Fuzzy Approach for Image Near-Duplicate Detection Using Gray Level Vertex Matching in Attribute Relational Bipartite Graphs

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Abstract. Shape of different regions of an image depends on the detection of the corners. .However vague information such as blurring, noise etc in an image is normally due to missing curvatures in the regions of image and therefore for the reliable decision for the detection of images in the corresponding domains based on corners in gray level images of source image and its duplicate and for their equivalence we give an algorithm linking it to the set theoretic fuzzy technique. We propose Attribute Relational Bipartite Graph (ARBG) for image near-duplicate (IND) as an important model. The application of the proposed algorithm works well as vertex detectors in their respective two domains. The performance is tested on a number of test images to show the efficiency of the fuzzy based algorithm.

Keywords: ARBG, IND, Fuzzy ARBG, BVT.

1 Introduction

Image near- Duplicate(IND) refers to a pair of images G1 as source (original) image and G2 as target (Duplicate) image.Detection and retrieval of IND is very useful in a variety of real world applications. For example, in the context of copyright infringement detection. one can identify likely copyright violation by searching over the internet for the unauthorized use of images [1].Some prior work in this direction of Image Exact Duplicate (IED) detection has been exploited in various contexts. Extensive research has been performed on the Content Based Image Retrieval (CBIR) over several decades. We have yet to achieve the desired accuracy from fully automated CBIR systems [2]. In CBIR systems low as well as high level feature extractions are one of the very important tasks and as its application lots of related work has been carried out in face detection. In view of traditional image similarity model not being able to capture scene composition of IND, Zang and Chang [1]used part based image similarity measure for stochastic matching of **attribute relational graph**(ARG) related to crisp data. In many real life situations the data are not always crisp since these are usually uncertain in nature. The uncertainty is mainly of two types: Stochastic uncertainty and fuzzy uncertainty. The traditional two valued logical system based on 0 and 1 termed as crisp set theory and crisp probability theory are inadequate for detecting precise uncertainty.

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This paper highlights the part based image similarity measure of edges with the help of Attribute Relational Bipartite Graph matching using Fuzzy membership for different grades of edges (strong, moderate and weak edges).

Some of the possible causes of IND are scene changes, movement and occlusion of foreground objects, absence or presence of foreground objects and background changes. Also camera view point change, camera tilting, exposure of lighting conditions etc. are also the causes of the variations of two near duplicate images.

Fig1 shows some examples of image near duplicate. This illustrates some of the IND due to camera position changes, a change in illuminations and position change of the objects in the image.

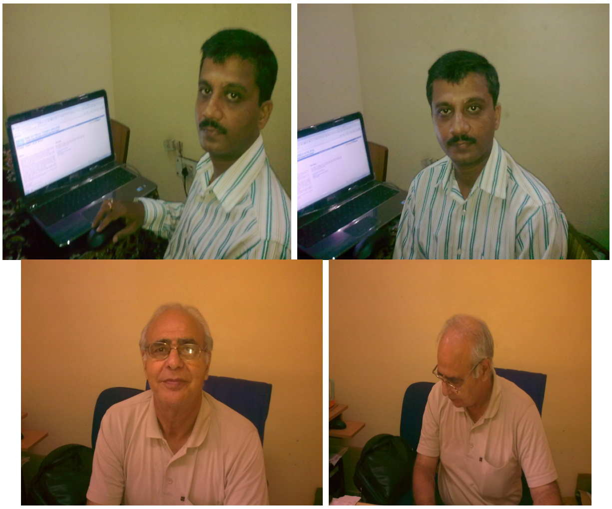

Fig. 1. Examples of some Image near Duplicate

Colour histogram is the most commonly used color representation.However; it does not include any spatial information [3]. Barrow [4] introduced ARG matching technique in his seminar work, as a result of which much research work has been done in this direction. He used energy minimizing technique (EMT) for possible modeling of the vertices of two attributive relational graphs (ARG). The computation of the similarity of the two images in their respective domain is done with the computation using heuristic rule or random algorithm like genetic algorithm. Spectral methods have assumed prominence in the machine learning for the graph partitioning [5]. This method for ARG matching [5] is a computational technique for Expectation Minimization (EM) formulation.. Zeng and Chang [1] used a Stochastic process to model the transformation from one ARG to the other. They have used the similarity of the two models by the likelihood ratio, for which STP(Stochastic Process) is decomposed in two steps. Step first refers to VCP (Vertex Copy Process) and step second as ATP (Attribute Transformation process). The Transformation process requires random as intermediate variableX= {0, 1} to specify correspondence between the vertices in G1 and G2. In order to certify the constraints Xiu≤1, they represent VCP by Markov Random Field (MRF) with two node potential that ensures 1-1 constraint being satisfied. The stochastic ARG model is based on log partition function Z(h). However, in view of h taking the values. 0 and 1 ' Z(h) can not be obtained corresponding to various values of h..as a result of which neither stochastic nor EM model can be applied. The approximate computation of likelihood ratio normally can not as well be realized by Loopy belief propagation (LBP) algorithm. Learning of similarity model under supervised fashion can neither be carried in vertex level nor unsupervised fashion in the graph level easily. Wilson and Hancock [6] used Bayesian frame work formulation for crisp related matching problem in relation to ARG's.

