A novel Approach of Image Registration Based on Normalized Dissimilarity Index

Amina Kharbach, Amar Mardani, Ouiam Jelti, Benaissa Bellach, Mohammed Rahmoune, Mohammed Rahmoun

Abstract—Image Registration is a fundamental task in image processing used to match two or more pictures taken at different times and from different sensors. A various registration measurement have been developed for different types of problems. In this paper we present a novel registration approach based on normalized dissimilarity index which is resulting from local dissimilarity map that is a useful means to compare images. We compared its quality to classical registration measurements (Correlation and Mutual information) carried out on both binarized and grey-level images. We obtained good results for the two types of images. We showed afterwards the robustness of the proposed measure against the pepper and salt and Gaussian noise. We applied finally our registration approach on a medical images database on which we confirmed that the accuracy of alignment error estimation is improve compared to classical registration methods.

Index Term—Correlation, images registration, local dissimilarity map, mutual information, normalized dissimilarity index.

I. INTRODUCTION

IMAGE registration is an important tool in different fields. Its applications are various in many situations in order to analyze the objects behavior and to follow the localization of dissimilarity between images [1] [2]. The accuracy of an alignment offers new possibilities of treatments, for example, medical images often yields additional clinical information not apparent in the separate images. For this purpose, the spatial relation between the images has to be found. Image registration is the task of finding a spatial one-to-one mapping from pixel in one image to pixel in the other image. The registration term appeared during the course of the Seventies. There has great deal about it in the literature.

The alignment approaches based on the intensities of the images were introduced by Woods in 1992 [9]. Multimodal registration was then carried out by minimizing the variance of the ratios of image intensity. Immediately afterwards, Hill introduced the concept of joint histogram [10]. Van den Elsen published a registration method by gradients correlation [11]. Collignon [12] proposed to use the entropy like registration measures. The same year, Viola and Collignon find simultaneously an approach based on mutual information [3] [13] [8]. Each technique has advantages that make it attractive for many applications but it has also disadvantages that potentially may limit its applicability [1]. Our work is concerned with finding a rigid registration, it presents a novel approach to image registration basing on normalized dissimilarity index. Our measure is based on the local dissimilarity map which allows to localize and quantify differences between two images. This map was proposed by Etienne Baudrier and Frederic Morain-Nicolier [4] [5], and it presented a research subject of some works where the authors use it to evaluate the accuracy of image alignment [17] or to correct sampling problems in tomography volumes acquisitions [6].

This paper is organized as follows. Section 2 introduces registration concepts and presents the classical registration measures. In section 3, we give our index based in distance transform and we present the results of simulation with discussion. Finally, we give a conclusion.

II. CLASSICAL REGISTRATION MEASURES

Registration is carried out by transforming an image and measuring corresponding pixels similarity between two images. Generally, its framework is shown in Figure 1. In this paper we propose two images I\(_1\) and I\(_m\) with the same size. The first one presents the reference image and the second I\(_m\) is the moving one. We consider T\(_m\) the transformation that makes I\(_m\) spatially aligned to I\(_1\) with the parameter vector contains one rotation angle and the translations in x and y direction. Commonly, the registration problem is formulated as an optimization problem in which the similarity function is minimized:

\[
T_{\mu} = \text{argmin} - S(T_1, T_\mu (I_m))
\]  

(1)

Where S is a metric or similarity measure that defines the quality of alignment.
After $T_{\mu}$ is determined, it is applied to the moving image to produce the registered moving one which is then compared to the reference image in order to test if the registration process is performed.

In this work, we take an interest in the registration measure. Several choices can be found in the literature[18]. Correlation and Mutual information are the most successful techniques for registering images. These measures are described below:

A. Correlation

Maximizing Correlation function can be used to determine how to align the images by translating one of them. It general equation is defined by:

$$\text{Corr}(I_f, I_m, \mu) = \sum_{x \in \Omega} I_f(x) I_m(T_\mu(x))$$

Where $\Omega$ is the domain of the fixed image, in our case only of rigid transformation (rotation and displacement) will be considered. The function of correlation varies according to the common surface between the fixed and moving images. More this surface is large, more the correlation will be important, but if the images are superposed on a small surface, the correlation will be weak. In other to avoid this situation, there exists the normalization of correlation function that is given by:

$$\text{CorrN}(I_f, I_m, \mu) = \frac{\sum_{x \in \Omega} I_f(x) I_m'(T_\mu(x))}{\sqrt{\sum_{x \in \Omega} (I_f(x))^2 \sum_{x \in \Omega} (I_m'(T_\mu(x))^2)}}$$

