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Image Matching Scheme by using Bhattacharyya Coefficient Algorithm

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ABSTRACT: A recurring problem that arises throughout the sciences is that of deciding whether two statistical distributionsdiffer or these are consistent - currently the chi-squared statistic is the most commonly used technique for addressing thisproblem. This paper explains the drawbacks of the chi-squared statistic for comparing measurements over largedistances in pattern space and suggests that the Bhattacharyya measure can avoid such difficulties. The originalinterpretation of the Bhattacharyya metric as a geometric similarity measure is reviewed and it is pointed out thatthis derivation is independent of the use of the Bhattacharyya measure as an upper bound on misclassification in a Two-class problem. The affinity between the Bhattacharyya measures is described and thatthe measure is applicable to any distribution of data. I explain that the Bhattacharyya measure is consistent withan assumption of a Poisson generation mechanism for individual measurements in a distribution which is applicableto a frequency (histogram) or probabilistic data set and suggest application of the Bhattacharyya measure to thefield of system identification.

KEYWORDS: Image understanding, Image matching, Attribute Modelling, Image Model Matching, Bhattacharyya Coefficient

I. INTRODUCTION

Computer vision and Programming go hand in hand in our World. One needs to use programming to materialize the theory so it can be applied to real world problems. Computer vision is an exciting field and we try to make sense of images. These images could be static or could be retrieved from videos. Making sense could be things like tracking an object, modelling the background; pattern recognition etc. [1].I will implement and contribute of computer vision and image understanding a few state of the art algorithms in Computer vision, covering areas such as object tracking, background modelling, pattern recognition etc.

Image understanding is the most essential features of Computer vision and Image processing. An image is composed of many dots called Pixels. More the pixels, higher the resolution of the image. When an image is grabbed by the camera, it is often in RGB format. RGB is one of many colour spaces used in Computer vision. Other colour spaces include HSV, Lab, and YIQ etc. RGB is an additive colour spaces where I get different colours by mixed red, green and blue values. In a 24-bit RGB image, the individual values of R, G and B components range from 0 to 255.

Interactive image segmentation is so great practical importance in image editing, interactive segmentation uses minimal user interaction, for instance simple scribbles or bounding boxes, to learn prior information from the current image. Embedding clues on user intention facilitates segmentation, and has been intensively researched in recent years. Segmentation with offline learning is thesegmenting a class of images with similar patterns occurs in important applications such as medical image analysis. In this case, offline learning of prior information from segmented training images is very useful.

Image matching, which measures the degree of similarity between two image sets that are superimposed on one another, plays an important role in many areas such as pattern recognition, image analysis and Computer vision. The images to be matched are required to go through a number of operations before the similarity is determined. These operations include feature extraction, distance transformation, similarity measurement and searching for the best match. Thus, an effective approach to image matching concerns with the following key issues: What kind of features are used for matching? What is the criterion for best matching? How to find the best matching?

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Although the pixel-based methods are simple to implement, they are very sensitive to any changes between images and will not be able to identify the same results structures in images from different sensors. On the other hand, the high-level matching methods are very insensitive to these changes, however, in most cases the extraction and representation of the relationship itself is a difficult problem. In the past, a number of matching algorithms had been developed based on the edge detection and distance transform. The typical examples are Chamfer matching [2], Borgefors' hierarchical Chamfermatching[5] and the Huttenlocher's Hausdorff distance matching [12]. All of these Algorithms involve the following steps in sequence: detecting edge points, converting the original gray-scale images to binary edge images, applying distance transform on the binary images, and finally measuring the similarity between the template image and the target image.

In this paper, I explored the potential of parallel vision computing on a network of workstation clusters. I adopted Bhattacharyya coefficient to implement the proposed histogram images matching in a parallel virtual machine (PVM) computing environment [11], where a complex task is divided into a number of sub-tasks and those sub-tasks are later reorganized into clusters according to granularity before being mapped on computers for simultaneous operation.

II. RELATED WORK

Active contours and level sets: The use of a global similarity measure in image segmentation often leads to challenging optimization problems. The solutions were generally sought following gradient-based optimization via active contour (or level set) partial differential equations .An Euler-Lagrange equation of contour motion is derived so as to increase the consistency betweenthe foreground region enclosed by the active contour and a given model [4], [9] or to maximize the discrepancy between the two segmentation regions [1], thereby reaching a local optimum at convergence. Several measures were studied within the active contour framework, for instance, theKullback–Leibler divergence [2], the Earth Mover's distance [3] and the Bhattacharyya coefficient [6], The Bhattacharyya coefficient has a fixed (normalized) range, which affords a conveniently practical appraisal of the similarity, and several other desirable properties [9].