Vertex points in an image are generally formed at the junction of different edge segments which may be the meeting(or crisscrossing) of two images in each of the domains G1 or G2. Vertex point of an edge segment depends solely on the curvature formed at the meeting point of the two line segments in each of the images G1 and G2. We further note that firstly the vertex detection on gray level image can be classified by the gray level image being converted into its binary version for extraction of boundaries using some threshold techniques. And after the extraction of boundaries the vertex of high curvatures are detected using directed code and other approximation techniques. Secondly, we take a gray level image directly as vertex detection .We have used topology or auto correlation based approach [8-13] for purpose of gray level vertex detection of the image.

In this paper we have proposed the above analysis of STP and , introduce Attributive Relational Bipartite Graph (ARBG) to generalize ordinary graph by associating discrete or continuous feature of edges joining the vertices of corresponding intensities from source domain of G1 to target domain of G2. It is a bijective function in view of range of G1 being equal to the co-domain G2. ARBG based modeling is to compare the similarity of two images G1 and G2.

Here we use fuzzy based statistical framework that takes care of all types of variations in IND.Our frame work based on ARBG, to our best knowledge is the first of its kind regarding the detection of IND. The edge joining the node (vertex) in each of the two domains (source image) G1 and (target image) G2 does depend solely on the curvature formed at the meeting points at two lines in their respective domains. In this case maximum likelihood of similarity of the two ARBG's i.e. G1 and G2 is based on learning of forward and backward edge detection at vertex pairs. Non-detection of image usually arises due to the missing of significant curvature functions corresponding to the vertices. However Fuzzy set theory based modeling is well known for efficient handling of impreciseness. It is therefore reasonable for the sake of reliable decision making that we model image properties in fuzzy frame work to handle any incompleteness arising due to the imperfect data since it has been shown that vertices having high curvature are one of the dominant classes of patterns giving us significant amount of shape information[7].

The paper is organized as the following: Section 2 briefly describes the mathematical model used in this work. Section 3, as Fuzzy ARBG matching .Section 4 ,as Algorithm of Extraction of vertices. section 5 describes the experimental results and section 6 gives the conclusion.

Frame work for ARBG similarity Attribute Relational Bipartite Graph(ARBG) is an extension of the ordinary graph by associating discrete or real-valued attributes to its vertex and edges. The use of attributes allows ARBG not only be able to model the topological structure of an entity but also its non-structural properties, which often can be represented as feature vectors ARBG as defined by the following section.

2 Bipartite Graphs and Fuzzy Framework for Attribute Relational Bipartite Graph(ARG) Similarity in Two Domains Corresponding to G1XG2

Definition1: Bipartite Graphs: If the vertex set V of a simple graph G=(V,E) can be partitioned into two disjoints non empty sets V1 and V2 so that every edge in G is incident with vertex in V1 and vertex V2 then G is Bipartite.

Definition2:An attribute relational bipartite graph G=(V(i,j)xV(u,v), E,AxA), where V(i,j)xV (u,v) is Cartesian product of two vertex sets in two domains as subset of G1xG2 ,E is the edge setV(ij,uv)=(V(i,j),V (u,v))join of two vertices V(i,j) in G1 and V(u,v) inG2 and AxA is the attribute set that contains a binary attribute a(ij,uv) attaching to each edge $e_{ij,uv}$=V(ij,uv) in E.

2.1 Some Mathematical Model of Gray Level Corners in Bipartite Graphs G1 and G2

ARBG measures the similarity of the two images G1 and G2 . We apply the technique to visual scene matching and establish a part based similarity measure for detecting Near -Duplicate image using fuzzy technique. Their framework has helped us to reduce the computational time to detect the near duplicate image database.

