Image Registration from Mutual Information of Edge Correspondences

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Abstract. Image registration is a fundamental task in image processing. Its aim is to match two or more pictures taken with the same or from different sensors, at different times or from different viewpoints. In image registration the use of an adequate measure of alignment is a crucial issue. Current techniques are classified in two broad categories: pixel based and feature based. All methods include some similarity measure. In this paper a new measure that combines mutual information ideas, spatial information and feature characteristics, is proposed. Edge points obtained from a Canny edge detector are used as features. Feature characteristics like location, edge strength and orientation, are taken into account to compute a joint probability distribution of corresponding edge points in two images. Mutual information based on this function is maximized to find the best alignment parameters. The approach has been tested with a collection of medical images (Nuclear Magnetic Resonance and radiotherapy portal images) and conventional video sequences, obtaining encouraging results.

1 Introduction

Image registration is the process of overlaying two or more images of the same scene taken under different conditions. It is a crucial step of image analysis methods where the final information is obtained from the combination of various data sources. Some applications of registration are found in remote sensing (change detection, environmental monitoring, image mosaicing), medicine (monitoring tissue or injury evolution, treatment verification), cartography (map updating) and computer vision (surveillance systems, motion tracking, ego-motion).

To register two images, a transformation must be found so that each point in one image can be mapped to a point in the second one. It can be assumed that correspondent objects in both images present similar intensity values, and this can be used to accurately estimate the transformation [1]. However, specially in medical imaging modalities, one or both images could be of very low contrast, and significant features should be used instead of intensity values.

A new approach to compute a measure of image alignment was introduced by Viola and Wells [2], and by Maes *et al.* [3]. This measure, *mutual information*,

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is based on entropy concepts developed as part of Shannon's information theory. Mutual information is used to measure the statistical dependence between the image intensities of corresponding pixels in two images. The use of mutual information as a criterion for image similarity has been reported quite often in the literature in recent years. It enjoys the reputation of an accurate, robust and general criterion.

We describe a registration method based on ideas of mutual information. But, instead of a joint probability distribution derived from grey levels, used in classical mutual information registration, we propose a joint probability function derived from the spatial localization of features, and features similarity. The possibility of a multifeature approach of mutual information has been introduced by Tomazevic *et al.* [4]. They presented a method that allows an efficient combination of multiple features to estimate the mutual information.

Our work is mainly motivated by improving quality assessment in radiotherapy by performing automatic registration of portal images. Portal images are extremely low contrast images. Although still they show some steady characteristics like bone edges. So, in the method we present edges are used as features and edge points are determined using conventional edge extractors.

In our approach, we define a probability function that two edge points correspond combining three attributes of edges: edge point location, gradient magnitude, and gradient orientation. A joint probability table is computed for all possible correspondences. A minimization of the entropy of this table is applied to obtain the best match, and the registration parameters. The measure we are proposing allows us to incorporate spatial information in the estimation of the joint probability distribution. The lack of this type of information is a drawback in classical mutual information, where only correspondences of intensity values are used. This problem can lead to erroneous results when images contain little information, in the case of poor image quality, low resolution, etc. Our method has been tested with portal images from radiotherapy and from Magnetic Resonance (MR) modalities. It has also been tested with outdoor video sequences.

The structure of this paper is as follows: in Section 2 some related work is discussed. Section 3 describes theoretical aspects of mutual information, and of the approach we are proposing. In Section 4 we present results obtained using our new measure based on mutual information and feature characteristics. Finally, in Section 5 conclusions and further research directions are drawn.

2 Related Work

Registration algorithms have applications in many fields. Currently, research is directed to multimodal registration and to cope with region deformations [5]. A recent study about image registration can be found in the work by Zitova and Flusser [6]. A more specific reference dedicated to the field of medical imaging is the work by Maintz and Viergever [7].

Depending on the information used to bring images into alignment, current techniques are classified in two broad categories: *feature-based* and *pixel-based*

approaches. *Feature-based* approaches aim at extracting stable features from the images to be registered. The correspondences among extracted features is found and used to estimate the alignment between the two images. These methods tend to be fast. Leszczynski *et al.* [8] manually selected contours of notable features and used their points for registration using chamfer matching. The introduction of the chamfer distance [9] reduces the computation time, although the method depends on user interaction.

Pixel-based approaches use all the pixels of an image. A Fourier transform-based cross correlation operator was used by Hristov and Fallone [10] to find the optimal registration, accounting for translations and rotations.