Where:

$I_f'(x) = I_f(x) - \bar{I}_f(x)$ and $I_m'(T_c(x)) = I_m(T_c(x)) - \bar{I}_m(T_c(x))$

with $\bar{I}_f(x)$ respectively $\bar{I}_m(T_c(x))$ are average values of two images. To maximize the performance of index correlation Corr(T), its derivative should theoretically be cancelled. In practice, the research of the maximum can be done by digital methods that optimize each dimension until there is convergence.

B. Mutual information

Mutual information is the information quantity of an image contained in a second one. Images are identical when their mutual information reached the maximum value. So, to try to transform an image more similar to the second one can thus be done by maximizing their mutual information. It defined as follows:

$$\text{MI}(I_f, I_m) = H(I_f) + H(I_m) - H(I_f, I_m)$$

Where $H(I_f)$ respectively $H(I_m)$ present the entropy measure which describe the amount of information of fixed and moving images. It is expressed by:

$$H(I_f) = \sum_{a \in I_f} p_a(a) \log p_a(a)$$

Respectively

$$H(I_m) = \sum_{b \in I_m} p_b(b) \log p_b(b)$$

Where $p_a(a)$ is the probability that a pixel of image $I_f$ has the value $a$ and $p_b(b)$ is the probability that a pixel of image $I_m$ has the value $b$.

The common information of $I_f$ and $I_m$ that measures the quantity of information brought at the same time can be expressed as:

$$H(I_f, I_m) = \sum_{a \in I_f} \sum_{b \in I_m} p_{ab}(a,b) \log p_{ab}(a,b)$$

Where $p_{ab}(a,b)$ is the probability that a pixel of image $I_f$ has the value $a$ and $b$ in $I_m$.

The maximization of mutual information is well adapted to multimodal registration. Indeed, if two images represent the same anatomical structure there will have mutual information between them. Contrary to the correlation method which supposes that the images to be aligned have similar intensities.

$$\text{NMI}(I_f, I_m) = H(I_f) + H(I_m)/H(I_f, I_m)$$

The maximum of this similarity measure is reached when images are identical. Registration images can thus be done by maximizing their mutual information. Its normalization is proposed by using a fraction of two terms depending on the common surface of the two images (equation 8).

Correlation and mutual information are frequently used functions to measure similarity between two images. Generally, the mutual information treats the general dependence, while the correlation function measures the linear one. In this context, we propose in the next section a novel dissimilarity measure that we use it to image registration.

III. PROPOSED METHOD

In this article we follow a novel approach to the image registration problem. The idea is to build a scalar that represents the dissimilarity between two images to be aligned and to apply then the transformation research algorithm by its minimization. This scalar is a simple quadratic summation of local measurement resulting from Local dissimilarity map which treats not only binary images but also gray scale ones.

A. Binary images

For binary images, the intensity information is weak and the form extraction is often difficult. Consequently, binary images must be compared without using the extraction characteristics, the local dissimilarity map (LDM) is a useful means to
compare two binary images by offering a quantification and localization of information [4].

It can be calculated from:
- Algorithm based on Hausdorff distance
- Algorithm based on the transform of distance

In our case, we based on the second algorithm thanks to its simplicity of implementation and its speed in time. It is generally calculated from the following equation:

$$LDM = I_f * td(l_m) + I_m * td(l_f)$$

(9)

Where \(td\) is the transform distance of the image that makes possible to know the distance between a given pixel and the nearest one[19]. Here is an example illustrating the effectiveness of the LDM for the localization of the difference between two binary images.

From this example we could detect the difference existed in this game without segmentation that gives an absolute value to a given moment and does not take into account the evolution of the structures through the time. Our proposed index is based on local dissimilarity map and it is normalized as follows:

$$NI_{l_{dm}} = \sqrt{2} * \sqrt{\sum_p (LDM(p)/N * M)^2}$$

(10)

The product \(N*M\) presents the size of local dissimilarity map.