Now we define a transform T1 as bipartite vertex transformation (BVT) associating the vertex from its (source) imageG1 to the vertex in target (image) G2 and the transform T2 as attribute transformation process(ATP) similarly defined for the attributes of the original and copied vertices and given by:

$$T1: V^{s}_{ij} \rightarrow V^{t}_{uv} \quad (1)$$

where,

$$V^{s}_{ij,uv}=\{V^{s}(ij,uv)\} , (i.j)x(uv) \in G1xG2 \quad \text{and}$$

$$T2: F^{t}_{ij,uv}=\{F^{t}(ij,uv)\}, (ij,uv) \in G1xG2.$$

The transformation process as defined above requires an intermediate variable to specify the correspondence between G1 and G2.

Now we introduce a fuzzy random number X= X(h),h belonging to 0<=h<=1.In view of correspondence of vertices of the original and target image we denote Xij,uv as the sequence bearing the correspondence of ijth vertex in the original image G1 to the uvth vertex in the target image G2 with the membership function μA where xij belongs to A.And therefore 0≤μA(xij)≤1, i= 1,2,….M ; j=1,2,….N where the size of source of G1and G2 each is NXM. We draw graphs for TP and ARBG as shown:

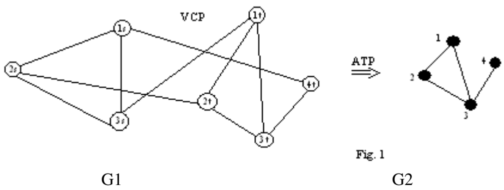

Fig. 2. Transformation Process(TP) from G1 to G2

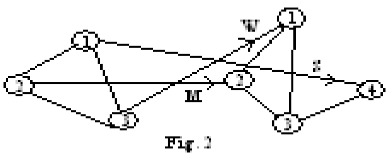

Fig. 3. Correspondence of W=WNDI,M=MNDI,S=SNDI correspondence of fuzzy ARBG,

Where WNDI=weak,MNDI=medium, SNDI=strong intensity of edges connecting V(i,j) to V(u,v).

Vertex correspondence of two ARBGsthe transformation as given in fig.1 requires an intermediate variable to specify the correspondence between the vertices in Gs and Gt. We denote it by xijuv represent it by X and referred to as a correspondence matrix which is random taking the values from 0 to 1 (inclusive) such that X=[0,1] of order NXM. Here xijuv=X having values greater than 0.75 means that the (i,j)th vertex in Gs =G1 correspondence strongly to the (u.v)th vertex in Gt=G2.Similarly the values lying between greater than 0.50 and 0.75 indicate the moderate correspondence and the values less than 0.5 indicates the weak correspondence between the source image and target image.We further note here that in view of injective function that is one to one correspondence of the vertices in Gs and Gt we need to have following constraints that is

$$\sum_{i,j} x_{ijuv} \le 1; \quad \sum_{u,v} x_{ijuv} \le 1;$$

The matrix given by fig.3 as being represented by Fig.2 according to the above definition with regard to the strength of the edge corresponding pixels being strong, moderate and weak in each of the domains of G1 and G2 is given by the following:

	1	2	3	4
1	0	0	0	1
2	0	.75	0	0
3	.25	0	0	0

Fig. 3
Matrix Representation of Fig. 2

(Intensity of the edge corresponding to the equivalence or nearly equivalence of pixels in their respective domains)

One of the most widely used mapping function to fuzzify for converting each of the digital images G1 and G2 to corresponding subset A denoted by $\mu A(x)$ and otherwise defined by standard gamma function ¥ is given as follows:

$$¥(x:\alpha, \beta)=0, \quad x\leq \alpha$$
$$=(x-\alpha) / (\beta-\alpha), \quad \alpha<x\leq\beta \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2)$$
$$=1 \quad x>\beta$$

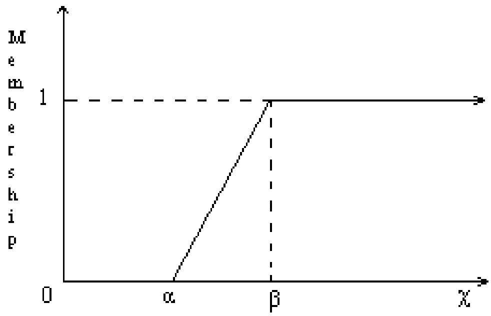

Fig. 4
S (χ, α, β)

Fig. 4. Pictorial representation of the γ function is given in fig.4

Here fig.4 shows the graphical representation where the parameter β is the cross over point at which the image signal of G1 and G2 transforms from moderate to strong and is given by $\gamma (\beta;\alpha,,\beta)\geq 0.75$ and the initial point α on x axis at which the image signal transforms from weak to moderate signal and is given by $\gamma (\alpha;\alpha,,\beta)\geq 0.25$

Fuzzy Alpha Cut: A fuzzy subset can be divided by a suitable thresholding membership values around the range of interest.