In the last decade, a new *pixel-based* approach has been introduced: the mutual information measure. Similarity measures based on this concept have shown to be accurate measures for selecting the best rigid or non-rigid transformation in mono and multi-modal registration. However, being an area-based technique it has limitations, mainly due to the lack of spatial information.

Portal imaging consists of sensing therapeutic radiation applied from electron accelerators in cancer treatment [11]. They are formed when a high energy radiation excites a sensor after being absorbed by anatomical structures as it goes through the body. Due to the high energy of the radiation, there is a poor contrast in portal images compared to x-ray, axial tomography or magnetic resonance images. Detection of patient pose errors during or after treatment is the main use of portal images. Recently, Kim *et al.* [12] reported results on using classical mutual information as the measure of alignment in registration of portal images. Good average accuracies for motion parameters estimation were achieved, but the long computation time of the proposed method makes it difficult to estimate the patient setup error in real time. Since our method deal with a shorter amount of data, only features characteristics, its application in real time would be possible.

Hybrid techniques that combine *pixel-based* and *feature-based* approaches have been proposed. In the work by Rangarajan *et al.* [13] mutual information is computed using feature points locations instead of image intensity. The joint probability distribution required by the mutual information approach is based on distances between pairs of feature points in both images. From this distribution a measure of the correspondence likelihood between pairs of feature points can be derived. The authors report results with autoradiograph images.

Pluim *et al.* [14] extended the mutual information in a different way to include spatial information. The extension is accomplished by multiplying the classical mutual information by a gradient term. This term includes the gradient magnitude and orientation. The method computes a weighting function that favors small angles between gradient vectors. Then, its value is multiplied by the minimum of gradients magnitude. Finally, summation of the resulting product for all pixels gives the gradient term. This combined criterion seems to be more robust than classical mutual information.

The method we propose provides the registration parameters of a pair of images by maximizing the mutual information computed from a joint probability

table of feature correspondence feasibility. The probability of correspondence of two edge points is estimated using points attributes. A search of the best registration parameters implies recomputing the joint probability table but not the feature points themselves. The registration parameters giving the lowest entropy, and so the highest mutual information are selected as the best alignment.

3 Registration Based on Feature Characteristics and Mutual Information

3.1 Mutual Information

Mutual Information is a concept from information theory, and is the basis of one of the most robust registration methods [15]. The underlying concept of mutual information is entropy, which can be considered a measure of dispersion of a probability distribution. In thermology, entropy is a measure of the disorder of a system. A homogeneous image has a low entropy while a high contrast image has a high entropy. If we consider as a system the pairs of aligned pixels in two images, disorder or joint entropy increases with misregistration, while in correct alignment the system has a minimum disorder or joint entropy. The mutual information of two images is a measure of the order of the system formed by the two images. Given two images A and B, their mutual information I(A,B) is:

$$I(A,B) = H(A) + H(B) - H(A,B) \ , \tag{1}$$

with H(A) and H(B) being the entropies, and H(A,B) being the joint entropy. Following Shannon's information theory, the entropy of a probability distribution P is computed as:

$$H = -\sum_{p \in P} p \log p \ . \tag{2}$$

In classical mutual information, the joint probability distribution of two images is estimated as the normalized joint histogram of the intensity values [2]. The marginal distributions are obtained by summing over the rows or over the columns of the joint histogram:

$$H(A) = -\sum_{a} p_A^T(a) \log p_A^T(a) \ , \tag{3}$$

$$H(B) = -\sum_{b} p_B^T(b) \log p_B^T(b) \ , \tag{4}$$

where p_A^T and p_B^T are the marginal probability distributions for certain values of the registration parameters T. They are not constant during the registration process because the portion of each image that overlaps with the other changes. The registration parameters T represent a spatial mapping (rigid, affine) that aligns one image with the other.

The mutual information can be estimated with respect to the marginal entropies p_A^T and p_B^T [16] as:

$$I(A,B) = \sum_a \sum_b p_{AB}^T \log \frac{p_{AB}^T}{\sum_a p_A^T \sum_b p_B^T} \ , \tag{5}$$

where p_{AB}^T represents the joint probability for a given T.