In order to follow the evolution of the suggested index compared to the transformation and to prove its effectiveness in registration. We considered at first a binary image and we applied on it a series of rotation varied from 0 to 360 degrees.

In this example (figure 3) the normalized dissimilarity index corresponds to the ideal registration when it tends towards zero, this leads us to deduce that by minimizing this dissimilarity scalar we will obtain an exact alignment.

B. Gray-scale images

The dissimilarity index that we employ to register binary images, can be also formulated with transform distance extensions for gray-scale images [20]; Two approaches are retained: Gray weighted distance transform (GWDT) where the selected distance is defined by the weighted sum of the gray scale along the discrete way connecting two points and Weighted distance transform on curved space (WDTOCS) where the distance in this case is defined as the length of smallest geodetic way between these two points.

In our case we are based on weighted distance transform algorithm because of its simplest implementation and its fastest execution time.

In order to envisage the behavior of our method basing on GWDT, we generated curves to have its effectiveness in grayscale images registration. For that the image of Lena (figure 4) is aligned with the same image undergoing a series of rotation without translation. In return, we note that the progression of the dissimilarity index value for various rotations is very regular and does not introduce local minimum, moreover its minimum show clearly the ideal transformation.

In the next section, we analyze the performance of the local dissimilarity index compared to the principal classical approaches presented previously.

IV. RESULT AND DISCUSSION

The validation is an important step to determine the precision and the accuracy of the suggested method. In this section, we evaluate the behavior of the local dissimilarity index compared to the mutual information and the correlation, we evaluate then its validity on registration algorithm applied on the binary and grayscale images.

A. Validity of proposed index robustness

In this section, we compare the local dissimilarity between the binarized and the gray-scale images. We validate then the robustness of the local dissimilarity index compared to the
mutual information and the correlation by applying series of modifications (luminance variation and noise) on models of images.

1. **Comparison between gray scale and binary images index**:

We deprive image of a great quantity of information. For that, we decomposed at first the reference image (human brain) by using Aujol-Chambolles algorithm [14] that splits an original image into three components: Structures, textures and noise. Their assumption is to consider noise as a distribution modelized by the Besov space[16].

Second, we identified structure edges with a Canny edge detection filter. Thresholds for Canny edge detection are adaptively selected using binary search to have approximately the same number of edges in each image. The number of edge points is controlled by changing the upper and lower values of the threshold parameters in the edge detector. The figure 5 presents an example of obtained results by implementing Aujol-Chambolles algorithm and Edge detection by Canny method.

Third, we applied a simple translation from [-3 -3] to [+3 +3] on the original image, we got results in figure 6. It illustrates studied registration measurements compared to the translation variation. These curves are very good tools to envisage the behavior of a minimum/ maximum search algorithm. Notice that our proposed index behaves like the others functions.

![Fig. 5. Aujol-Chambolle’s Algorithm implementation results and Edge detection by Canny method for human brain image. (a): Reference Image, (b): Structure, (c): Texture, (d): Noise, (e): Edge of structure.](image1)

![Fig. 6. The similarity/dissimilarity measurement behavior of original human brain image compared to the translation variation. (a): Normalized local dissimilarity index compared to the translation variation, (b): Normalized Mutual information compared to the translation variation, (c): Normalized correlation compared to the translation variation.](image2)

Their maximum/minimum show clearly the ideal alignment that answers to our research assumption (Employing our approach like registration means).

By comparing values resulting of the three alternatives applied on the untreated image and that which has undergoes a pretreatment, it is noticed that the behavior of our index remains stable even if that we deprived the original image by a great quantity of information. The curve in figure 8 illustrates clearly this study that allows to reduce the computing time of the registration algorithm by using the local dissimilarity index in binary images.

2. **Index robustness compared to an object’s luminance variation**:

In order to envisage the behavior of our method, we generated curves to have its effectiveness compared to the various registration measurements described above according to two cases:

a. **Images of identical intensity**

An evolution carried out on image database representing the behavior of a clock. By comparing different registration functions illustrated on the figure 8, we would point out that this example shows clearly the effectiveness of our measurement compared to the other studied methods. Indeed, the normalized dissimilarity index is evaluated in a regular way, and its minimization provides good result. Also let us note that correlation algorithm appears as a good choice for monomodal registration even if it presents certain vibration. However the approach based on the maximization of mutual information appears less adapted in this test.

