A Novel Similarity Measure to Evaluate Image Correspondence

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Abstract. We have developed a novel similarity measure to evaluate image correspondence. Our method is based on the mutual information between images. The main difference to other mutual information approaches is that we incorporate spatial information using grey-level co-occurrence matrices, leading to a more robust measurement. We have used this technique to evaluate three registration algorithms, which use affine and thin plate splines transformations, applied to a dataset of mammographic images.

1 Introduction

In many computer vision applications, a comparison between images is needed (i.e. medical imaging, remote sensing) but, most of the time, this comparison can not be done by direct subtraction of images. Instead, a registration algorithm is used, which applied to a set of images, deforms the target image trying to match the reference image. Once alignment between the images has been achieved, a direct subtraction can be done, leading to smaller errors. This approach provides a way to detect changes in objects between the set of images. Many different methods have been proposed in the literature (see [1] and [2] for a general overview). A registration method is characterised by different aspects: a feature space (i.e. raw pixel, edges), a similarity measure between these features (i.e. correlation, squared error, mutual information) and a search strategy to find a efficient way to match these features.

In digital mammography, as in many other fields in computer vision, there is a need to evaluate the accuracy and robustness of a proposed algorithm for a specific application. In this paper we propose a novel evaluation technique, based on the work developed by Bello and Colchester [3], which uses mutual information to compute a similarity measure between images. In our approach, we have extended the mentioned work by using spatial information provided by grey-level co-occurrence matrices. We have used this technique to evaluate the accuracy of three registration algorithms (local affine transformation [1] affine transformation using mutual information and thin plate splines [4]). Such techniques can be used for the detection of abnormal structures in mammography by comparing mammographic images from the same patient obtained at different times.

2 Image Registration

The main purpose of image registration is to recover a deformation in corresponding images. Therefore, this process is shown as a mapping between two images (I_1 and I_2),

$$I_2(x_2, y_2) = I_1(f_x(x_1, y_1), f_y(x_1, y_1)) \tag{1}$$

where f_x, f_y are the deformation functions which map spatial coordinates $I_1(x_1, y_1)$ to coordinates $I_2(x_2, y_2)$.

We can classify registration algorithms taking different aspects into account. First, complexity of deformation, refers to what kind of deformation our algorithm can deal with. For example, a rigid body deformation only takes into account rotation and translation. Affine transformations extends rigid body deformations by adding scaling and shearing capabilities. The most complex deformation is a non-rigid transformation, where pixels can move independently. Another classification of algorithms refers to whether the deformation parameters are computed from the whole image (global) or from a subset of pixels (local). Although local algorithms are computationally costly, they give better results dealing with non-uniform deformations. We describe two local registration algorithms, both of them use landmark (control) points to obtain the deformation parameters, and a global method based on mutual information measure. We use affine transformation with local and global approaches. The local method solves the parameters of the deformation function for each pixel using its three closest control points. On the other hand, the global approach computes affine parameters by minimising a cost function based on a similarity measure, mutual information which is explained in the next section. The thin plate splines method, popularised by Bookstein [4], deals with local non-rigid transformations. It uses thin plate splines to solve mapping between 2D points by minimising a measure of bending energy of a thin plate surface.

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3 Similarity Measure

As explained in the introduction, having a large number of registration algorithms, we have to be able to select the most suitable technique for a particular application. In this section we analyse a novel similarity measure based on mutual information [3]. Mutual information has proved to be very efficient in measuring spatial correspondence between objects and it has been used as a basis of multi modal registration algorithms [5] [6]. Our approach uses mutual information in combination with grey-level co-occurrence matrices (GLCM). GLCMs are widely used in computer vision where they have obtained satisfactory results as texture classifiers in different applications [7]. By using GLCM we obtain more information about similarity between two images as GLCMs incorporate spatial information.

3.1 Mutual Information

Mutual information (MI), based on information theory concepts, measures the amount of information we can obtain from one random variable (A) relative to another random variable(B). This measure is related to the entropy of the variable distribution and in its normalised form it is determined by,

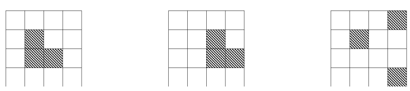
$$\overline{C(A,B)} = \frac{\sum_{i,j} p_{AB}(i,j) \log \frac{p_{AB}(i,j)}{p_A(i)p_B(j)}}{\sum_i p_A(i) \cdot \log \frac{1}{p_A(i)}} \tag{2}$$

where p_A, p_B are the marginal distribution of the random variables A and B, respectively, and p_{AB} is their joint distribution. Applied to images, each image is identified as one random variable, therefore we can determine the similarity of one image to another by using Eq. 2. In this case, probabilities are obtained from normalised marginal and joint histograms.