3.2 Including Feature Information

Although successful results are reported when mutual information-based registration is applied, there are cases where it can fail. This may happen in low quality images as we mention in previous section. Some researchers like Papademetris *et al.* [17] have proposed the inclusion of spatial information in the registration process using an approach that integrates intensity and features in a functional with associated weights. Results suggest that this method yields accurate nonrigid registrations.

We propose a new measure of mutual information computed only from features. The use of features for registration seems well suited for images where, like in some medical images, the local structural information is more significant than pixel's intensity information. It also reduces, generally, the amount of data that must be handled during registration. We use edge points as features, and point location, edge strength and edge orientation as feature characteristics. Edge points are a significant source of information for image alignment, they are present in almost every conventional image, as well as in every medical imaging modality like MR, computed tomography (CT) or portal images, so they are useful for intra and inter modality registration. In optimal registration edge points from one image should match their corresponding edge points in location and also in edge strength and orientation.

Let a_1,a_2,...,a_N and b_1,b_2,...,b_M be two sets of feature points in two images A and B. Let D_{ij}^T denote a distance measure between two points a_i and b_j (e.g. Euclidean distance) after applying the transformation T on the set of b_j. When the two images are registered, point a_i will be located close to its matching point b_j. If a joint probability table is built considering the distances from each a_i to all the b_j, with j=1, 2,...,M, in one of the M cells of the i-th column, there will exist the maximum of that column, point b_j, having the biggest likelihood of being the match of a_i. Re-computing the joint probability table for different transformations T, one of the tables obtained will be the best, having the highest likelihood of matched points and so the highest mutual information. Similarly, with the images registered, an edge point a_i will match some b_j having similar edge strength since they represent the same edge point. The edge orientation after the mapping has to be also similar.

Denoting as D_{ij} the distance between a_i and b_j, S_{ij} the difference in edge strength, and O_{ij} the difference in edge orientation after the mapping, we can estimate the mutual information $I(A,B)$ as a function on these feature points characteristics $f(D_{ij}, S_{ij}, O_{ij})$.

The principal modification we propose with respect to the classical mutual information is the use of several feature attributes to estimate the joint probabilities. We use the gradient magnitude at a feature point as an estimation of the edge strength, and the gradient direction as an estimation of the edge orientation:

$$D_{ij}^T = \|a_i - b_j^T\|^2 \ , \tag{6}$$

$$S_{ij} = \Big| |\nabla a_i| - |\nabla b_j| \Big| \ , \tag{7}$$

$$O_{ij}^T = \cos^{-1} \frac{\nabla a_i \nabla b_j^T}{|\nabla a_i||\nabla b_j^T|} \ . \tag{8}$$

Note that S_{ij} does not depend on the registration parameters since the strength difference (gradient magnitude difference) of two edge points remains the same after moving an image. This does not hold for the Euclidean distance D_{ij}^T, or the orientation difference O_{ij}^T, which are affected by translation and rotation. Gradient magnitude at edge points can be different in corresponding edges detected in different images due to the possibly different sensing devices used to take the images. This can be overcome by scaling the gradient magnitude at the edges in both images, giving, for example, a relative measure between zero and one.

To estimate the joint probability of match between two edge points in two images we introduce an exponential function based on the feature attributes, so that if D_{ij}^T, S_{ij} and O_{ij}^T are small, there is a high probability of correspondence between those edge points. The proposed joint probability is expressed as follows:

$$p_{ij}^T = \frac{\exp - (\frac{D_{ij}^T}{\gamma_1} + \frac{S_{ij}}{\gamma_2} + \frac{O_{ij}^T}{\gamma_3})}{\sum_i \sum_j \exp - (\frac{D_{ij}^T}{\gamma_1} + \frac{S_{ij}}{\gamma_2} + \frac{O_{ij}^T}{\gamma_3})} \ , \tag{9}$$

with γ_k being constant weights. Using the probability distribution function given in (9), mutual information is computed as described in (5), but replacing p_{AB}^T with p_{ij}^T.

The main advantage of our approach compared to the classical mutual information is that this latter method does not use the neighbouring relations among pixels at all. All spatial information is lost in the classical approach, while our approach is precisely based on spatial information. Compared to the method reported by Rangarajan *et al.*. [13], we add new feature information in the estimation of the joint probability distribution, so the similarity criterion is improved and this can be particularly effective with images of poor quality, like portal images. With respect to the work reported by Pluim *et al.* [14], our approach is only based on feature points, a smaller amount of data than the classical approach, that uses all the pixels, resulting in a faster estimation of the mutual information. The computation of S_{ij} is done only once at the beginning of the registration as it does not depend on T, O_{ij}^T changes only if the transformation T involves a rotation, while D_{ij}^T is affected by translation and rotation.