![Fig. 7. Normalized dissimilarity index behavior compared to the translation variation. (a): Normalized dissimilarity index behavior of original human brain image, (b): Normalized dissimilarity index behavior of binary edge structure of human brain image.](image3)

![Fig. 8. The evaluation of a clock behavior by comparing different registration functions. (a): Clock example, (b): Normalized dissimilarity index curve, (c): Normalized mutual information measure curve, (d): Normalized correlation values compared on time.](image4)
b. Objects of non identical brightness

By carrying out the same test on an image series having different gray tons (figure 9), correlation function shows that the result is not the same and it depends on tons used, its value is increased by increasing the intensity that is directly due to the dominating force of pale tons compared to dark one, what stresses that correlation depends on aligned gray tons intensity. Contrary, mutual information and normalized dissimilarity the index remain unchanged if we change form gray tons which we try to align. This result is a good proof of the higher quality of suggested index and mutual information than correlation in different gray tons registration.

In this section, we reproduce as comparison curves illustrating the evolution of the three alternatives applied to two image of reversed tons undergoing, this time, translation from [-4 -4] to [+4 +4], the first image shows a circle having 233 as value, the second image is the same one with a reversed intensity (figure 10). We note that the maximum of our approach shows clearly the ideal transformation, we notice also that the Normalized Mutual information behavior marks a relative change if we change gray level of the form. This result is very good indicator of the higher quality of our proposed index and the mutual information measurement compared to the correlation which was ineffective; Its maximum presents a ring of the maximum values around ideal registration that corresponds to the overlapping of the gray areas. This test presents the monomodal registration difficulty by maximization of correlation. According to these results we can deduce that the normalized dissimilarity index is reliable and robust in spite of the presence of a great variability in the image data.

Fig. 9. The evolution of registration functions behavior on a image series having different gray scales. (a) : Circle image example, (b) : Normalized dissimilarity index curve compared to intensity, (c) : Normalized mutual information measure curve compared to intensity, (d) : Normalized correlation values compared to intensity.

Fig. 10. The evolution of studied functions on two images with reversed gray-scale. (a) : Circle with intensity = 233, (b) : Circle with intensity = 22, (c) : Normalized local dissimilarity index for image 1, (d) : Normalized local dissimilarity index for image 2, (e) : Normalized mutual information for image 1, (f) : Normalized mutual information for image 2, (g) : Normalized correlation function for image 1, (h) : Normalized correlation function for image 2.

3. Noised images:

In order to study the behavior of our approach facing the noise, we have to try to register the Lena image with the same noised one and round it by a step of 30. The noise is here pepper and salt with density equal to 0.02 and Gaussian with default mean and variance equal to 0.02. By varying the rotation parameter, the normalized dissimilarity index minimum always indicates the ideal transformation. By increasing the pepper and salt noise density to 0.5, the minimum of our measure continues to indicate the ideal transformation. This measurement thus appears to be rather robust with the noise (Figures 11-12).

We note that the local dissimilarity index is evaluated in a regular way in spite of Gaussian noise (figure 12).
B. Validity of the registration algorithm

Image registration algorithm is based on two essential points:
- The choice of similarity/dissimilarity measure that will determine the degree of alignment between the reference image and the transformed floating image.
- The transformation Optimization function until stopping criterion is met.

In this work we applied the normalized dissimilarity index as our chosen metric, and we used the Powell method [21] as our optimization technique for research of maximum. This algorithm enabled us to determine quickly ideal registration and it was used to find the maximum value(or minimum value) for the transformation.

On the following example (Figure 13), the obtained result by our registration algorithm applied to binary images turns over \([dx = 0; dy = 37; d\theta = 0]\) that presents the optimal transformation (expected result). It is evident that two images (fixed and moving) are geometrically and spatially aligned, yielding a correctly registered image.

