of the physician when comparing different modalities images of the same patient. 3D PET to 3D MRI and 3D MRI to 3D CT are two common application in medical area.

In this article, a 2D/3D multi-modality image registration scheme is applied on NDE application for the first time. Radiography is one of the few NDE methods that can examine the interior of the object and the only NDE method that works on all materials [3]. Among all the techniques in radiology, CT scan can take three dimensional data of the object; therefore, expert can go through CT data slice by slice and inspect potential defect in the interior of the object. However, going through hundreds slices of data can be time consuming and the X-ray used in CT system can create safety concerns.

As another common method used in NDE application, thermography integrates infrared imaging with external heating source to assess subsurface structure via the thermal response of the object. The derived IR image is a two dimensional image with the intensity of every pixel representing the thermal response of object. The thermal response is determined by thermal conductivity of the object subsurface material; therefore, defect that causes material discontinuous will be shown in the IR image [2]. Inspecting a 2D IR image of an object for potential defect is much easier compared with going though CT data of the same object, however, CT data is much more subtle and accurate because it is built in three dimension. To combine the knowledge contained in IR and CT image brings the necessity of 2D IR/3D CT image registration.

1 Model Setup

The CT volume is set along the coordinate system, with its center at the origin (0,0,0), and a 6-degree transformation is applied on it. A ray source point is set on -z axis, and a simulated IR image is generated on a 2D image plane by projecting the ray through CT data. The image plane is parallel with x-y plane on +z side, and its distance to origin is much less then the distance between origian and ray source point, thus the projection can be considered as parallel projection.

The simulated IR image is then compared with given IR image, and the registration proceeds based on how well these two images match with each other.

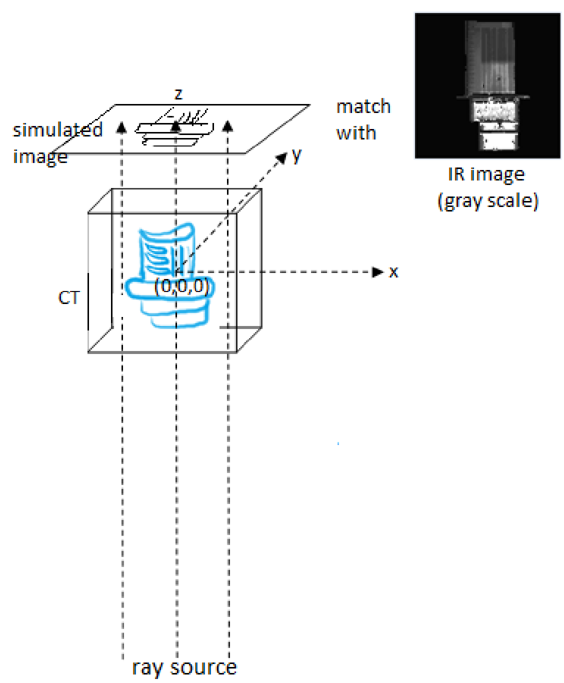

Figure 1: Model Setup

2 Registration Scheme

The registration process is an optimization process that looks for the optimal transformation set μ that aligns 3D CT and 2D IR image. The figure below shows the basic registration scheme.

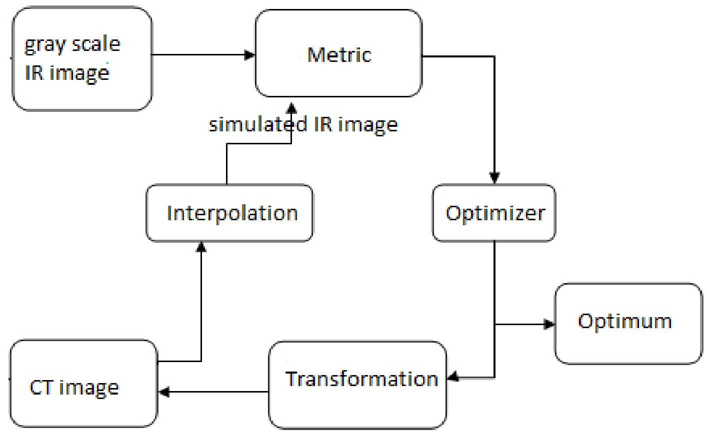

Figure 2: Registration Scheme

- Transformation μ is applied on 3D CT volume, and it contains rotation and translation, both in three directions, therefore $\mu = [R_x, R_y, R_z, T_x, T_y, T_z]$ with the first three parameters denoting rotation and last three parameters for translation.