It is also possible to control the contribution that each term introduces in the joint probability with the weights γ_1, γ_2 and γ_3.

3.3 Edge Detection

Extraction of edges can be done by several methods, first derivative-based methods (Sobel masks), or second derivative-based, like Laplacian of a Gaussian or Canny [18]. In this work we have used the Canny edge detector, that selects edge points at locations where zero-crossings of the second derivative occur. Since the amount of resulting edge points can be big, a selection of a certain percentage of the strongest ones can be done, using only the selected points for the registration.

3.4 Optimization

Optimization of the registration function is done by exhaustive search over the space of parameters. We assume a rigid transformation to align one image with the other, a rotation followed by a translation, both in 2D, so the search space is three-dimensional. A revision of optimization strategies can be found in the work by Maes *et al.*. [19] where various gradient- and non-gradient-based optimization strategies are compared.

Since the principal purpose of our work is to prove the feasibility of a new form of obtaining the joint probability used for the computation of the mutual information, no analysis on the convenience of using a certain optimization has been made. Exhaustive search is a sufficiently simple method for a bounded three-dimensional search space, and it finds a global optimum, avoiding the main drawback of other optimization algorithms, that may converge to a local optimum.

4 Results

We have tested our approach with a number of pairs of images of different sources: portal images provided from sessions of radiotherapy treatments at the Provincial Hospital of Castellón, Spain, MR images obtained from the internet (http://www.itk.org/HTML/Data.htm) and video sequences. Figure 1 shows pairs of images used in our experiments. Note that pa the pair of MR images, although obtained with the same sensor, are multimodal in the sense that different tissue characteristics are represented. So, we are also testing our method in multimodal registration. We assume that the registration parameters to align the second image with the first one represent a two-dimensional rigid motion. The parameters of this transformation are denoted as θ for the angle of rotation, and as (t_x, t_y) for the translation vector. In portal images, the true image registration parameters were determined by human operators that selected corresponding landmarks in both images. For MR images and video sequences true image registration parameters were available along with the images.

