# A new similarity measure for image segmentation

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***Abstract*** **- We try to extract the component image virtually hidden in the principle image. Information theoretic quantities are used to measure similarity of images in a statistical frame work. Statistical method describes the texture in a form suitable for statistical pattern recognition. This is suggested from large primitives and fine structure of smaller primitives. Co-occurrence matrix method is used to edge frequency detection and separation. Here we appeal to the mutual information to bring out the component image from a complete image presentation.**

***Keywords- Image segmentation, texture, Similarity measure, Mutual information***

## I. INTRODUCTION

Image Processing and Machine vision are the recent fields of advanced research in computer science and technology.[10] Different techniques are adopted to solve problems in the registration, segmentation and split of component images from a unified image acquisition. Here we address the problem of extracting an invisible component from an unified image with a single outlook and over view. We appeal to a similarity measure based on mutual information and cross correlation. This type of analysis throws light on the study of bio-medical images and satellite images to capture the subroutines to extract the required component for further analysis. Our method can be extended to have a better understanding of 3-dimensional perspectives with the help of front elevation and side view. This novel approach can be put in the category of statistical zero knowledge interactive protocol in which a statistical difference and entropy difference are used with ease. Our approach is based on the mutual information difference to have such a statistical interactive protocol for alignment and rendering of 2-D images.[4]

*Related Work*

Pattern recognition is used for region classification, and basic methods of pattern recognition must be understood in order to study more complex machine vision process. The theory of pattern recognition is thoroughly discussed by various researchers such as Milan Sonka et.al. In addition, T.J.Ross [8] introduced some other related technique like graph matching, neural nets, genetic algorithms, simulated annealing, and fuzzy logic.

No recognition is possible without knowledge. Decisions about classes or groups into which recognition objects are classified are based on such knowledge about objects and their classes give the necessary information for object classification. Both specific knowledge about the objects being processed and hierarchically higher and more general about object classes is required. The ability to develop relations in classification is studied through similarity measures. Similarity method based on data manipulation is computed using cosine amplitude and max-min method in uncertainty environment. Other methods estimate similarity through exponential functions. The principle of non interactive between sets can be introduced on the assumptions of independent probability modelling. Measures of information in particular measure based on mutual information is found to be more suitable in the extraction of component images well embedded in an image. This notion is studied by statistician like Rainy [9] and other scientists.

Image similarity-based methods are broadly used in medical imaging. A basis image similarity-based method consists of a transformation model which is applied to reference image coordinates in the target image space, an image similarity metric, which quantifies the degree of correspondence between features in both image spaces achieved by a given transformation, and an optimization algorithm which tries to maximize image similarity by changing the transformation parameters.

The choice of an image similarity measure depends on the nature of the images to be registered. Uniformity are commonly used for registration of images of the same modality.

Simplex method and Powell's routine [2] are commonly used for registration problem. Both these methods do not require function derivatives to be calculated. The simplex method considers all degree of freedom simultaneously and is not know for its speed of convergence.

Powell's method optimizes each transformation parameter in turn and it is relatively sensitive to local optima in the registration function.

## II. SECTION I

### A. Basic Concepts

We start with the following definitions used in the subsequent work

### B. Definition 1 Entropy

The entropy, $H(X)$, for the discrete random variable $X$, with probability distribution function p, is defined as

$$H(\Xi) = H(\pi) = -\sum \pi(\xi)\, \lambda o \gamma\, \pi(\xi)$$

where or reasons of continuity, we define
0 log 0 = 0.

Note the entropy of $X$, $H(X)$, may also be denoted $H(p)$. The notation $H(p)$. Emphasizes the dependence of entropy on the probability distribution of $X$, as opposed to the actual intensity values of $X$.

### C. Definition 2 Joint Entropy

The joint entropy, $H(X,Y)$, for the discrete random variables $X$ and $Y$, with joint probability distribution r, is defined as

$$H(\Xi, \Psi) = H(\rho) = -\sum \rho(\xi, \psi)\, \lambda o \gamma\, \rho(\xi, \psi).$$

### D. Definition 3 Relative Entropy

Relative entropy distance is a measure of the distance between one probability distribution and another. It measures the error of using an estimated distribution $q$ over the true distribution $p$.

The relative entropy, $D(\ p \parallel q)$, of two probability distributions $p$ and $q$ over $X$, is defined as

$$\Delta(\ \pi \parallel \theta) = \sum \pi(\xi)\, \lambda o \gamma(\ \pi(\xi) \,/\, \theta(\xi))$$

where, for reasons of continuity, we define 0 log(0 / $q$) = 0 and $p$ log( $p$ / 0) = ¥.

