A New 2D/3D Multi-Modality Image Registration Application for Non-Destructive Generic Aerospace Casting Evaluation

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Abstract—Non-Destructive Evaluation (NDE) is a group of data analysis techniques used in industry to evaluate the property of a material, component or product from sensors without causing damage. It often requires different techniques, each proving a distinct set of useful data. Infrared (IR) thermography-based and computed tomography (CT) radiography-based methods are the most common imaging methods. While a multi-modality solution may provide a richer information for making inspection decisions, there is a need to find the optimal spatial transformation necessary to register the useful information carried in different modality sources. Currently, there is a lack of methods for multi-modality image registration in industrial inspection applications. An image registration scheme for finding spatial transformation between 2D IR image and 3D CT images of generic aerospace castings is presented for the first time. Information theory based similarity measure is shown to be applicable with both theoretical support and experimental verification.

Keywords: Image registration, multi-modality, NDE application, thermal infrared image

1. Introduction

Image registration is the process of determining an optimal transformation between two images that would map the corresponding points. Through image registration, data contained in different images can be compared, integrated and analyzed.

Image registration can be classified into either single-modality or multi-modality. Single modality registration involves two images that are acquired by the same sensor type, while the multi-modality registration works with images acquired from different sensor types. Multi-modality image registration is widely used in the medical imaging area as images of a subject are frequently obtained from different imaging sensors [1].

In this paper, a multi-modality image registration scheme is applied to another application domain – Non-Destructive Evaluation (NDE) of industrial inspection.

Radiography is one of the few NDE imaging methods that can examine the interior of products and the only one that works for all materials. Among all the radiography methods, CT scan can obtain three-dimensional data of the product, therefore, an inspection expert can go through CT data by slice or as a whole volume to inspect the potential defect of the physical object.

As another common imaging method used for NDE, thermography integrates infrared imaging with external heating source to assess the subsurface structure via the thermal response of the part [2]. The derived IR image is a two-dimensional image with the intensity of every pixel representing the thermal response of the part which is determined by the thermal conductivity of the subsurface material. Defects that cause material discontinuity will be shown in the IR image. Inspecting a 2D IR image is a lot easier compared to going through CT data of the same object; however, CT data is more subtle and accurate. To combine the knowledge contained in both IR and CT images, they have to be spatially aligned first, and this brings the necessity of 2D-IR/3D-CT image registration.

More specifically, the 2D-IR/3D-CT image registration problem consists of finding the optimal 3D transformation parameters set \( \mu \) which is applied on a CT image of the target object, so that the given IR image can be aligned with the simulated 2D image obtained from the transformed CT image, see Fig. 1.

To the best of our knowledge, an image registration based on IR and CT images for industrial inspection application has never been given in the literature. The different imaging procedures of IR and CT bring up a high degree of difference between the two images, and thus resulting in significant difficulty in the spatial transform process. In addition, though there are a few methods for the general multi-modality registration, they are specifically developed for medical imaging applications. Therefore, to show that the proposed registration scheme works for NDE, both theoretical and experimental verifications are needed.

This paper presents a review of the related works in section 2. Section 3 presents the system model, followed by experimental results in section 4. Conclusion is given in section 5.

2. Related Work

2D/3D multi-modality image registration is widely used in the medical area; therefore, quite amounts of works have been done in this area for different images pairs. For example, 2D ultrasound image with 3D CT image for endoscopic...
interventions [3], 2D portal image with 3D CT image for treatment setup verification in radiotherapy [4], and 2D X-ray image with 3D CT image for orthopaedic surgery routines [5]. A complete list of publications in 2D/3D multi-modality image registration has been given in [1]. However, in the literatures, there is still lack of real medical application that registers thermal IR image with CT image. In fact, medical thermography (digital infrared thermal imaging) plays an important role in breast pathologies and vessel disease diagnosis. The information fusion of IR and CT images will greatly facilitate the diagnosis process. However, its imaging procedure, which is based on body heat, decides that medical IR image can only show the rough structure of the patient’s body instead of the anatomical detail as CT does or functional detail as magnetic resonance imaging does. High degree difference between IR and CT images brings up the challenge of the registration between IR and CT images.

To measure the similarity of two images of different modalities in registration problem, information theory based methods show great reliability. It is originally from the Shannon entropy of an image [6]. For an image, its Shannon entropy \( H \) tells the average information contained in the image and is defined as

\[
H = \sum_i p_i \log_2 \left( \frac{1}{p_i} \right) \tag{1}
\]

where \( p_i \) is the probability distribution of the grey values of the image.