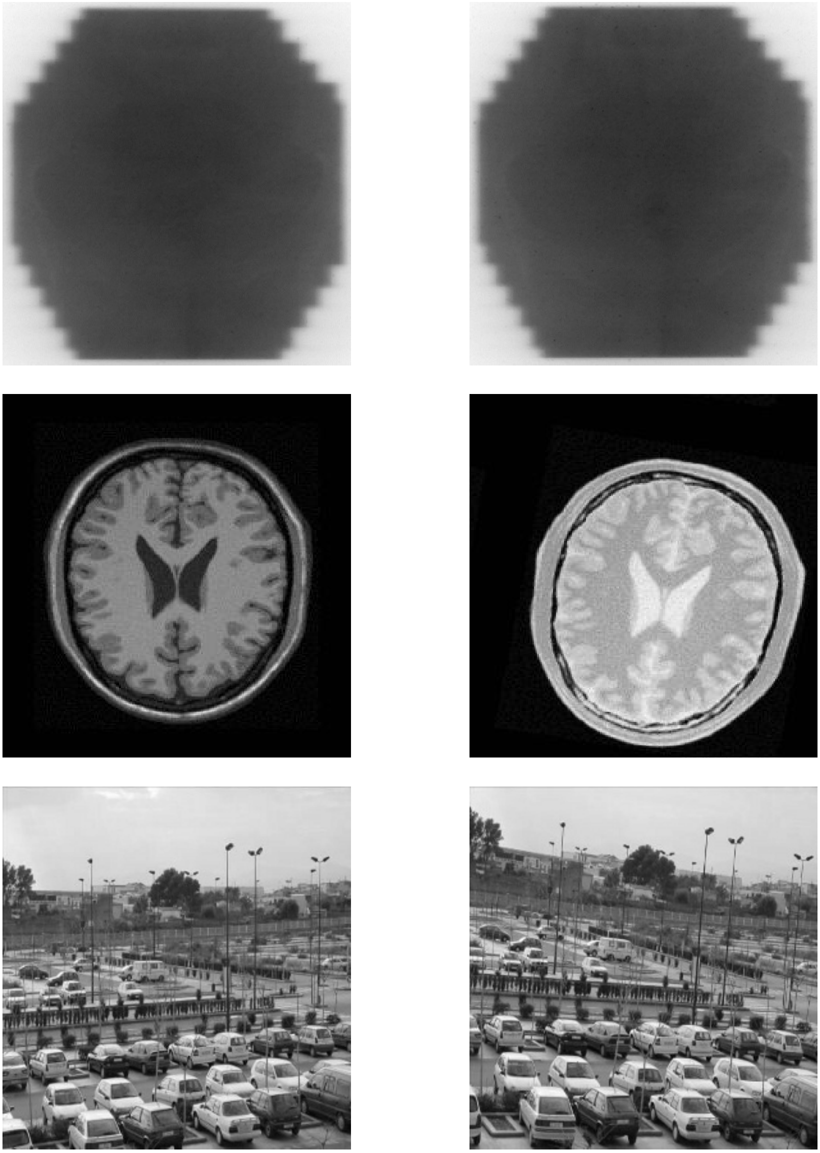

Fig. 1. Pairs of images used in the experiments. Top: portal images obtained in two different sessions. Middle: MR images, T1-weighted (left) and proton-density-weighted (right). Bottom: two images of a video sequence.

Table 1 shows the errors in the estimation of the rigid transform parameters: θ(degrees), t_x and t_y (mm). Results using the classical mutual information (MI) and using our method are presented.

Table 1. Errors in the estimation of rigid transform parameters

	Classical MI			Our method		
	θ	t_x	t_y	θ	t_x	t_y
Portal Images	0.1	2.01	1.93	0.238	0.510	0.396
MR images	0.5	1.12	1.58	0.5	1.35	0.97
Video Sequence	2.02	2.36	2.52	1.30	1.01	1.04
Average	0.87	1.83	2.01	0.68	0.96	0.80
Standard Deviation	1.01	0.64	0.47	0.55	0.42	0.35

Remember that classical MI is based on grey level correspondences at every pixel of two images, where one image has been moved to be aligned with the other. So, to obtain the classical MI registration results, we gave values to the registration parameters aligning an image with the other, we computed the joint histogram of grey levels, which is an estimation of the joint probability that two grey levels correspond, and we selected the registration parameters that provide a maximum of the mutual information.

In the computation of p^T_{ij} the values of γ_1, γ_2 and γ_3 were fixed heuristically. These values are like time constant of the decreasing exponentials that appear in (9). In the zone where the independent variable of an exponential function has a value similar to the time constant, the function decreases quickly. We are interested in quick changes of correspondence probability around values of D^T_{ij}, S_{ij} and O^T_{ij} that are typical in our images. So, we registered some images manually, and we selected the values of γ_1, γ_2 and γ_3 as the mean of the distances $(D^T_{ij}, S_{ij}, O^T_{ij})$ found between correspondent feature points.

Figure 2 shows the registration results for images in Figure 1. Observe that for the pair of images from a video sequence the mismatch of some edges after registration is still notable. This is due to perspective effects. We assumed a 2D rigid transformation as a motion model, that can not account for real 3D scenes.

Although we assumed a rigid transformation in our tests, there is no a priori restriction to a particular type of transformation, an affine motion model could be used also. Figure 3 shows the joint probability tables of each pair of images after registration using our feature-based method. Low intensity values correspond to high likelihood of correspondence. It can be observed that the information concentrates in an area of the table, as expected.

5 Conclusions and Further Work

The inclusion of spatial information in the computation of the mutual information is a subject under current investigation. In this paper we have proposed a new measure of registration that combines mutual information with spatial