Along with an incremental gradient-flow evolution, active contours may require a large number of updates of computationally onerous integrals, namely, the distributions of the regions defined by the curve at each iteration and the corresponding measures. This can be very slow in practice: it may require up to several minutes on typical CPUs for a color image of a moderate size [8]. Furthermore, the robustness of the ensuing algorithms inherently relies on a user initialization of the contour close to the target region and the choice of an approximating numerical scheme of contour evolution.

Graph cuts: Discrete graph cut optimization [6], [7], [10], which views segmentation as a label assignment, has been of intense interest recently because it can guarantee global optima and numerical robustness, in nearly real-time. It has been effective in various computer vision problems [9], for instance, segmentation tracking [11], motion estimation [13], visual correspondence [4] and restoration [7]. Unfortunately, only a limited class of functions can be directly optimized via graph cuts. Therefore, most of existing graph cut segmentation algorithms optimize a sum of pixel dependent or pixel-neighborhood dependent data and variables. Global measures of similarity between distributions have been generally avoided because they are not directly amenable to graph cut optimization. Notable exceptions include the co-segmentation works in [9] as well as the interactive segmentation algorithms in [5], [6]. For instance, in the context of co-segmentation of a pair of images, the problem consists of finding a region in each image, so that the histograms of the regions are consistent.

Thispaperinvestigatesand contributionofefficient the otheralgorithms have many problems for examples;
(1) finding a region in an image, so that the distribution (kernel density estimate) of an image feature within the region most closely matches a given model distribution; (2) co-segmentation of image pairs and (3) interactive image segmentation with a user-provided bounding box and etc. Each algorithm seeks the optimum of a global functional based on the Bhattacharyya measure, a practical alternative to other matching measures such as the Kullback-Leibler divergence. These functionsare not directly amenable to graph cut optimization as they contain nonlinear functions of fractional terms, which make the ensuing optimization problems challenging1. I first derive a family of parametric

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bounds of the Bhattacharyya measure auxiliary functions of the Bhattacharyya measure, a result which allows us to solve each problem efficiently via graph cuts.

I show that the proposed optimization procedures converge within very few graph cut iterations. Comprehensive and various experiments, including quantitative and comparative evaluations over two data sets, demonstrate the advantages of the proposed algorithms over related works in regard to optimality, computational load, accuracy and flexibility. These advantages are summarized as follows.

• Computational load: The proposed bound optimization brings several computational advantages over related methods. First, it builds graphs that have the same size as the image, unlike the graph cut methods in [13], [11]. Second, the ensuing algorithms converge in very little iteration. This will be demonstrated in the experiments. Third, the algorithm is robust to initializationand does not require sophisticated initialization procedures as with TRGC [8]. It is possible to use trivialinitializations.

• Accuracy and optimality: Quantitative comparisons with related recent methods over a severalpublic databases demonstrate that the proposed framework brings improvements in regard to accuracy andsolution optimality.
• Flexibility: Unlike the unnormalized histogram models in [9], [13], [11], the proposed frameworkyields co-segmentation and segmentation algorithms, which handle accurately and implicitly variations inthe size of the target regions because the Bhattacharyya measure references kernel densities and, therefore,is scale-invariant.

III. PROPOSED ALGORITHM

Finding a region consistent with a known (fixed) model distribution is the cost function: Let C = [0, 1] n be an N-dimensional color space and I = (I_1, I_2, I_N) a given image, where I_i 2 C denotes the color of pixel i and N is the number of pixels in the image. Each segmentation of I can be identified by a binary vector x = (x_1, x_2, x_N), with x_i = 1 indicating that pixel i belongs to the target region (foreground)andXi = 0 indicating background membership. Each segmentation x yields a distribution over colors c 2 C within the corresponding foreground region:
$p_x(c) = P_i\ x_iK_i(c)|x|$
where $|x| = P_i\ x_i$ is the size of the foreground region corresponding to binary vector x. Possible choices of K_i are the Dirac function (I_i−c) = 1 if I_i = c and 0 otherwise, which yields the normalized histogram, or the Gaussian kernel n2 exp−kI_i−ck_2,with the width of the kernel. The purpose of the algorithm is to seek a segmentation x so that the corresponding foreground color distribution px most closely matches a known target distribution q. To achieve this, we use the negative Bhattacharyya coefficient:B(x|q) = −ZC ppx(c)q(c) .