Woods et al. first introduced a similarity measure for multi-modality images based on the assumption that regions of similar tissue (and hence similar grey values) in one image would correspond to regions in the other image that also consist of similar grey values (though probably different values to those of the first image) [7]. This heuristic assumption is very important for the theory support of our new application.

Adapted from Woods’ measure, Hill et al. [8] constructed a joint histogram. A joint histogram is a two-dimensional plot that shows the combinations of grey values in two images for all corresponding points. Its pattern changes as the alignment of the images changes. When the images are correctly registered, corresponding structures overlap and the joint histogram shows certain clusters for the grey values of those structures. When the images become misregistered, structures will start overlapping with structures that do not correspond to them (skull overlaps with brain, brain overlaps with background). Consequently, the intensity of clusters decreases as new grey values combinations emerge. This shows up in the joint histogram as a dispersion of the clustering. From joint histogram, joint entropy is calculated as

\[
H = \sum_{i,j} p_{i,j} \log_2 \frac{1}{p_{i,j}} \tag{2}
\]

where \( p_{i,j} \) over \((i,j)\) is the joint probability distribution of grey values in two images. Joint entropy is suggested to be used as multi-modality images similarity measure by both Collignon et al. [9] and Studholme et al.[10]. It is low when the joint probability distribution has sharply defined peaks (which means two images are correctly registered), and it is maximal when the distribution is dispersed (which means two images are misregistered). Therefore, to register images is to find the optimal transformation that minimizes their joint entropy.

3. System Model

3.1 Mutual Information and Normalized Mutual Information

Joint entropy, a measure from information theory, shows great reliability for the registration of multi-modality images. Mutual Information (MI), which is proposed by Collignon et al. [11] and by Viola and Wells [12], is related to joint entropy by

\[
MI(A,B) = H(A) + H(B) - H(A,B) \tag{3}
\]

where \( H(A) \) and \( H(B) \) are the Shannon entropies of image A and B respectively, and \( H(A,B) \) is the joint entropy of them. It is maximized when image A and B are optimally registered. The advantage of MI over joint entropy is that it includes the marginal entropies \( H(A) \) and \( H(B) \) [6]. An improvement over MI is Normalized Mutual Information (NMI) which is defined by Studholme et al. [13] as

\[
NMI(A,B) = \frac{H(A) + H(B)}{H(A,B)} \tag{4}
\]

to solve the sensitivity problem against overlap changes.
Fig. 2: Example of generic aerospace casting data. (Left) A processed grey scale IR image, hollow arrows point at indications (drilled holes) on the casting, they are not part of the original image. (Right) A simulated 2D image obtained from CT.

The above-mentioned information theory based similarity measures all evolved from Woods’ assumption: regions (or structures) with similar grey values in one image would correspond to regions (or structures) in the other image that also consist of similar grey values, though probably different values to those of the first image since they are of different modalities. The inspected product in this application is a generic aerospace casting, as illustrated in Fig. 2, and all the images data is provided by General Electric. The upper parts of both images clearly show the subsurface detail of the casting air foil with high grey value representing metal and low grey value representing hollow air tunnels. Thus, though the IR image has lower resolution than the simulated 2D image which is obtained from CT, the condition for Woods’ assumption is well satisfied. However, the lower part of the IR image renders a quite homogeneous grey value while the simulated 2D image shows clear subsurface structure of the casting root. With part of the image satisfying Woods’ assumption, experiments needs to be conducted to verify that information based similarity measure is applicable for IR/CT registration.

3.2 Registration Scheme

The registration process is an iterative optimization process that seeks the optimal transformation parameters set \( \mu \) or equally, the optimal similarity measure value. At each iteration, the simulated 2D image is compared with the given IR image with similarity measure value calculated, and then \( \mu \) is updated based on this value. Fig. 3 illustrates the registration iterative scheme. Each component in the process is briefly described as following.

3.2.1 Transformation

Transformation parameters set is:

\[
\mu = [R_x, R_y, R_z, T_x, T_y, T_z]
\]

with first three parameters represent rotation in each dimension and the rest three represent translation in each dimension. Scaling factor is not considered since the registration of the casting images are rigid.

3.2.2 Interpolation

After the transformation, grey values at non-grid points are estimated by bilinear interpolation. Simulated 2D image is the projection of the transformed CT image along simulated thermal rays, and grey value \( g \) at each pixel is the line integral along the ray \( x \cos \theta + y \cos \beta + z \cos \gamma = \rho \); this is also known as Radon transform \([14]\)

\[
g = \sum_x \sum_y \sum_z f(x, y, z) \delta(x \cos \theta + y \cos \beta + z \cos \gamma - \rho) \quad (5)
\]

where \( f(\cdot) \) is the grey value of transformed CT image at \( (x, y, z) \), \( (\theta, \beta, \gamma) \) is the angel of the ray, and \( \rho \) is the distance from the origin to the ray. The right side of (5) is zero unless the argument of impulse function \( \delta \) is zero, indicating that the integral is computed only along the ray \( x \cos \theta + y \cos \beta + z \cos \gamma = \rho \).