The fuzzy alpha cut γ-alpha comprises all elements of X whose degree of membership in γ is greater than or equal to alpha where

$$\gamma\text{- alpha}=\{x \in X: \mu A(x)>\alpha\} \text{ where } 0\leq \alpha\leq 1$$

2.2 Fuzzy Modeling of Detection of Image and Its Duplicate Based on Fuzzy Connectivity Strength of the Pixels in Their Two Domains

Here Vertex V(i,j)=V(ij) in G1 corresponds to its equivalent strength of intensity to the node V(u,v)=(V(uv) in G2 in reference to the bipartite graphs as given by equation (1) such that their equivalent strength determining the intensity in their respective images based on the connecting edge eijuv=V(ij,uv) In this case fuzzy member controls the probability that the vertices in the source graph are copied to the target graph. For stochastic ARBG we do not assign the crisp values 0 and 1 but fuzzy based values lying between 0 and 1 (inclusive). Thus under the hypothesis H=h, we have$0 \leq h \leq 1$.

The features associated to the vertices is given by Eq: (1). The generative model for ARBG matching is given by graph in Fig.5:

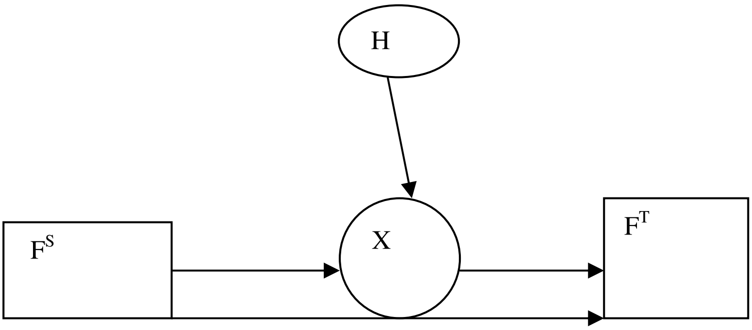

Fig. 5. Fuzzy based similarity related ARBG,H=h, $0 \leq h \leq 1$

3 Algorithm of Forward and Backward Edge of Gray Matching of the Vertex Pixels in G1 and G2 for IND

Computation of features is based on two Phases. The first being that the general (i,j)th pixel P=Pij of source image G1 as in Fig.6 is associated to the general (u,v)th pixel with the nearly same intensity in the target image G2 and given by the edge $e_{ij,uv}$=V(ij,uv) which is extracted from the respective regions with their respective near intensities of the two domains.

$(i-1,\ j-1)$	$(i, j-1)$	$(i+1, j-1)$
$(i-1, j)$	(i, j)	$(i+1, j)$
$(i-1, j+1)$	$(i, j+1)$	$(i+1, j+1)$

Fig. 6.

The edge V(ij,uv)is referred to by the membership function μ[P] based on its respective gradient strength. This gives rise to the fuzzy edge set:

$$E(d)=\{ V(ij,uv),F_{ijuv}\} =\{P,\mu P\}, \quad (3),$$

and secondly two membership functions associated to fuzzy connectivity strength through forward and backward direction with respect to the pixel be given by μf(P) and μb(P).

Each of the original images G1=I(i,j) and target image G2(u,v)=I(u,v) is convolved with the Gaussian function $G(m_i,n_i)$ to obtain the Gaussian smoothened image matrix.

$$I_{uv}(m_i,n_i)=I_{ij}(m_i,n_i))*G(m_i,n_i) \quad (4a)$$

$$\text{where } G(m_i,n_i)=1/\sigma i\sqrt{2}\prod*\exp(-(m_i*m_i+n_i*n_i))/2\sigma_i*\sigma_i \text{ ,i=1,2} \quad (4b)$$

Here σ_i is the degree of smoothness to the small distortion of noise and blurred boundaries. We choose σ=1.2 to smoothen those noise and blurred boundaries corresponding to 3X3 pixels. The membership of edge e_{ijuv}=V(ij,uv) given otherwise by μ(P) belongs to the cross product G1*G2image . Thus for every edge- pixel P(ij,uv) where gray value of the (i,j)th vertex in G1 is associated to equal or nearly equal gray value of (u,v)th vertex in G2.We consider as usual 3x3 windows in each of source G1 and Target image G2.In the adjoining figure no.7 , the symbols representing gray values in G2 are on parallel lines as the gray values in G1 as given below :