The range of B(x|q) is [−1, 0], 0 corresponding to no overlap between the distributions and −1 to a perfect match. Thus, our objective is to minimize B(x|q) with respect to x. The Bhattacharyya coefficient has the following geometric interpretation. It corresponds to the cosine of the angle between the unit vectors (ppx(c), c 2 C) T and (pq(c), c 2 C) T (These vectors are unit if we use the L2 norm). Therefore, it considers explicitly px and q as distributions by representing them on the unit hyper sphere. Note that the Bhattacharyya coefficient can also be regarded as the normalized correlation between (ppx(c), c 2 C) T and (pq(c), c 2 C) T.

The Bhattacharyya coefficient has a fixed (normalized) range, which affords a conveniently practical appraisal of the similarity. This is an important advantage over other usual similarity measures such as the Kullback–Leibler divergence or the LP norms. It is worth noting that the distribution-matching term is not invariant with respect to illumination changes. This will be demonstrated in the experiments.

To avoid complex segmentations and isolated fragments in the solution, we add a regularization term to our objective function: S(x) = X {i, j} 2Nwi, j [1 − (x_i − x_j)] where N is the set of neighboring pixels in a t-connected grid(t = 4, 8 or 16). Pairwise weights wi, j are typically determined either by the color contrast and/or spatial distance between pixels i and j. This purpose is to minimize the following function with respect to x: E (x|q) = B (x|q) + S(x), with a positive constant. As we will eventually use graph cuts in the main step of our algorithm, I assume wi, j = 0, which means S(x) is a sub-modular function of binary segmentation x.

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IV. PSEUDO CODE

Algorithm 1: Finding a region consistent with a model
Step 1: Iter. t = 0;
(a) Initialize the fixed labeling to $y^{(0)}$
(b) Set $\alpha=\alpha_0\geq 0$
Step 2: Repeat the following Steps until convergence:
(a) Update the current labeling by optimizing the auxiliary function over x via a picture:
$y^{(t+1)} = \text{argmin}\quad E(x, y^{(t)})$
$x: x\leq y^{(t)}$
(b) If $\alpha\leq \frac{1}{2}$go to Step2. (d)
(c) If $\alpha>\frac{1}{2}$(This Step is necessary only when $\alpha> 1$
• If the actual energy does not increase, i.e., E(y (t+1)) ≤E(y (t)):Go to Step. (d)
• If the actual energy increases, i.e., E(y (t+1)) > E(y (t)):Return to Step2. (a)
(d) tt← 1
Step 3: End.

In Algorithm 1, α increase, the bound yields a better approximation of the energy. In other words, higher values of α favor lowervalues of thenegativeBhattacharyya coefficient. Consequently, when Ihave a strict upper bound ($\alpha\in [0, \frac{1}{2}]$), one expect that $\alpha= \frac{1}{2}$ yields the best solution; I will confirm this experimentally.In summary, αcontrols the quality of the approximation for low values of the negative Bhattacharyyacoefficient: the higher, the better the approximation. Recall that one cannot increase arbitrary α asa value of $\alpha>\frac{1}{2}$ does not guarantee anymore that the energy does not increase within each iteration.However, the some values of $\alpha>\frac{1}{2}$, most of the blue surface still liesbelow the upper-bound plane, even though we do not have a strict bound anymore. Therefore, it is naturalto introduce in Algorithm 1 additional optional steps, which guarantee that the energy does not increaseeven for an initial choice of α bigger than $\frac{1}{2}$ (Steps 2.c in Algorithm 1). These steps allow to choose thebest tradeoff between approximation quality and optimality guarantee; we will confirm experimentallythe benefits of such steps. Starting from an $\alpha >\frac{1}{2}$, we verify whether the bound optimization did notincrease the energy at the current iteration, i.e., $E(y^{(t+1)})$ _ $E(y^{(t)})$. If this is the case, we accept theobtained solution and proceed to next iteration t+1, while keeping the same $\alpha >\frac{1}{2}$. Otherwise, we rejectthe obtained solution and re-optimize the auxiliary function at iteration t, but with a smaller value of α[14].

V. SIMULATION RESULTS

The simulation studies involve an image attribute as a histogram and to perform recognition. So, I use a Target histogram and a Candidate histogram, and match the histogram to see how closely the candidate object resembles the Target object and I implement this paper with C# programming. There are many techniques available, such as Bhattacharyya coefficient, Earth Movers Distance and Euclidean distance etc.