3.2 Including Spatial Information

The MI similarity measure, previously discussed, is based on the grey-level histograms of both images. As histogram does not provide any spatial information about the pixels of an image, we believe the use of another metric (instead of histogram information) which will take spatial information into account resulting in a more robust similarity measure. We propose to use grey-level co-occurrence matrices (GLCM), which are defined by the grey-level co-occurrence between pixels within an image taking a particular translation into account. Each position (i, j) of the GLCM contains the number of pixels with intensities i and j, where the pixels are separated by translation t. Usually, more than one GLCM is computed using various translations t.

We propose to calculate the amount of MI between images using their GLCMs instead of using their histogram distribution. To indicate the validity of this approach, lets consider the following example. In Fig. 1 we have three images. Using (a) as the reference image, we want to measure the similarity between images (a) and (b) and between (a) and (c). By visual inspection, we would say that (b) is more similar to (a) than the image (c). If we calculate the amount of MI using intensity histograms, we obtain the same value of 0.0298 for (a)-(b) and (a)-(c). This is because the joint histograms between images are exactly the same. On the contrary, using our GLCM approach with a translation of 1 pixel and four different orientations, we obtain a mean similarity of 0.4284 for (a)-(b), while for (a)-(c) we obtain 0.2375, which indicates that (b) is more similar to (a) than (c).



(a) (b) (c)

Figure 1. Example of local image structure to demonstrate the validity of the proposed similarity approach (see main text for explanation)

Our approach is based on the computation of the joint GLCM structure. We build a four dimensional matrix where each position (i, j, k, l) contains the number of pixels which intensities are (i, j) from the reference image and (k, l) from the other image, in addition the distance between pixels i and j and between pixels k and l is the same and defined by the translation and orientation GLCM parameters. From this joint GLCM we can obtain the marginal GLCM, the GLCM of each image,

$$G_A(i,j) = \sum_{k,l}^{K,L} G_{AB}(i,j,k,l) \tag{3}$$

$$G_B(k,l) = \sum_{i,j}^{I,J} G_{AB}(i,j,k,l) \tag{4}$$

where G_{AB} is the joint GLCM and G_A and G_B are the marginal GLCM of the images A and B, respectively. The MI measure is obtained as a four dimensional extension of Eq. 2

$$C_{GLCM}(A,B) = \frac{\sum_{i,j,k,l} G_{AB}(i,j,k,l) \log \frac{G_{AB}(i,j,k,l)}{G_A(i,j)G_B(k,l)}}{\sum_{i,j} G_A(i,j) \log \frac{1}{G_A(i,j)}} \tag{5}$$

3.3 Validation

We have carried out two experiments to demonstrate the validity of our approach. Fig. 4a shows the evolution of the MI measure, using histogram and GLCM approaches, between two images as a function of a translation performed on the second image. Compared with intensity histogram approach, we obtain higher similarity values and a slightly closest to linear behaviour of the curve. Fig. 4b shows results of applying additive noise to one of the images. We obtain a more robust measure dealing with noisy images.

The computation of the four dimensional GLCM is time consuming, therefore we have studied the possibility of reduce the number of gray levels as this is strongly related to computational cost. Results are shown in Fig. 2 , where we plot the error measure obtained in different images using 8, 16 and 32 gray levels, taking 64 gray levels as reference. Using 32 gray levels we obtain acceptable accuracy while the computation time is reduced considerably .

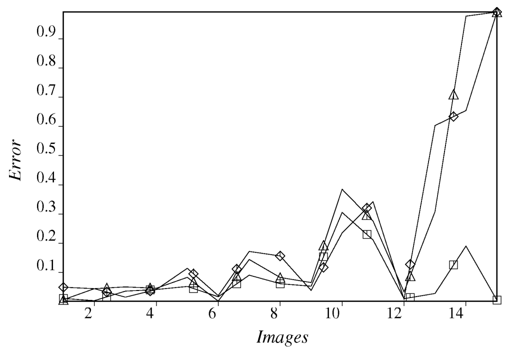


Figure 2. Error related to 64 gray levels (a) with ◇ 8, △ 16, and □ 32 gray levels

