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KNOWLEDGE BASED APPROACH FOR ALIGNMENT PROBLEMS

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ABSTRACT

Machine vision is an area in which all problems related to image analysis are handled in a different outlook. In analyzing biomedical images and other coherent imaging systems one is interested in identifying the part from the whole. This is done usually by adopting different similarity measures like joint entropy. Here a knowledge base is created on which an affine transmission having specific translation and rotation are used to complete the solution to the above problem besides the use of statistical ZKIP (zero knowledge interactive protocol) based on mutual information differences. This method solves the problem with 95% confidence level while compared with earlier techniques.

Keywords: *Alignment Problem, Affine Transformation, AI And Machine Vision, Joint Entropy.*

1. INTRODUCTION

We broadly introduce the development of the subject under consideration of four categories.

At the outset the problem can be viewed in the first step, image analysis Components and as the measure of intelligent system by mutual information system.

Images virtually hidden as components play an important role in medical diagnosis and imaging acquisition and segmentation analysis sonaka [3] and other image processing experts have developed methods based on pattern recognition and formal grammatical rules. Viola [10] has studied the problem from the point of view of removal of additive noise in creating an image from particular pose. As coherent imaging system need for removal of multiple noise, the transformations employed by earlier authors are to be modified.

This problem has been addressed as a problem in artificial intelligence robotic vision. The knowledge base available in the data stream is we use in a different orientation while controlling alignment problem and pattern recognition problem. We can view for automaton of our image cognition of brain. New similarity measures based on mutual information are used to design a machine vision.

In the second stage the same problem can be formulized as a problem on approximate reasoning. Gonzalez and Rafael C. [2] studied in a reasoning problem to reach a pre-defined goal state from one or more given initial states. The lesser the number of transitions for reaching the goal state, the higher the efficiency of the reasoning system. Increasing the efficiency of a reasoning system thus requires minimization of intermediate states, which indirectly calls for an organized and complete knowledge base. An expert system consists of a knowledge base, database and an inference engine for interpreting the database using the knowledge supplied in the knowledge base.

No recognition is possible without knowledge. Woods, Richard E. and Eddins, Steven [2] said

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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 more general about object classes are required. The ability to develop relations in classification is studied through similarity measures. Similarity measure 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 nature between sets can be introduced on the assumption of independent probability modeling.

Revathy studied [6], image similarity-based methods are broadly used in the study of coherent imaging systems. This 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 is commonly used for registration of images of the same modality.

The third step the problem can be regarded as an alignment problem. Digital image can be regarded as a two-dimensional array of pixels containing gray levels corresponding to the intensity of the reflected illumination received by a video camera. Amit konar [1] said, for interpretation of a scene, its image should be passed through three basic processes: low, medium and high level vision. The importance of low level vision is to pre-process the image by filtering from noise. The medium level vision system deals with enhancement of details and segmentation (i.e., partitioning the image into objects of interest). The high level vision system includes three steps: recognition of the object from the segmented image, labeling of the image and interpretation of the scene. Most of the AI tools and techniques are required in high level vision systems. Recognition of objects from its image can be carried out through a process of pattern classification, which at present is realized by supervised knowledge-based computation.

As a last step regional segmentation and splitting are the areas in which the problem can be posed. Regional segmentation is accomplished by growing or splitting regions. In the first instance, neighboring regions having some form of homogeneity such as uniformity in gray level or color or texture are grouped together to form a larger region. The process of building a larger region is continued recursively, until a specific type of known structure is identified. Region growing is generally called a bottom up approach, as the regions, representing leaves of a tree, are grouped to get the intermediate node (describing the complex regions), which after grouping at several levels form the root, describing the complete image.

Konar [1] studied region Splitting starts with the entire image and splits it into larger regions of more or less uniform features including gray levels, texture or colors. The regions thus obtained are sub-divided recursively until regions

describing some known 2-D shapes are identified. Region splitting is called a top down approach for regional segmentation. It may be noted that segmenting an image into regions without any knowledge of the scene or its modules is practically infeasible. Generally, the partial knowledge about the image such as an outdoor scene or a classroom or a football tournament helps the segmentation process.

2. BASIC TECHNIQUES

2.1. Mutual Information

Mutual Information (MI), often speed up the registration is implemented exploring the coarse to fine resolution strategy (the pyramidal approach).

Programs that can perform controlled warping according to mathematically defined relationships or calculate those matrices of values from a set of identified fiducial or reference marks that apply to the entire image are generally specialized [10].

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Step 1:

From the window, pixel values are obtained for both perimeter of the whole and edge of the interior part of the image.