The reason for selecting histogram is because it is very popular in Computer Vision, plus it forms the foundation for articles coming up. For elementary statistics a color histogram is the frequency of different colors in the image. Using normalization, I can add scale invariance to a histogram. That means that the same object with different scales will have identical histograms. The Bhattacharyya Coefficient works normalized histograms with an identical number of bins.Given two histograms with p and qand then it calculates the Bhattacharyya Coefficient value. The equation is as follow:

$$\rho = \sum_{u=1}^{m} \sqrt{p_u q_u}$$

Considering the following two histograms, the calculation of Bhattacharyya coefficient is shown below.

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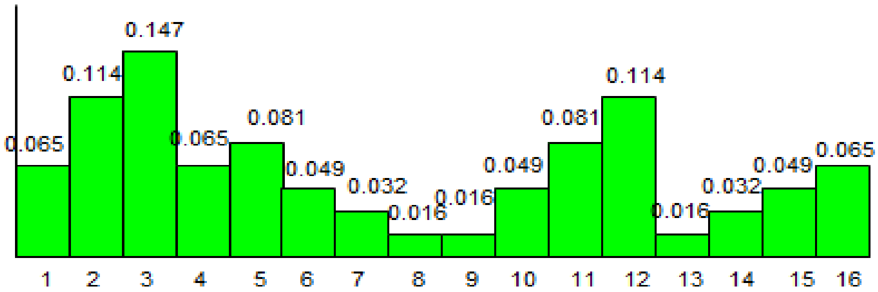

Fig.1..Histogram chart of Target frequency

In Fig.1.shows thehistogram of the Target frequency value p_u.

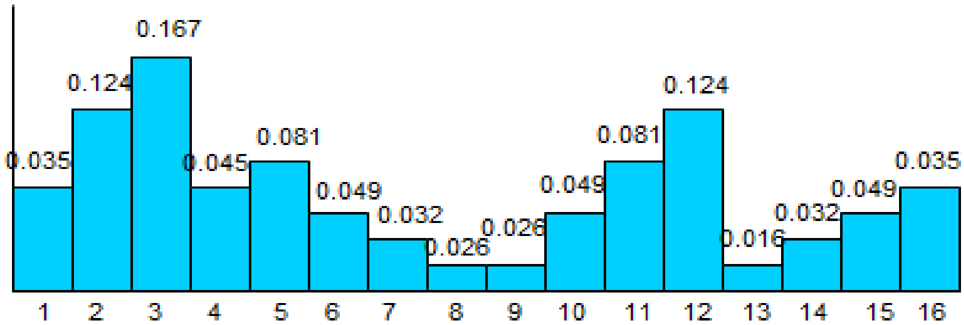

Fig.2.Histogram chart of Candidate frequency

In Fig.2.showsthe histogram of the Candidate frequency value q_u .

Bin	Target Frequency p_u	Candidate Frequency q_u	$\sqrt{p_u q_u}$
1	0.065	0.035	0.04769
2	0.114	0.124	0.11889
3	0.147	0.167	0.15668
4	0.065	0.045	0.05408
5	0.081	0.081	0.081
6	0.049	0.049	0.049
7	0.032	0.032	0.032
8	0.016	0.026	0.02039
9	0.016	0.026	0.02039
10	0.049	0.049	0.049
11	0.081	0.081	0.081
12	0.114	0.124	0.11889
13	0.016	0.016	0.016
14	0.032	0.032	0.032
15	0.049	0.049	0.049
16	0.065	0.035	0.04769
		Bhattacharyya Coefficient	0.9737

Table.1.Comparison between Target frequency, Candidate frequencyand BhattacharyyaCoefficient valuetable.

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In Table.1 shows to calculate the Bhattacharyya Coefficient values for Target frequencyand Candidate frequency the result is 0.9737 so that is different images. If the two images are identical, the result of Bhattacharyya coefficient will be 1. For correlation, a high score represents a better match than a low score.A perfect match is 1 and a maximal mismatch is -1; a value of 0indicates no correlation (random association). Image matching deals with transforming of two images and measuring the resemblance with another one some similarity measures. So, this similarity measures are essential ingredient values (p_u and q_u) of matching.