- Since IR image shows the subsurface structure of the object in two dimentions and CT represents the structure detail of the same object in three dimensions, the intensity of each pixel on IR image can be considered as the intensity accumulation in CT volume along the thermal wave of a certain direction. If the thermal wave source is fixed, then the direction is changed by rotating/translating the CT volume. Therefore, intensity of each pixel on the gray scale IR image can be simulated by integrating intensities along the artifically ray (See Figure 3). To find the voxel intensities along the ray after the CT volume is transformed, bilinear interpolation is used.

- Metric is the most important part in the whole registration scheme. It provides a measurement of how well the simulated IR image is matched with the given IR image. Generally, metrics can be classified into three categories: intensity-based metric, gradient-based metric and statistic-based metric. Intensity-based metric directly compares certain number of pixel intensity from both images, and gradient-based metric only compares some features from both images, such as edges and surfaces. Statistic-based metric considers image as a signal, and therefore, compares the information contained in the two images. In the following section, two metrics from two categories will be introduced and compared.

- Optimization controls the whole registration scheme converge towards the optimum by iterations. In each iteration, optimization updates each transformation parameter based on the metric values in the current and previous iteration. When the constraint condition is reached, the optimization stops to return the final optimal transformation. Regular step gradient descent optimization is used in this article.

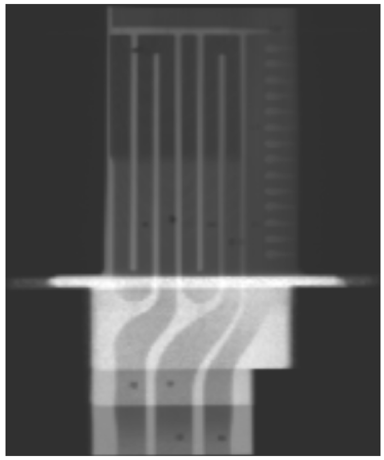

Figure 3: An example of the simulated IR image under a certain transformation

3 Discussion on metric based on the data

In this section, we discuss two metrics that represent two categories of metric, and then we choose one out of two based on the requirement of the data set. Let us define the simulated IR image to be image A, and gray scale IR image to be image B.

Gradient Difference (GD) metric: this metric is from the gradient-based metric category. The value of this metric is calculated by

$$GD(A,B) = \sum_{i=1}^{N}\left(\frac{V_0}{V_0+[V(A)-V(B)]^2} + \frac{H_0}{H_0+[H(A)-H(B)]^2}\right)$$

in which $V(A)$ and $H(A)$ are the sobel vertical and horizontal gradients of image A, and $V(B)$ and $H(B)$ are the gradients of image B. V_0 is the constant matrix with every element equals to the viriation of $V(A)$, and H_0 is for $H(B)$. The computation inside the parenthesis is element-wise computation, and metric value is the summation over N number of pixels considered [1]. It is obvious that only when the difference of both vertical and horizontal edges from both images reaches minimum, which is also when the edges from two images match with each other, the metric achieves its maximum value.

