Analysis of Similarity Measure for Image Registrion

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Abstract—In this paper, Image registration is the fundamental task used to match two or more partially overlapping images taken into one panoramic image comprising the whole scene. It is a fundamental image processing technique and is very useful in integrating information from different sensors, finding changes in images taken at different times, inferring three-dimensional information from stereo images, and recognizing model-based objects. Choosing a suitable similarity measure for image registration is always challenging task. In image registration, the images may consist of noise, cloud, highly undulating terrains etc. Choice of similarity measure plays an important role in image registration task.classified according to their nature area-based and feature-based similarity measure and according to four basic steps of image registration procedure: feature detection, feature matching, mapping Function design, and image transformation and resampling.Main contributions, advantages, and drawbacks of the methods are mentioned in the paper. Problematic issues of image registration and outlook for the future research are discussed too. The major goal of the paper is to provide a comprehensive reference source for the researchers involved in image registration, regardless of particular application areas. Choosing a suitable similarity measure for image registration is always challenging task.In image registration,the images may consist of noise,cloud,highly undulating terrains etc.Choice of similarity measure plays an important role in image registration task.classified according to their nature area-based and feature-based similarity measure Similarity measure are mutual information,normalise mututual information,jaccard co-efficient,partial hauss-drauff distance,image quality index,cross commulative resuadal entropy,normalise cross correlation,encludian distance are study and between two image anlysis similarity measure w.r.t. time and various parameters.

Keywords: image registration, similarity measure.

I. INTRODUCTION

Image registration is the fundamental task used to match two or more partially overlapping images taken into one panoramic image comprising the whole scene.It is a fundamental image processing technique and is very useful in integrating information from different sensors,finding changes in images taken at different times,inferring three-dimensional information from stereo images,and recognizing model-based objects.Choosing a suitable similarity measure for image registration is always challenging task.In image registration,the images may consist of noise,cloud,highly undulating terrains etc.Choice of similarity measure plays an important role in image registration task.classified according to their nature area-based and feature-based similarity measure and according to four basic steps of image registration procedure:feature detection,feature matching,mapping function design, and image transformation and resampling. Provide sparse disparity maps.ok for applications like visual navigation.Relatively insensitive to illumination changes.The goal of image registration is to find a geometric transformation (rigid or non-rigid),denoted T,that aligns two given images,denoted F and M,where F is fixed,m is moving image,to denote spatial coordinates. Feature- based image registration methods achieve this goal by maximizing a similarity measure based on the image intensity values.If we parameterize the transformation Tusing (e.g., three translation and three rotation parameters for rigid transformation), the image registration becomes a parameter estimation problem:

$$\mu = \arg\min C(F, M, T)$$

II. SIMILARITY MEASURES

In this paper,we will only study similarity measures becoz the similarity measure are an important role in image registration.The similarity measures are jaccard co efficient, mutual information,normalise mutual information,partial hauss dauff distance.A detailed discussion on similarity measures for image registration can be found in [8].We discussed area based and feature based similarity measure for particular apllication.Suitable when good features can be extracted from the scene.Faster than correlation-based methods.

A. Sum of Absolute Difference:

For images I1 and I2 with voxels i.,

$$SAD = \sum_{(i,j)} \left| I1(i,j) - I2(x+i, y+j) \right|$$

Sum of Absolute Differences (SAD) is one of the simplest of the similarity measures which is calculated by subtracting pixels within a square neighbourhood between the reference

Image I1 and the target image I2 followed by the aggregation of absolute differences within the square window, and optimization with the winner-take-all (WTA) strategy [1]. If the left and right images exactly match, the resultant will be zero.

B. Mutual information

Entropy minimization is not a robust voxelsimilarity measure for all types of image registration.The problem is that the PDF from which the joint entropy is calculated is defined only for the region of overlap between the two images.The range and distribution of intensity values in the portion of either image that overlaps with the other is a function ofT.The change in overlap with T can lead to histogram changes that mask the clustering effects described above.The solution to this difficulty,proposed independently by researchers [12] is to use the information-theoretic measure mutual information (MI) instead of entropy H.MI normalizes the joint entropy with respect to the partial

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entropies of the contributing signals. In terms of image registration, this measure takes account of the change in the intensity histogram of images A and B with T.

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

C. Normalised Mutual Information

Mutual information overcomes many of the shortcomings of joint entropy but can still fail for some types of clinical image, particularly those which contain large amounts of air (noise) around the outside of the subject. Improved performance of mutual information can be obtained by various normalization schemes.These algorithms are not taken from the information theory literature but have been arrived at through images. Despite its heuristic origins, the variant given below (from [10]) works extremely well in practice. Current validation studies have shown that it works at least as well as mutual information and in some cases performs better.

$$NMI(u,v) = \frac{H(u)+H(v)}{H(u,v)}$$

- Normalised mutual information is analyzed effect of changes in image overlap.
- It showed improved behavior in synthetic and clinical images over range of fields of view.