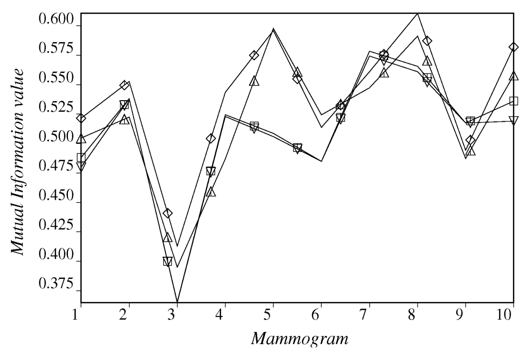
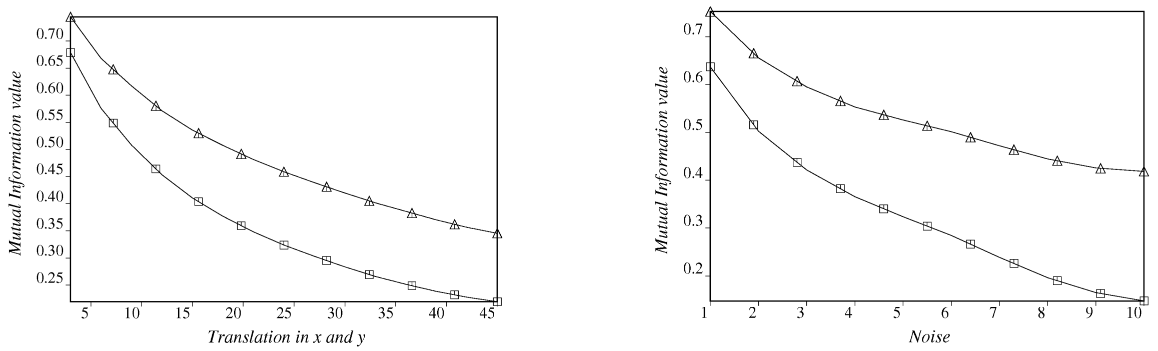


Figure 3. Evaluation of the registration algorithms applied to a set of mammograms, where △: Local Affine Transformation, □: Affine Transformation using MI, ◇: thin plate splines and ▽: No registration

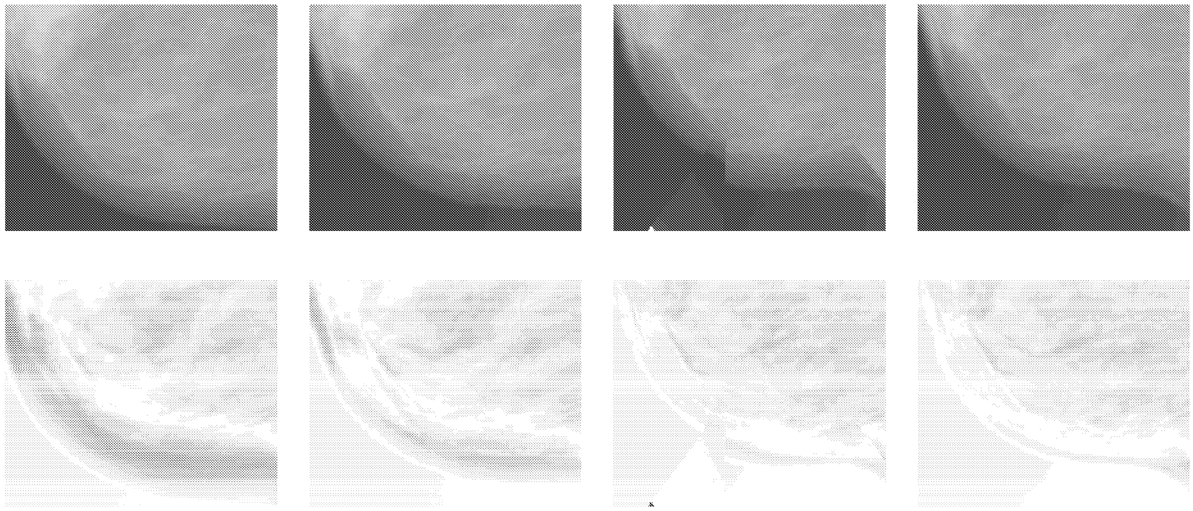


(a) (b)

Figure 4. Comparison of MI measure in (a) translation and (b) noise experiments, using (△) GLCM and (□) histogram approaches

4 Evaluation

As explained in the introduction, we will use our similarity measure as way to evaluate the accuracy of registration algorithms described in section 2. Our aim is to evaluate which method gives better overall results in a concrete application, such as breast cancer diagnosis. A way to help radiologists in the detection of mammographic abnormalities is to compare mammographic images of a patient, either taken sequently in time or using right and left mammograms. We have applied the proposed similarity measure between registered pairs of mammograms. Our set presents no abnormalities and it is obtained from registration of images of the same breast taken in three years time.In Fig. 5 we can observe a mammogram registration and the difference image obtained using the mentioned methods. And, agreeing with the results stated in Fig. 3, we conclude that thin plate splines obtains better overall results.



(a) (b) (c) (d)

Figure 5. Results using (a) no registration, (b) affine and MI (c) local affine and (d) thin plate splines

5 Conclusions

We have developed a novel similarity approach, based on mutual information and grey-level co-occurrence matrices. And we have applied it to evaluation of registration methods. As shown in section 3, our method takes into account in image spatial information which is omitted by the method of Bello and Colchester [3]. However, we have to pay a highly computational cost for calculating the 4-D joint GLCM. Future work should include a way to reduce computational cost without loose of accuracy and the applicability of the measure to image registration.

References

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