Step 2:

These pixels are classified in to class interval frequency table.

Step 3:

Each class is regarded as an event and the probability is given by $P_i = \frac{F_i}{\sum F_i}$ ……….(1)

Mutual Information = $-\sum P_i \log_2 P_i$ …….(2)

Being an area based method the MI, has principle limitations. To overcome this some authors [6, 10] combine MI with other preferably feature-based methods to gain higher robustness and reliability. Unfortunately when the images have significant rota1tions they often employed pyramidal image representation along with fast optimization algorithms.

Mutual information is a combination of entropies of two images, separate and attached:

$$MI(A,B) = H(A) + H(B) - H(A,B) \text{ ...(3)}$$

2.2. Entropy

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

$$H(X,Y) = H(r) = -\sum r(x,y) \log r(x,y).$$
………(4)

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.[11]

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

$$D(p \| q) = \sum p(x) \log(p(x)/q(x))$$
……..……………..…..(5)

For reasons of continuity, we define

$$0 \log (0/q) = 0 \text{ and } p \log(p/0) = \infty.$$
…………………..……..(6)

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.

Let X and Y be two random variables with probability distributions 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,

$$I(X;Y) = D(r \| d)$$
$$= \Sigma\Sigma r(x,y) \log (r(x,y)/ p(x)q(y)))$$
………….(7)

2.3. Entropy difference reduces to Statistical Difference in the consideration of statistical ZKIP

Proof

Salil vadhan [7] has studied statistical Interactive protocol based on stat difference. Here we modify his results using mutual information differences. Given an instance (X,Y) of Entropy Difference, we describe how to efficiently produce an instance (A,B) of statistical difference such that the latter

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is a YES or NO instance according to whether the former is. By artificially adding gates if necessary, we may assume that both X and Y have m input gates and n output gates. Let k be a large constant (to be determined from the proof). Set $q = 9km^2$ and define $X' \otimes^q X_j$, $Y' = \otimes^q Y, X'$ and Y' have input (resp., output) length $m' = qm$ (resp. n' = qn). Let $H = H_{m'+n'.m'}$.

A: Choose $r \leftarrow \{0,1)^{m'}$ and let $x = X'(r)$. Choose $h \leftarrow H$ and $y \leftarrow Y'$. Output $(x, h, h(r, y))$.

B: Choose $x \leftarrow X', h \leftarrow H,\ and\ z \leftarrow \{0,1\}^{m'}$. Output (x, h, z).

Now we analyze this construction. We denote the components of the distributions by $A = (A_1, A_2, A_3)$ and $B = (B_1, B_2, B_3)$. X' and Y' are Δ-flat for

$\Delta = \sqrt{9km^2}.m = 3\sqrt{k}.m^2$. Noting that $q > 2\sqrt{k}\Delta + k$, we have:

Claim

$$(X,Y) \in ED_Y \Rightarrow H(X') > H(Y') + 2\sqrt{k}\Delta + k$$

$$(X,Y) \in ED_N \Rightarrow H(Y') > H(X') + 2\sqrt{k}\Delta + k$$

……………….(8)

Now we show that A and B are statistically far or close according to whether X and Y are larger entropy

Assume that two knowledge sources KB1 and KB2 submit two frames of discernments θ_1 and θ_2 respectively. Let m_1 (.) and m_2 (.) be the BPA at the subsets of θ_1 and θ_2 respectively. The new BPA, m(.) can be computed based on m_1(.) and m_2(.) by using

$$m(x) = K \sum_{X = X_i \cap X_j} m_1(X_i).m_2(X_j) \quad \text{and}$$

$$K = 1 - \sum_{X_i \cap X_j = \phi} m_1(X_i).m_2(X_j)$$

…………..(9)

Where X_i and X_j are focal elements of θ_1 and θ_2 respectively.

Definition I: Subset of θ, which are assigned nonzero probability masses are called focal elements of θ.

Here θ represents frame of discernment.

Definition II: A belief function [4, 5] Bel(x), over θ, is defined by

$$\text{Bel (x)} = \sum_{Y \subseteq X} m(Y) \quad \text{…………..(10)}$$

3. EXPERIMENTATION AND METHODS

3.1 Problem Formulation

The general problem of alignment model entails comparing a predicted image of an object with an actual image. Given an object model and a pose (coordinate transmission) a model of imaging process could be used to predict the image that will result. Given a model $u(x)$ and pose $v(y)$, we can formulate an image equation

$$v(T(x)) = F(v(x)Q) + N$$
$$v(y) = F(v(inverseT(y.q) + N \quad \text{…….(11)}$$

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Where T represents transformation or pose, F represents image function and N represents noise (generally Gaussian noise). We seek an estimate of transformation that aligns the model u and image v by maximizing information over transformation of T. This alignment problem is reformulated to get the hidden part from the whole image as a problem on artificial intelligence and machine vision. From the knowledge of mutual information and mutual information differences we have designed a routine that will extract the part. By proper choice of the entries in the general matrix equation suggested by AI expert system analysts, this problem can be the combined effect of 2-D transformations representing rotation and translation.