D. Normalise cross correlation:

Normalised cross correlation computes pixel wise cross correlation and normalise it by square root of the autocorrelation of the images. NCC perfect alignment gives value 1.It is insensitive to multiplicative factors between image intensities. It produces well defined minima and sharp peaks.

$$NCC(\mu; If, Im) = \frac{\sum_{xi\in\Omega}(If(Xi)-If)(Im(T\mu(Xi))-Im}{\sqrt{\sum_{xi\in\Omega}(If(Xi)-If)^2\sum(Im(T\mu(Xi))-Im)^2}}$$

It is insensitive to multiplicative factors between image intensities. It produces well defined minima and sharp peaks. On the other hand, it has a relatively small capture radius. The correlation technique described for calculating rotation and scale parameters have far greater signal-to-noise ratios than its predecessors. The most important facet of the technique described in this report is the elimination of the false peak near 0. The presence of a false peak at 0 destroys the ability to detect and measure small rotations and small changes of scale because they are completely hidden within the false peak.NCC is less strict, which assumes a linear relation between the intensity values of the fixed and moving image. It is insensitive to multiplicative factors between image intensities. It produces well defined minima and sharp peaks.

E. Cross-cumulative residual entropy

An automatic registration method requires the choice of an image discrepancy criterion that measures the similarity of the test image to the reference image.The measure we choose is defined based on a new information theoretic measure called Cumulative Residual Entropy (CRE) which was introduced and is reproduced here forconvenience.Let x be a random variable in R, and F(γ) := P(|x| > γ) is the cumulative residual distribution,which is also called survival function in the Reliability Engineering literature. The cumulative residual entropy (CRE) of x is dened as:

$$E(x) = -\int F(\gamma)\log F(\gamma)d(\gamma)$$

A multi-modal non-rigid registration technique which is based on a recently introduced information theoretic matching criterion [5] called cross cumulative residual entropy (CCRE) to measure the similarity between two images.We now dene the cross-CRE (CCRE) using CRE defined in Eqn. 6.

$$C(X, Y) = \sum_{u=1}^{L}\sum_{v=1}^{L} G(u,v)\log\frac{G(u,v)}{G(u)P(v)}$$

The CCRE is then minimized over a class of smooth non-rigid transformations expressed in a B-spline basis.The key strengths of our proposed nonrigid registration scheme are:

(1) it can accommodate images to be registered of varying contrast+brightness,and it is also robust in the presence of noise;

(2) It can be empirically shown toconverge faster in comparison to other registration methods that use information theory based cost functions;

(3)The cost function and its derivative share common terms and this leads to computational savings being accrued in the numerical optimization process;

(4) It is well suited for situations where the source and the target images have field of views with large non-overlapping regions (which is quite common in practice).

F. Image Quality Index:

Image quality index that may be used as image and video quality distortion measure. It is mathematically defined by modeling the image distortion relative to the reference image as a combination of three factors: loss of correlation, luminance distortion, and contrast distortion.If two images *f* and *g* are considered as a matrices with *M* column and *N* rows containing pixel values *f*[*i*,*j*], *g*[*i*,*j*], respectively ($0 \geq i > M$, $0 \geq j > N$),the universal image quality index *Q*may be calculated as a product of three components:

$$Q = \frac{6fg}{6f6g} * \frac{\bar{f}\ \bar{g}}{(\bar{f})^2 + (\bar{g})^2} * \frac{26f6g}{6f^2 + 6g^2}$$

The first component is the correlation coefficient, which measures the degree of linear correlation between images *f* and *g*. It varies in the range [-1, 1]. The best value 1 is obtained when *f*and *g* are linearly related, which means that $g[i,j] = af[i,j]+b$ for all possible values of *i* and *j*. The second component, with a value range of [0, 1], measures how close the mean luminance is between images. Since σ_f and σ_g can be considered as estimates of the contrast of *f* and *g*, the third component measures how similar the contrasts of the images are. The value range for this component is also [0, 1].

The range of values for the index *Q* is [-1, 1]. The best value 1 is achieved if and only if the images are identical.

G. Partial Hausdorff Distance:

A more general definition of Hausdorff distance would be :

$$H(A, B) = \max\{ h(A, B), h(B, A) \}$$

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which defines the Hausdorff distance between A and B, while eq.applied to Hausdorff distance from A *to* B (also called directed Hausdorff distance).The two distances h(A, B) and h(B, A) are sometimes termed as forward and backward Hausdorff distances of A to B.If sets A and B are made of lines or polygons instead of single points,then H(A, B) applies to all defining points of these lines or polygons,and not only to their vertices.The brute force algorithm could no longer be used for computing Hausdorff distance between such sets, as they involve an infinite number of points.One of the main application of the Hausdorff distance is image matching, used for instance in image analysis,visual navigation of robots,computer-assisted surgery,etc.Basically,the Hausdorff metric will serve to check if a template image is present in a test image ; the lower the distance value, the best the match. That method gives interesting results, even in presence of noise or occlusion (when the target is partially hidden).