Normalized Mutual Informatin (NMI) metric: this catogry considers images as signals, measures the information they carries, and does not consider the spatial relation between pixels in images. The most commonly used measurement of information in signals is the entropy H that is first introduced by Shannon, originally developed as part of communication theory.

$$H = -\sum_{i=1}^{N} p_i \log(p_i)$$

Entropy H gives the average information supplied by a set of N symbols whose probabilities are given by p_1,p_2,...,p_N. In image registration problem, it measures the average information of N pixels in the image. Shannon also brought up the idea of joint entroppy (1948), which measures the amount of information of the two signals combined.

$$H(A,B) = -\sum_i \sum_i p(A_i,B_i)\log(p(A_i,B_i))$$

Joint entropy is simultaneously proposed for multi-modality image registration by Studholme (1995) and Collignon (1995), however, the joint probability $p(A_i,B_i)$ is very dependent on the overlap region, which is

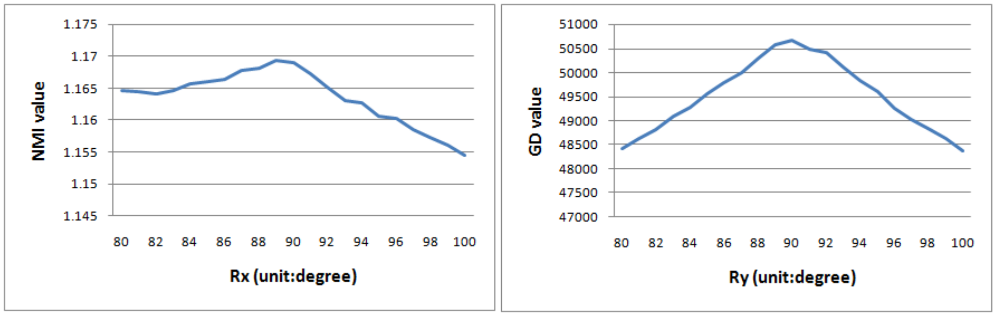

Figure 4: The values of two metrics when Rx is the only variable, the other five parameter are set to be fixed

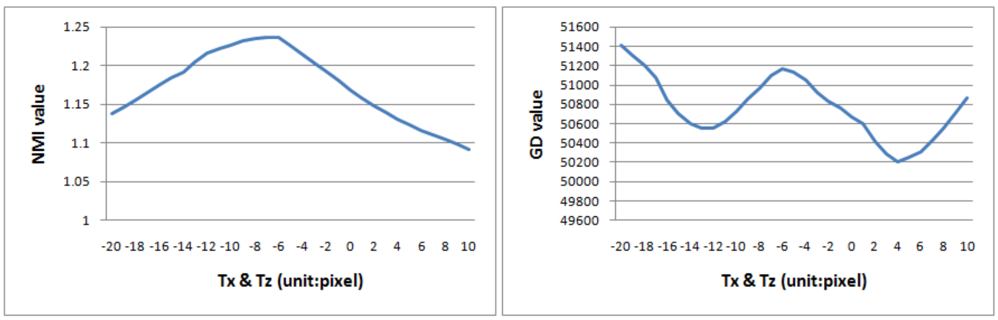

Figure 5: The values of two matrics when Tx and Tz are the only variables, the other four paramters are set to be fixed

undesirable.
Mutual information(MI) is a plausible approach, proposed independently by Viola and Wells (1995) and Collignon (1995).

$$MI(A,B) = H(A) + H(B) - H(A,B)$$

However, mutual information violates some of the basic metric conditions which may limit its application domains. For example, it considers only the shared information from two images, and addresses no conditions of the rest of $H(A)$ or $H(B)$. In order to provide overlap invariance, normalized mutual information (NMI) is brought up [4]. NMI considers not only the mutual information, but also the marginal entropy of $H(A)$ and $H(B)$. In this article, we used NMI as the metric to evaluate the matching between images of two modalites.

$$NMI(A,B) = \frac{H(A)+H(B)}{H(A,B)} = \frac{\sum_i p(A_i)\log(p(A_i)) + \sum_i p(B_i)\log(B_i))}{\sum_i \sum_i p(A_i,B_i)\log(p(A_i,B_i))}$$