Step 1:

Information through joint entropy is calculated at all data points listed on the boundary.

Step 2:

These points are put to mutual information and specific rotation matrices with the value act on these points, is stored as a knowledge _base

Step 3:

This is shifted by a translation. The translation of this knowledge is regarded as an alignment of image and pose. Validity is judged by mutual information difference at 5% level.

3.2 Methods

3.2.1 Normalized cross-correlation

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.

$$CC(i,j)= \frac{\sum_{w}(w-E(w)(I_{ij}-EI_{ij})}{\sqrt{\sum_{w}(w-E(w))^2\sum_{i,j}(I_{ij}-EI_{ij})^2}} \quad \ldots\ldots\ldots\ldots(12)$$

For the statistical ZKIP we have verified the data for the verification of fair registration. Through computation the cc is computed as .73 and .82. This shows the registration done fairly well.

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 [8, 9].

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.

3.2.2 Construction of 2-D lines from noisy 2-D points

We shall directly apply the filter equation for the construction of affine 2-D lines from noisy 2-D points. Here, given the set of points $x_i{*} = (u_i{*}, v_i{*})$, we have to estimate the parameters $a = (a, p)^T$. The

$$f(x_i, a) = au_i + v_i + p = 0$$

$$y = M_i a + w_i \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(13)$$

Where

$$y_i = -f_i(x_i * a_{i-1}*) + (\partial f_i / \partial a)(a - a_{i-1}*)$$

$$= -v_i$$

$$M_i = (\partial f_i / \partial a)$$

$$=(u_i, 1)$$

The measurement noise w_i is given by

$$w_i = (\partial f_i / \partial x_i)(x_i - x_i*) \quad \ldots\ldots\ldots\ldots\ldots(14)$$

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Where ($(\partial f_i / \partial x_i) = [a_{i-1}*,1]$

The covariance matrix w_i , is given by

$$w_i = (\partial f_i / \partial x_i) \wedge_i (\partial f_i / \partial x_i)^T$$

Where $\wedge_i$ =1.

3.2.3 Construction of 3-D points using 2-D image points

The 3-D object points are mapped onto an image plane by using the principle of perspective projection. Let the 3-D object point be P having co-ordinates $(x,y,z)^T$, which is mapped onto the image plane at point $(U, V, S)^T$. Let T be the perspective matrix. Then

$$\begin{bmatrix} U \\ V \\ S \end{bmatrix} = \begin{bmatrix} t_{11} & t_{12} & t_{13} & t_{14} \\ t_{21} & t_{22} & t_{23} & t_{24} \\ t_{31} & t_{32} & t_{33} & t_{34} \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \end{bmatrix}$$

…………………………………(15)

Where t_{ij} is the (i,j) th element of the perspective projection matrix. Let u = U/S and v = V/S. Now, after elementary simplification, let us assume for brevity that $t_i = (t_{i1}\ t_{i2}\ t_{i3}\ t_{i4})^T$ and P is (x, y, z), also assume that a=(t_1 t_{14} t_2 t_{24} t_3) ^{T}. For a match of an image point I with an associated scene point P, we now have the following relationships between P, u and v.

Rotation Matrix

$$\begin{bmatrix} \mathrm{Cos}\theta & -\sin\theta & 0 \\ \mathrm{Sin}\theta & \cos\theta & 0 \\ 0 & 0 & 1 \end{bmatrix}$$ ....(16)

Translation Matrix

$$\begin{bmatrix} 1 & 0 & t_1 \\ 0 & 1 & t_2 \\ 0 & 0 & 1 \end{bmatrix}$$ ....(17)

4. DATA REDUCTION TECHNIQUE

Fig.1 – Total Image (Registered)

Fig.2 – Component Image (Implemented)

Table 1. Sample date from large database simulated by AutoCad and Matlab commands