H. Jaccard coefficient:

Jaccard index is a name often used for comparing similarity, dissimilarity, and distance ofthe data set.Measuring the Jaccard similarity coefficient between two data sets is the result of division between the number of features that are common to all divided by the number of properties as shown below.

$$JCE = 1 - J(A,B)$$

$$\text{Where, } J(A,B) = \frac{A \cap B}{A \cup B}$$

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III. SIMULATION RESULT

There are the various similarity measure introduce here,mean square error,mutual information,normalise cross correlation,normalise mutual information,cross commulative resuidal entropy,partial hauss daurff distance,jaccard coefficient,image quality index.Here,we

Take two images 1.pout and 2.cameraman, first table same image (both source and target image are same) and take average time anlysis.Second time, one was original and second image was rotated at 35. Between two images take similarity measure and various reading.

Fig. 1 :pout

Fig. 2 :cameraman

SM	Image1 Cameraman				Image2 Pout			
	same	avg time	rotate 35	avg time	same	avg time	rotate 35	avg time
MSE	0	1.8	0.16	1.16	0	1.08	0.25	1.03
MI	-2	0.32	-1.07	0.43	-2	0.30	-1.03	0.45
NMI	1	4.0	0.14	5.57	1	0.99	0.61	2.0
CCRE	-80	0.2	-11.6	0.2	-26.6	0.17	-8.93	0.23
JCE	1	0.19	0.83	0.36	1	0.20	0.82	0.27
PHD	0	1.92	199.2	1.96	0	2.15	194.2	2.17
IQI	1	0.18	0.59	0.18	1	0.16	0.82	0.20

Table. 1: Similarity measure between same and rotated images

In the second, table various similarity measure between source(original) and target image (noisy image). We can see the mutual information as similarity measure and take result,there is the increase niose in target image,the mutual information is decrease by increasing noise.Then after normalise mutual information as similarity measure between two images,one by one increasing noise in target image and take result, we can see there is normalise mutual information decrease.The third similarity meausre cross commulative resuidal entropy and take result.we can see,the similarity measure ccre between two images measure that one by one increase noise in target image,thera is decrease in the cross commulative resuidal entropy. It is well suited for situations where the source and the target images have field of views with large non-overlapping regions.jaccard coefficient between two image source and target image,there is the jaccard coefficient increase.In the partial hauss dorff distance take as similarity measure and take result between two image,we can see the partial hauss dorff distance can decrease by increase the noise,the partial hauss dorff distance can decrease.In the image quality index there is the one best,after increaes noise the image quality index decreases.All similarity meausre vs. Noise plot given belove.

SM	Noise			
	0.1	**0.2**	**0.3**	**0.4**
MI	-1.0930	-1.0934	-1.0964	-1.1028
NMI	0.1704	0.1702	0.1700	0.1698
CCRE	11.08	10.79	10.74	10.70
JCE	0.9861	0.9988	0.9999	1
PHD	80.46	30.95	15.96	0
IQI	0.9535	0.8099	0.7578	0.6656