Let us take a look at the characteristic of the above two metrics when they are implemented on the engine blade data set. When R_x is the only variable in transformation which is applied on CT, both NMI and GD show only one maximum at around $R_x = 90°$ (figure 4). On the other hand, when T_x and T_z varies, GD value has more than one maximum (figure 5). This means that when one image is translated along x and z direction from the other image, gradient difference metric has multiple maximum to represent the similarity between these two images. This is a bad news for optimization, because it can be easily led to wrong maximum if the initial transformation guess is not close enough to the correct optimum.
Observing both the given and simulated IR image, the blade structure consists of horizontal and vertical

components (figure 6). If gradient difference is used as metric, it would generate horizontal and vertical edges and the registration procedure would try to match these edges. In this case, translating one image towards one direction will not cause obvious difference of the edge matching since all the edges are along axes. Considering the unstability of gradient difference metric for the engine blade data set, normalized mutual information is chosen to be the metric for the experiments.

4 Experiments approach and results

- The IR image obtained from infrared camera is a pseudo-color image, it need to be converted back to gray scale image before registration procedure starts.
- By observing the IR image, different initial transformation guesses are decided.
- The complete registration procedure is performed starting from different intial guesses.
- The final transformation result is the average of the results from different initial guesses.

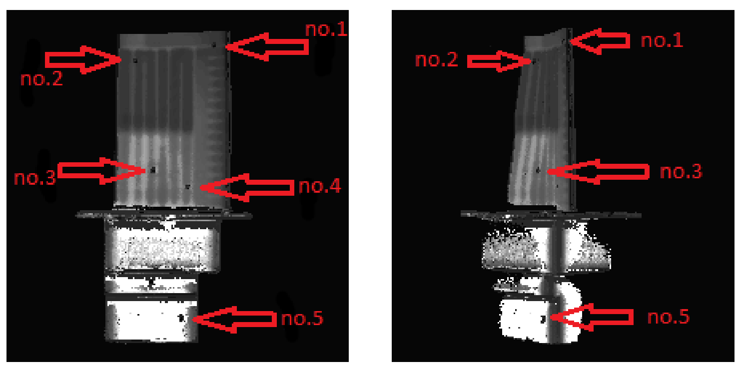

Figure 6: View1(left) and view2(right) of gray scale IR image with indications pointing to the holes

Take IR view1 image(figure 6 left)as an example, different initial transformations are decided based on observation first. Registration procedure starts from these initial transformations, and converges to the optimums. The final transformation shown in table 1 is the average of the optimums.
To provide another evaluation of the accuracy of the registration, holes are drilled on the blade before both modality images are taken so that they can be observed in both CT and IR image. Based on the location of the holes, we define *distance error* as the distance between hole's location on IR image and hole's location on simulated IR image after the CT image being transformed and projected. The resolutoin of the blade data set is $0.6mm/pixel$, therefore, for view1 case, the distance error of the final transformation is $0.83mm$.

R_x	R_y	R_z	T_x	T_y	T_z	*distance error*
89.98°	0.56°	184.66°	-8.72	-0.21	-6.77	1.39 pixel

Table 1: Registration result for IR view1 image

Results for IR view2(figure 6 right) image is listed in table 2.

The NMI metric value of each result is supposed to show the accuracy of the result: the bigger the metric value is, the more accurate the resulting transformation is, and the smaller the corresponding *distance error*

R_x	R_y	R_z	T_x	T_y	T_z	*distance error*
90.32°	0.85°	227.27°	-16.38	-3.-2	-7.51	2.59 pixel

Table 2: Registration result for IR view2 image

is suppose to be. The resulting transformation with the biggest NMI metric value should be chosen to be the optimum. However, the relation between them is not very clear in the testing experiments. Therefore, so far, the final result we accept is the average of the results derived from different initial guesses. To ensure that the final average result is correct, each result has to be correct which means that each initial transformation guess has to be close enough to the real transformation (unknown). This is the problem we need to conquer in the next stage.

References

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