Window Length	Data
(54.8, 75.2)	(59.8, 80.1)(62.3, 77.1) (64.2, 71.7)(68.2, 63.6)
(69.8, 135.2)	(67.4,131.2)(66.7,133.3) (66.7,127.7)(77.3,128)
(69.6, 80.3)	(69.3,72.4)(62,74.2) (68.5, 80.4)
(64.6, 60.3)	(65.2,56.7)(60.1,60.4) (62.5,65.8)

The choice for the angles of rotation used in this discussion are given in the following range

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Rotation in degrees

$$\begin{bmatrix} -60 & \text{to} & 0 \\ 0 & \text{to} & 50 \\ -10 & \text{to} & 10 \end{bmatrix} \quad ....(18)$$

Translation

0.2, 0.3, 0.4, 0.5, .6 ………………………(19)

5. RESULTS AND DISCUSSIONS

Implementation and results

Fig.3 – Total Image (Registered)

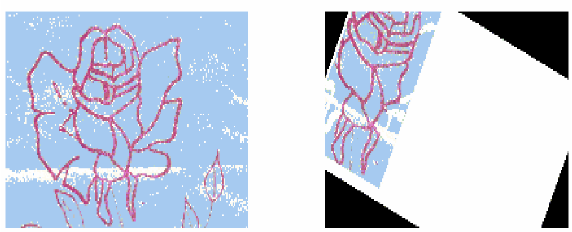


Fig.4 – Component Image1 (Implemented)

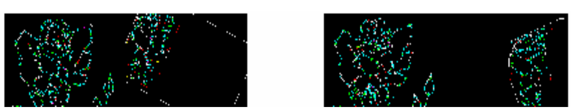
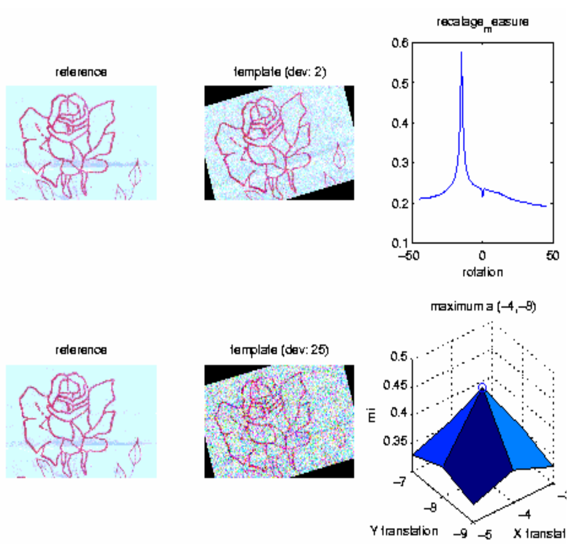


Fig.5 – Component Image2 (Implemented)



The mutual information differece evaluated by the specific rotation is illustrated in the shaded area of the fig.5

Table 2 Mutual Information for Split Image

MI	NMI	NCC
0.3314	0.3589	0.3300
0.3534	0.4619	0.3540
0.3296	0.3581	0.3312

Table 3 Mutual Information for Split Image

MI	NMI	NCC
0.05314	0.0589	0.0530
0.05135	0.0546	0.0535
0.04952	0.0535	0.0493

Information for $A \cup B$

Information for $A \cap B$

Use of result for $H(A,B) = H(A) + H(B) - H(A \cap B)$ ……..(20)

6. RESULT

$H(A)$,$H(B)$ are the split images. These rotations gives the values for extracting the inner figure with mutual information level extracted up to 95% on the component and the intersection which is shown in table 2 as compared to the earlier result given in table 3 giving only 66%.

7. CONCLUSION

Of the different definitions on Mutual Information we have used a similarity measure based on Shannon's entropy. The routine 'EMMA' suggested by Viola is used to bring out the Mutual

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Information from the component image. Here the scaling and dependency are studied by the cross correlation and normalized Mutual Information. The results obtained may be improved by removing the multiplicative noise present in the image under consideration. To compare the solution technique employed on Mutual information we have taken a statistical interaction based on Mutual Information difference. Simulated data through the statistical **ZKIP** zero knowledge interactive protocol) gives us an easy and an automated algorithm for such situations of removing a part from the whole image. The probability distributions generally used in such studies are method taken care of distributions having multi modes.

The statistical Zero Knowledge Interactive Protocol based on Mutual Information difference given as easy approach to study alignment problems. In analyzing biomedical images and other coherent imaging systems one is interested in identifying the part from the whole. This is done by joint entropy. Here a knowledge base is created on which an affine transmission having specific translation and rotation are used besides the use of statistical ZKIP based on mutual information differences. This method solves the problem with 95% confidence level while compared with earlier techniques.

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