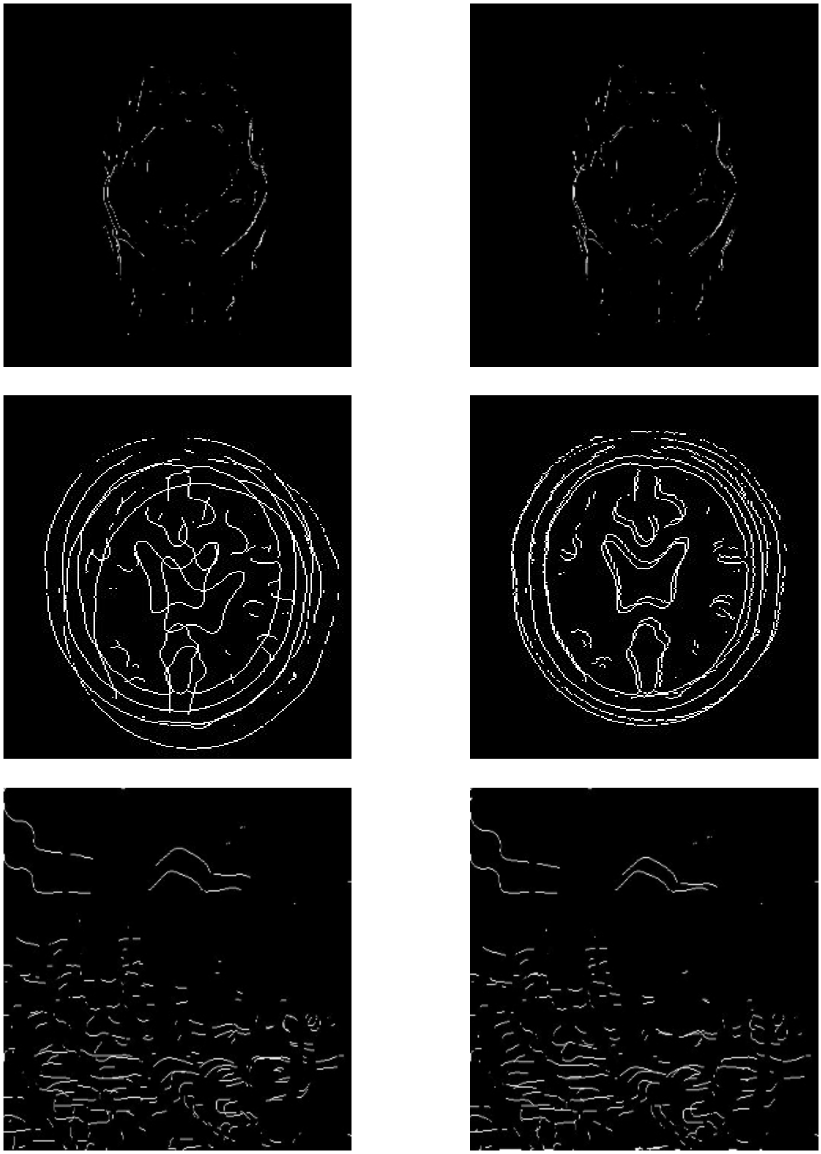

Fig. 2. Sets of edges detected in images of Figure 1 overimposed before the registration in the left column, and after the registration in the right column

information obtained from feature attributes, like edge points. Instead of a joint histogram of grey levels, the classical approach, we estimated a joint probability distribution based on feature points. We introduced a probability estimate that two feature points match based on points similarity. An optimization algorithm

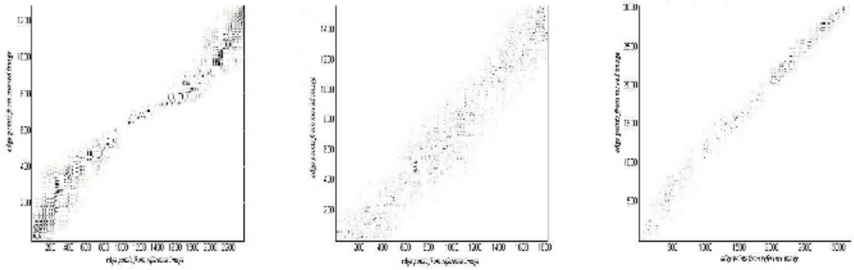

Fig. 3. Joint probability functions computed after registration for portal (left), MR (center) and video sequence (right) images

was then applied to find the best registration parameters where a maximum of the mutual information occurs.

The proposed approach can be used to register images from different sources, multimodal registration, since it can combine different features as needed. A way to compute the probability that two features in two images correspond has to be provided.

Our approach improves the classical mutual information method, which is based only on intensity values, by using feature characteristics. Furthermore, the number of points used to build the probability function is significantly smaller, only feature points, compared to the number used to build the joint histogram, the whole image.

Further work is addressed at investigating the use of other features in the approach, as boundaries of regions in segmented images, or their overlapping area. The key question is which attributes to include in the computation of the joint probability table, and how to combine them. In our work we have used as probability functions a combination of decreasing exponentials that account for differences in location, in edge orientation, and in edge strength, of two feature (edge) points.

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