Accuracy is one of the most important properties of registration method. Its validation of is generally not an easy task. In our case, validation approach was used to evaluate the performance of registration algorithm basing on normalized dissimilarity index compared to the same algorithm based on correlation and mutual information metrics. In addition, an evaluation on JSRT Digital Image Database (Digital Chest X ray database with images containing pulmonary nodules) is proposed (figure 14).

The average quadratic error percentage of our registration algorithm was calculated for each studied measurement on thirty transformations between -30 and 30 pixels and with rotations between -20 and 20 degrees.

The figure 15 and table 1 present the X-ray images results.

<table>
<thead>
<tr>
<th>Similarity measurement</th>
<th>Median</th>
<th>Average</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>NLDM</td>
<td>0.1605</td>
<td>0.0472</td>
<td>0.0472</td>
</tr>
<tr>
<td>NMI</td>
<td>1.7686</td>
<td>1.9565</td>
<td>0.7556</td>
</tr>
<tr>
<td>NCorr</td>
<td>1.1285</td>
<td>0.9591</td>
<td>0.9887</td>
</tr>
</tbody>
</table>

**TABLE I**

Statistical measurements of The quadratic error percentage of our registration algorithm for each studied measurement.
The registration algorithm based on our method allows to reach a remarkable precision compared to the others approaches. The maximization technique of correlation also provides good result whatever its performance is slightly lower than that of the normalized dissimilarity index. Let us note here also that the maximization approaches based on mutual information appear less adapted. These methods were conceived for the multimodal and no rigid registration on the most recent work.

We finally present an registration example for a sequence of the same image database. Let us note that we brought to reduce the quantity of information by binarizing images using a adaptive thresholding from a defined threshold. We carried out the same test described previously; the results are summarized in the following figure.

Fig. 16. Robust registration JSRT Image Database after binarization step.(a):Reference Image, (b) : Transformed Image(rotation: 7,translation: 15 pixels), (c) : Registered image, (d) : Difference between (a) and (c).

By comparing the images in figure 16, we note that our technique gives satisfactory results and it is adaptable for both gray-scale and binary images.

V. CONCLUSION

In this paper we present the quality of our suggested approach compared to various registration measurements: Mutual information and Correlation. By carrying out tests, we note that the Normalized dissimilarity index is a good tool for images registration and it does not require segmentation operating system that would allow it to entirely automate the procedure and would bring a very appreciable time-saver to the user. Finally, we underline that the proposed approach is general and it is not limited to gray-level images. As perspective, we plan on proving that their binarization allows to reduce the calculation time of registration algorithms.

REFERENCES


Amina Kharbach (a.kharbach@ump.ac.ma) graduated from ENSAO (National Higher School for Applied Science, Oujda) with a degree of state engineer in telecommunication and network in 2008. She is currently a Ph.D. candidate at LSE2I-Laboratory/ Mohammed First University of Oujda under the supervision of Pr. Mohammed Rahmoun and Pr. Benaissa Bellach. Her research activities focus on the local dissimilarity map functionality , by building a measurement allowing registration between images. She has served as a reviewer for several international conferences and journals.

Amar Merdani (merdani.amar@yahoo.fr) received his B.Sc. degree in Electronics and computing from Moulay Ismail University (2003, Morocco), and his M.Sc. in Electronics and telecommunications from Mohammed First University of Oujda (2010, Morocco). He is currently a Ph.D. candidate at LSE2I-Laboratory/ Mohammed First University of Oujda under the supervision of Pr. Mohammed Rahmoun. His main field of research interest is segmentation of medical image and measuring the quality of the result obtained by a segmentation algorithm.

Benaissa Bellach (benaisssa.bellach@gmail.com) received the M.Sc. degree in Electrical Engineering and Automation at the University of Science and Technology of Montpellier (1999,France) and Ph.D. degrees in Instrumentation and Computer Image from the University of Burgundy in 2000 and 2003, respectively. He is a professor at the National Higher School
Mohammed RAHMOUN (mohalrahmoun@gmail.com) is the head of Electronics Department, Computer Science and Telecommunications, he is the Coordinator of the die Electronics Engineering and Computer Engineering. He is the director of laboratory of electronic systems, computer and image (LSE2I) in National School of Applied Sciences, Mohammed first university, Oujda, Morocco. His current research interests include Digital Signal Processing, Intelligent Systems and Industrial Process Control.