A special case of relative entropy is mutual information. Mutual information measures the amount of information shared between two random variables, or the decrease in randomness of one random variable due to the knowledge of another [1].

### E. Definition 4 Mutual Information

Let $X$ and $Y$ be two random variables with probability distributions $p$ p and $q$ respectively, and joint probability distribution $r$. Mutual information, $I\ (X;Y)$, is the relative entropy between the joint probability distribution, $r$, and the product distribution, $d$, where $d(x, y) = p(x)\ q(y)$. That is,

$$I(\Xi;\Psi) = \Delta(\rho \parallel \delta) = \Sigma\Sigma\rho(\xi, \psi)\, \lambda o \gamma\, (\rho(\xi, \psi) \,/\, \pi(\xi)\theta(\ \psi)))$$

If the random variables $X$ and $Y$ are independent, then the joint probability distribution is equal to the product distribution, that is, $r = d$. Thus mutual information measures the correlation between $X$ and $Y$, with respect to $X$ and $Y$ being independent [2]. Mutual information to be expressed $n$ terms of entropy:

$$I(\Xi;\Psi) = H(\Xi) + H(\Psi) - H(\Xi, \Psi).$$

The mutual information MI $(A,B)$ of two images $A$, $B$ has 3 equivalent definitions. Each of them can explain the mutual information differently.

The first uses the difference in the entropy of an image and the entropy of the same image A knowing another image

$$B{:}MI(A,B) = H(A) - H(A|\ B) = H(B) - H(B \mid A)$$

Here, $H(A)$ measures the information contained in the image $A$, while $H(A|\ B)$measures the amount of information contained in the picture when the image $B$ is known. The mutual information corresponds to the amount of information that the image $B$ owns the image $A$, or similarly, the amount of information that owns Image $A$ on the image $B$.

The second definition refers to the distance $i\ pi$ log $(pi\ /\ qi)$, S which measures the distance between two distribution $p$ and $q$ :

$$MI(A,B) = \Sigma\alpha,\beta\ \pi\alpha\beta\nu\, \lambda o \gamma(\ \pi\alpha\beta \,/\, \pi\alpha\ \pi\beta\ )$$

is the measure between the distribution $pab$ images $A$ and $B$ and distribution $pa\ pb$ where images $A$ and $B$ are independent. This definition of information is therefore a measure of mutual dependence between images $A$ and $B$. There will be a shift when images $A$ and $B$ are most similar. [3]

The third definition of mutual information is a combination of entropies of two images, separate and attached:

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

## III. SECTION II

### A. Problem specification

To extract the component images virtually hidden in the principle image. Information theoretic quantities are used to measure similarity of images in a statistical frame work.

Statistic Description methods describe textures in a form suitable for statistical pattern recognition.

Morphological reconstructions are suggested are built from larger primitives, fine structure from smaller primitives. Co-accurance matrices are used to edge frequency detection and separation [7]. Here we appeal to the mutual information to bring out the component images from a complete images presentation.

As the images become misaligned, dispersion of their joint histogram increases. Therefore registration of two images can be accomplished by minimizing the joint entropy of the images, but mutual information is a better criterion as marginal entropies H (I) and H (J) are taken into account.

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

The optimal transformation can be gained by maximizing mutual information of the two images.

So if the images are of the same object, when they are correctly registered, corresponding pixels in the two images will be of the same anatomical or pathological structure.

Normalized measure of mutual information is defined as follows:

$$\mathrm{NMI}\ (A,B) = \frac{H(A) + H(B)}{H(A,B)}$$

Normalized mutual information has been shown to be more robust for intermodality registration than standard mutual information.

### B. *Normalized Cross-Correlation*

METRIC – A Comparison

The correlation between two images (cross-correlation) is a standard approach to feature detection. It can be used as a measure for calculating the degree of similarity between two images.

Its mathematical definition is given below

$$cc\,(i\,,\ j) = \frac{\sum_w (w - E\,(w))(I_{(i\,.\,j)}) - EI_{(i\,,\,j)})}{\sum_w w - E\,(w))^2 \quad E_{I_{(i\,,\,j)}}(I_{(i\,,\,j)} - E\,(I_{(i\,,\,j)}))^2}$$

This metric computes pixel-wise cross-correlation and normalizes it by the square root of the auto-correlation of the images. Misalignment between the images results in small measure values.

The metric is insensitive to multiplicative factors between the images and produces a cost function with sharp peaks and well-defined minima.

The correlation coefficient is a good measure of alignment in the case of images of the same subject acquired with the same modality at different times in order to detect subtle changes in intensity or shape of a structure.