3.2.3 Similarity measure

NMI is used in this scheme as the similarity measure as defined in (4).

3.2.4 Optimizer

Optimizer controls the registration scheme to converge towards the optimum via iterations. At each iteration, optimizer updates every transformation parameter separately based on the NMI value. When the stopping criterion is met, optimizer stops and returns the final optimal transformation parameters set. Gradient descent optimization is used in this scheme to maximize objective function \( NMI(\mu) \).

At \( k^{th} \) iteration, transformation parameters set is specified as

\[
\mu^k = [R_x^k, R_y^k, R_z^k, T_x^k, T_y^k, T_z^k]
\]

in which parameters are updated one by one. Take \( R_x \) for example, to decide its step length, let \( \varepsilon \) be a small number,
and 
\[
\mu^k(\varepsilon) = [R_x^k + \varepsilon, R_y^k, R_z^k, T_x^k, T_y^k, T_z^k]
\]
\[
\mu^k(-\varepsilon) = [R_x^k - \varepsilon, R_y^k, R_z^k, T_x^k, T_y^k, T_z^k]
\]

Then, the gradient of NMI over \(R_x^k\) is determined by
\[
\Delta_k = \frac{NMI(\mu^k(\varepsilon)) - NMI(\mu^k(-\varepsilon))}{2\varepsilon \cdot \lambda}
\]
(6)

where \(\lambda\) is a factor to balance the effect between rotation parameters and translation parameters. Take steps proportional to the gradient, and thus \(R_x^k\) is updated by
\[
R_x^{k+1} = R_x^k + \alpha_k \cdot \Delta_k
\]
(7)

where \(\alpha_k \cdot \Delta_k\) is the step length with \(\alpha\) being a constraint factor. The rest five parameters are updated in the same way in the \(k^{th}\) iteration.

Optimization involves some crucial factors, and they can greatly affect the convergence. For example, \(\varepsilon\) is generally a small number, but if it is too small, though the step direction will be more precise, the convergence speed will be very slow; the usage of \(\lambda\) is to balance the effect of one unit of rotation parameter (radian) and one unit of translation parameter (pixel), and \(\alpha\) decreases as the iterative process goes on so that the step length can be more and more accurate. In this paper, experiments are used to determine these values.

4. Experimental Results

With the registration scheme and NMI similarity measure that are introduced in the previous section, experiments are carried out to verify that they can register 2D IR image with 3D CT image of the generic aerospace casting.

4.1 Data Preparation

Before acquiring the image data, several holes are physically drilled into the casting. They are visible in both modalities as indications to evaluate the transformation results. An infrared thermal camera renders pseudo color IR images, which, before registration starts, need to be mapped to grey scale IR images. CT images are down scaled so that the simulated 2D images have the same spatial resolution as IR images, i.e., \(0.6 \times 0.6mm^2/pixel^2\).

After this, the registration scheme as illustrated in Fig. 3 is performed on the data.

4.2 Single Initial Set

To facilitate the iterative procedure of (6) and (7) from the 1st iteration, an initial transformation parameters set is needed. Since grey scale IR image and CT image are given and we know how they are set up in the coordinate system, as shown in Fig. 1, it is not difficult to give a close initial set based on physical observation. Take the IR image in upper right corner of Fig. 1 for example, if we first rotate the CT volume by about 90° counterclockwisely along x-direction based on right-hand rule, and then rotate it by about 180° counterclockwisely along z-direction, the projection of transformed CT image would be close to the given IR image. This is how initial transformation parameters set is estimated and determined.

For each data set, once an initial transformation set is determined, the spatial error \(d\) can be computed as
\[
d = \frac{1}{N} \sum_{i=1}^{N} \| M_i(T) - m_i \|
\]
(8)

where \(N\) is the number of drilled holes that are visible in IR image, \(M_i\) is the hole’s location in 3D CT image, \(m_i\) is the location of the same hole in 2D IR image, and \(T\) represents the transformation and projection operation. Error \(d\) is used to evaluate the transformation parameters sets, and it is not what drives the optimization. The optimization starts from the initial transformation parameters set and keeps updating \(\mu\) until the stopping criterion \(\alpha_k \approx 0.001\) is met, this is when \(\mu\) barely steps forward. Stopping criterion is an experience value too.