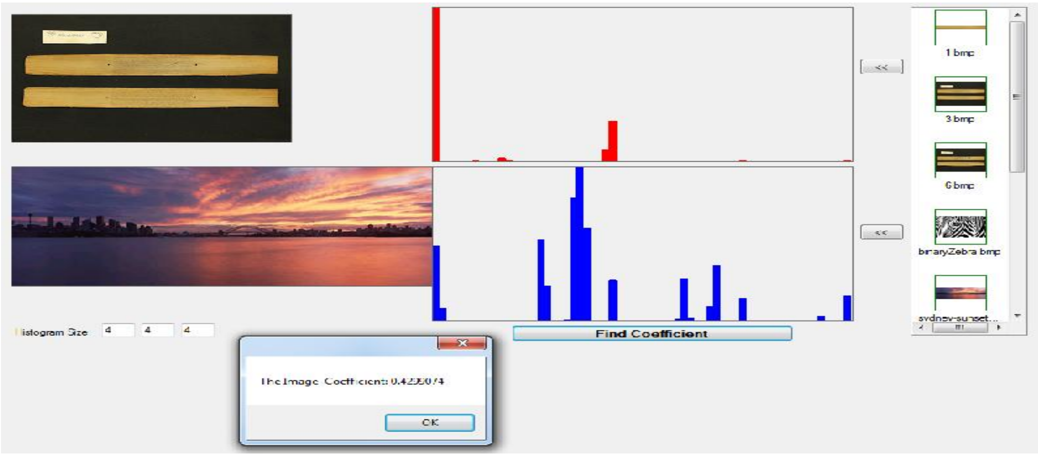

Fig.3.Performanceanalysis Unequalimages.

In Fig.3.shows the performance analysisof the twodifferent Myanmar Palm Manuscript and Natural scene imageshistogram, the resultof Bhattacharyyacoefficient is decimal point value.

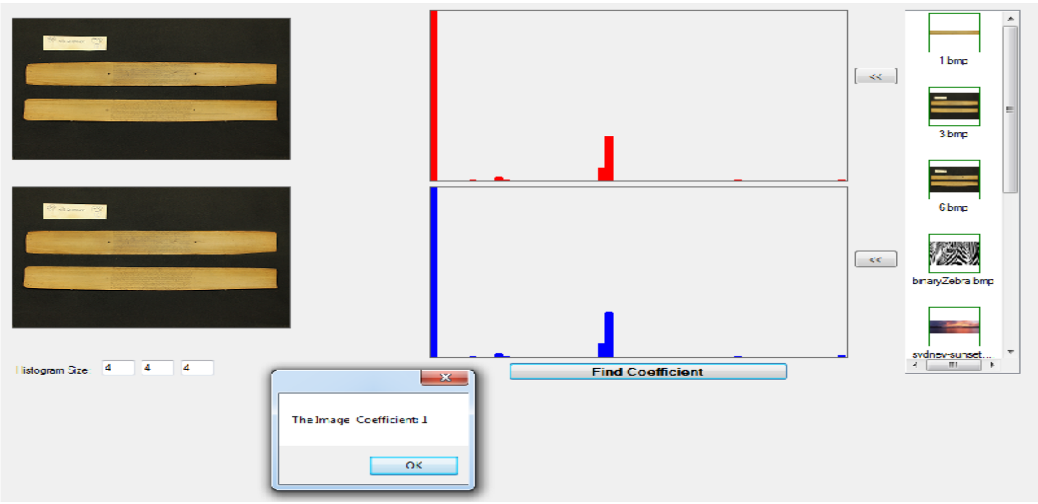

Fig.4. Performance analysis Equalimages

In Fig.4. shows the performance analysis of the two identical Myanmar Palm Manuscriptsimages histogram, the result ofBhattacharyyacoefficient is 1.

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VI. CONCLUSION AND FUTURE WORK

The simulation results showed that the proposed algorithm performs better with the same or not of the maximum number of hops metric. In this work we have presented the original geometric interpretation of the Bhattacharyya similarity measure. A derivation of the chi-squared statistic by maximum likelihood estimation has been given and the short comings of this statistic have been explained when applied over large distances in pattern space. We have shown that the Bhattacharyya measure is applicable to any data set irrespective of the distribution from which the data is sampled; moreover we have shown the measure to have all the properties that could be expected of a principledprobabilistic similarity function including self-consistency and lack of bias. So many arguments for the measure have been described and we have published previous work on the successful practical application of the measure I also describe the suitability of the measure to the field of system identification where we describe the link between prediction power and errors on data measurements used to define the model. The measure takes direct account ofthis correlation and can be seen to be consistent with standard approaches.

Many researchers have used the Bhattacharyya similarity measure and found it advantageous. Until now theBhattacharyya measure has been utilized by many as the result of a trial-and-error process with little understanding of why the measure works well. This work has demonstrated the reasons why the Bhattacharyya similarity measure should be used as an absolute similarity metric. The origin of the measure iswas independent of an upper bound on the Bayes error and its use should not be confined by such a limiting derivation. In further work I intend to examine the robustness of the Bhattacharyya measure by empirical methods and its application to problems of automatic model selection in the field of neural networks.

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BIOGRAPHY

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