## IV. SECTION III

### A. *Our Method*

Mutual system is estimated from image strategies and computed over the region of overlap that is the intersection of image spaces (or) video frames. In general the region of overlap grows image spaces (or) video frames become aligned. And since as images are video frames become misaligned. The region of overlap determines the overlap strategies on the images pixels contribute to the computation of the strategies. Normalized mutual information is the similarity measure that is less affected by overlap strategies.

Gradient mutual information determines the statistics for the images that includes spatial information. [5]

## V. SECTION IV

EXPERIMENTAL RESULTS

The proposed method was applied to register an image and its component. These are referred to us reference image and target image and the registered image for the three metrics. The pixel values are converted to mod 256 and a transformation is effected on the pixel values at the position x, y with the function based on the RGB values and the parameters for the linear fit fro the pixel values under consideration

The estimated function values are used in the metric for Mutual Information, Normalized Mutual Information and the normalized cross correlation coefficients. The parameter under consideration is put in different cases based on the residue classes modulo 256.

Change of origin and scale helps us to obtain the normalized values. We find the Mutual Information calculated from the registered image and the target image agree as per the table1 given.

Figure 1 – Total Image (Registered)

Figure 2 – Component Image (Implemented)

A. Implementation and results

Figure 3 – Total Image (Registered)

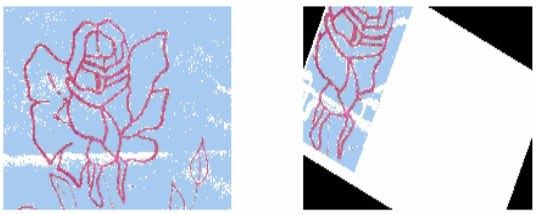
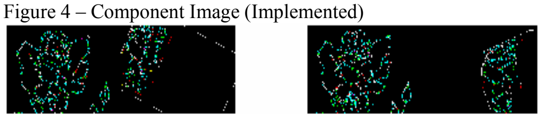


Figure 4 – Component Image (Implemented)



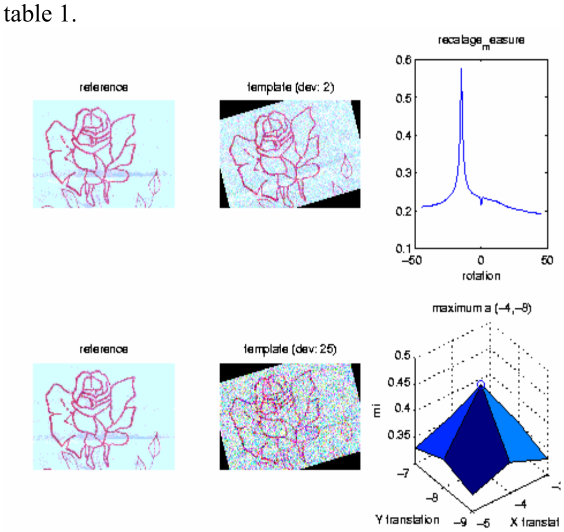
case 1

double(cat(4,avi(1:end).cdata))/255;

% Convert to RGB to GRAY SCALE

mutualinfo and normalizedmutualinfo';

The proposed method was applied to register two components of the images. The following figures present the reference image, target image and registered image for all the three metrics MI, NMI and NCC. The resulting values are summarized in table 1.




| NI | NMI | NCC |
|---|---|---|
| 0.3314 | 0.3589 | 0.3300 |
| 0.3534 | 0.4619 | 0.3540 |
| 0.3296 | 0.3581 | 0.3312 |

Table 1

Information for $A \cup B$

Information for $A \cap B$

Use of result for

$$H(A,B) = H(A) + H(B) - H(A \cap B)$$

*Result*

$H(A)$,$H(B)$ are the split images.

## VI. SECTION V

### A. Conclusion and Future work

The use of least sequences is the correlation seen in progress is institutive method allowing retaining of images whole being used on the intensities of the images. The probability distributions generally used in such studies are method taken care of distributions having multi modes.

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Hails from Thanjavur,Tamil Nadu. She received the B.Tech Degree in Computer Science and Engineering from Bharathidasan University ,Trichy in 1993 and M.Tech degree in Computer Science and Engineering from SASTRA University in 2005.She is currently with SASTRA University as a senior faculty in the School of Computing. Her research interests include Network security and

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He has graduated from university of madras at 1960 and Post Graduate from Annamalai University. He has obtained his M.Phil from the University of Madras with Specialization in Stochastic Processes and Application . He has guided more than 50 M.Phil research scholars and 20 Phd scholars. He has Published /Presented more than 100 papers in various known applications of stochastic processes invariant for and abstract algebra. At present he is guiding 4 people on Cryptography parallel algorithms and VLSI design. He is currently working as a Professor in the School of Computing of SASTRA University , Tanjore, Tamil Nadu.