Table. 2: Similarity measure between original and noise image

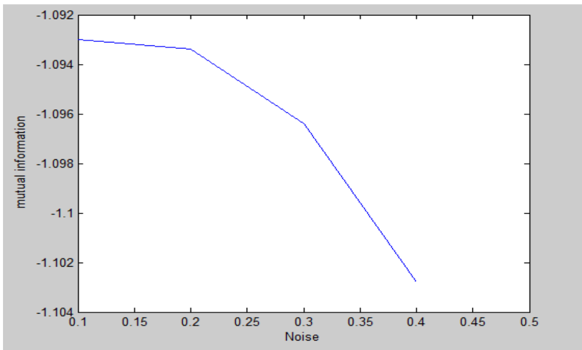

Fig. 3: Mutual information vs. Noise plot

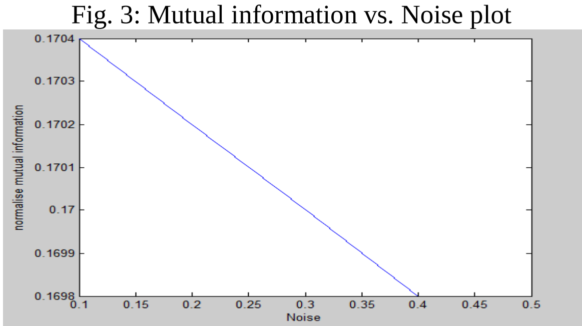

Fig. 4: Normalise mutual information vs. Noise plot

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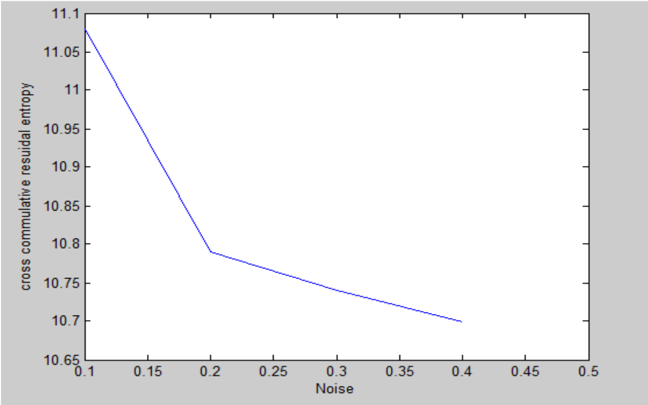

Fig. 5: CCRE vs. Noise plot

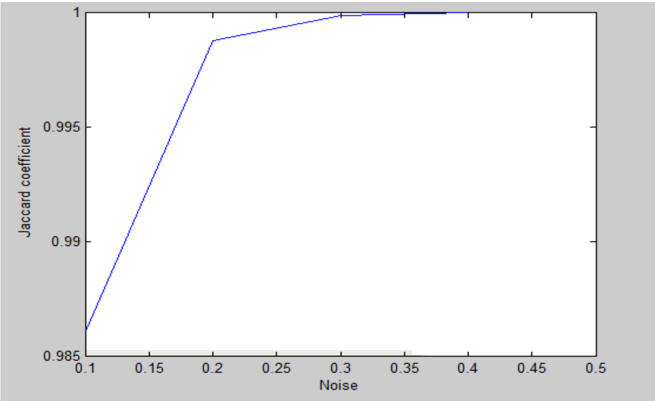

Fig. 6: Jaccard coefficient vs. Noise plot

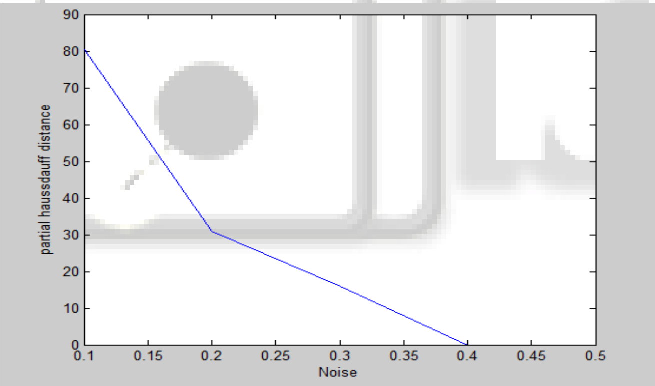

Fig. 7: Partial haussdroff distance vs. Noise plot

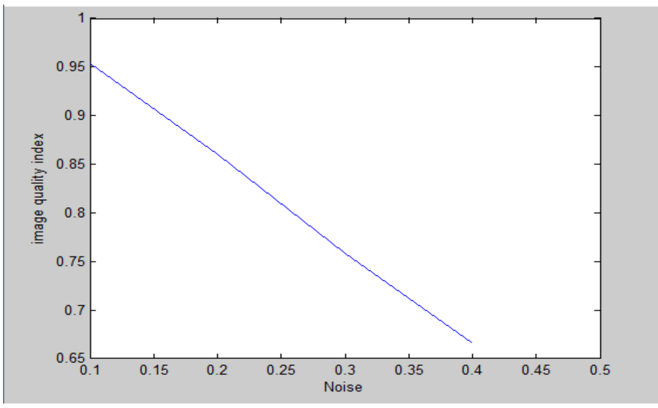

Fig. 8: image quality index vs. Noise plot

IV. CONCLUSION

By defining a similarity measure between two image, mutual information for same image,there is maximum mutual information and also time increase,but by adding noise or rotated there is mutual information decreases.Same result in the normalise mutual information by adding noise the normalise information decrease.Normalised cross correlation computes pixel wise cross correlation and normalise it by square root of the autocorrelation of the images. NCC perfect alignment gives value one.It produces well defined minima and sharp peaks.Image quality index is best match give value one.But after adding noise,it will decrease.Jaccard coefficient is best match give value minimum,but increase noise,it will maximum.In,CCRE is best match give value maximum but increase noise it will minimum.Partial hauss dorff distance is best match give maximum but after increase noise it should be decrease.

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