Parameters results are listed in Table 1 for data set 1 (Fig. 4(a)) and data set 2 (Fig. 4(c)). As shown in the "NMI" column, optimizer did increase the similarity value from around 1.1 to 1.2, and at the same time, error \(d\) decreases to around 4 pixels which equals to 2.4mm. Compared to the physical size of the casting that is used in the experiments.
Table 1: Results from one intial transformation.

<table>
<thead>
<tr>
<th>Dataset1 initial µ result</th>
<th>$R_x$ (degree)</th>
<th>$R_y$</th>
<th>$R_z$</th>
<th>$T_x$ (pixel)</th>
<th>$T_y$</th>
<th>$T_z$</th>
<th>NMI</th>
<th>$d$ (pixel)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dataset2 initial µ result</td>
<td>90.01</td>
<td>0.81</td>
<td>269.96</td>
<td>-6.25</td>
<td>-22.79</td>
<td>-5.53</td>
<td>1.21</td>
<td>3.98</td>
</tr>
</tbody>
</table>

(Height $\approx$ 120mm, length $\approx$ 70mm and width $\approx$ 46mm), the error $d$ is very small and acceptable.

As mentioned in the previous section, several factors (such as $\lambda$ and $\alpha$) can greatly affect the accuracy and speed of the optimization convergence. However, in this experiment, we focused on the realization of the new application, and therefore they are not our major consideration. Their values are from repeated experimental experience.

Generally, unless both the objective function NMI and the feasible region of $\mu$ are convex, there may be several local maxima. A large number of optimization algorithms, including gradient descent, fail to differentiate between local optimum and global optimum. Besides, factor $\alpha_k$ constrains the step length, and it is possible that $(\alpha_k \cdot \Delta_k)$ reduces to zero before $\mu$ reaches any maxima especially when the initial set is too far away from the maxima. Based on these observations, the transformation result derived from a single initial set may not be the true answer, thus multiple initial sets should be utilized to ensure a global optimum is obtained.

4.3 Multiple Initial Sets

Different initial sets are reasonably determined for each data set by observation. After registering, the obtained transformation parameters sets are analyzed by calculating the mean values and standard deviations $\sigma_i$, ($i = 1 \cdots 6$) for each parameter.

If $\sigma_i = 0$, ($i = 1 \cdots 6$), it means that, starting from different initial sets, every parameter in $\mu$ converges at the same result which is exactly the true answer. Therefore, minimizing $\sigma$ or forcing parameters to converge to narrow ranges is our goal in this part of the experiment.

In order to decrease $\sigma_i$ for every parameter, for those derived transformation parameters that are still far away from the mean values, what we can do is: re-start the registration process from where they stop and force them start to step towards the true maxima again until $\sigma_i$ is relatively close to zero. This is called intermediate perturbation.

For both data set 1 and data set 2, 10 initial transformation parameters sets are chosen respectively, and after registering with necessary intermediate perturbation, 10 transformation parameters sets are derived for each data set and their statistics are listed in Table 2. In both cases, all rotation parameters converge to a narrow range with $\sigma$ less than $1^\circ$. As for translation parameters, $T_z$ performs very well in both cases, however, $T_x$ has relatively large variation especially for data set 2. This phenomenon can be explained as follows.

For data set 2, after the rotation transformation, the simulated thermal ray came from the x-direction, and therefore translation along x-direction ($T_x$) will make no difference to the projection image. Compared to $T_z$, variation of $T_x$ is easier to be captured by NMI similarity measure.

With acceptable variation on rotation parameters and reasonable variation on translation parameters, we consider the mean of 10 derived transformation sets to be the final answer. Last column in Table 2 gives the error $d$ of mean transformations and Fig. 4(b), Fig. 4(d) show the simulated 2D image from mean transformations. Both data sets have around 4 pixels average error over 4 and 3 visible holes respectively, which is equivalent to 2.5 millimeters.

5. Conclusion

Driven by the constant need for better and robust NDE applications along with unique data sets and information theory based similarity measure for multi-modality image registration; this paper presents a registration scheme for 2D IR and 3D CT images of generic aerospace castings. Experi-
mental results are very promising, since they show that with proper initial transformation sets and necessary intermediate perturbation, this proposed method can successfully register a 2D IR image with a 3D CT image and achieve a spatial resolution of 2.5 mm. This resolution meets the requirements of casting inspection.

The heuristic assumption of Woods et al., from which Normalized Mutual Information is evolved, forms the foundation of this paper. However, given that the casting data sets only partially satisfy the assumption and there is a high degree imaging difference between IR and CT make the registration error inevitable. Considering that, optimization is a sophisticated problem itself and is currently out of scope of our focal point, the multi-modality image registration on NDE application offers plenty of room for improvement in the future.

References