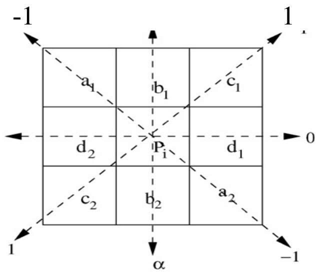

Fig. 7. Gray values in each Gi, i=1,2

If d(Pijkl,uvkl)=Ds's=1,2,3,4 denote the differences between the gray values at P(ij+kl,uv+kl) and P(ij,uv) for k,l= -1,0,1 in four different directions given by d(Pijkl,uvkl) =!P(ij+kl,uv+kl)-P(ij,uv)!,k,l=0,1,-1, so that the difference of these pixels are taken as gray level differences. The ratio of gray level changes as given by (Gr) are computed from two mutually perpendicular set of pixel pairs in the vicinity of respective central pixels P(ij,uv) in G1*G2.Following ,the contrast ratios Grij in G1 of the four values of the pixels obtained from the neighborhood central pixel P(i,j) is given by

$$Gr=[(1+D1)/(1+D2),(1+D2)/(1+D1),(1+D3)/(1+D4),(1+D4)/(1+D3) \quad (5)$$

where Ds,s=1 to 4 correspond to the distances of the pixels in the opposite corners with respect to the two mutually perpendicular directions through P(i,j) given by

D1=d(Pi-1,j+1)-d(Pi+1,j-1)=a1-a2,
D2==d(Pi+1,j+1)-d(Pi-1,j-1)=c1-c2|,
D3==d(Pi+1,j)-d(Pi-1,j)=d1-d2 and
D4= d(Pi,j+1)-d(Pi,j-1)=b1-b2|.

The contrast ratios Gruv in G2 of the corresponding four values of pixels obtained from the respective neighbourhood central pixel f(P(u,v)=Q(u,v) are defined on the same line.

Referring [6], since in a window of eight neighborhood, an edge pixel has a maximum gray level difference in a direction perpendicular due to edge direction Ψ and this direction points along minimum difference direction as a result of which minimum pixel contrast ratio(Gm(r)) is given by

$$((Gm(r))=\min\{Gm\} \tag{6}$$

where the parameter m (slope) is used for computing the gradient membership μ(Pij,uv)=μ(P). Here μ(P) is used to represent the uncertainties of edge strength and location of true edge point. It is more appropriate to represent it by γ-function derived by the computation of pixel contrast ratios. Having known the value of the contrast ratio of (Gm(r)), it is easy to obtain its maximum and minimum values which help us to obtain histogram representation of the pixel contrast ratio between the two images of G1 and G2.

The value of μ(P) determines the edge fuzzy membership strength corresponding to the join of the vertices(pixel)of equal or nearly equal strength intensity in G1 and G2 . Let μSij, μMij, and μ Wij represent the membership values of strong, moderate and weak of(i,j)th pixel of G1 such that (u,v)th target images corresponds to source image with (i,j)th pixel of equivalent of nearly equivalent intentisity. These characteristics can be represented in a tabular form and are called the fuzzy matrices with its elements as fuzzy values given in Fig.3.

We now select a subset of fuzzy gradient map E[ed].Here we first define two membership functions μf(P) and μb(P) and these are computed to estimate the strength of the fuzzy connectivity along the paths in forward and backward directions with regard to the pixel(P) . If P(ijuv,f,b) represent the set of points having μf(P)high and μb(P)low on the left side of the curvature junction of the pixel P then the edge corresponding to P(ij,uv) designates these set of points(edge detecting equivalences of vertex intensities in the two images) on the forward arm assigning the membership μf(P)-μb(P) and this difference varies with the sharpness of curvature and we represent these points of P(ij,uv,f,b) by fuzzy subset μfb as forward arm given by

$$\mu fb(P) = \mu f(P) - \mu b(P)\ . \tag{7}$$

On the other hand similarly if μf(P)is low and μb(P)is high on the left side of the curvature junction of the pixel P then P(ij,uv)designates these set of points on the backward arm and assigned the membership μb(P)-μf(P) and this difference varies with the sharpness of curvature .We represent these points of P(ij,uv,b,f) by fuzzy subset μbf as backward arm and is given by a

$$\mu bf(P) = \mu b(P) - \mu f(P) \tag{8}$$

We then define the fuzzy gradient map μ(ed) = {P,μ(P)}.Here we remark that the membership values associated to the pixel(P) in the forward and backward direction correspond to the gradient values m=1 and m=-1 respectively.

LetΨ ={ $\Psi1$, $\Psi2$,…..,Ψn}represent the slope(edge direction)corresponding to sequence of pixels on an edge segment Here we note that the directions of the forward and backward fuzzy membership values are computed from the difference in Ψth edges between the connected pixels. For example we further note that the edges correspond to the following slopes given by the slope set M={m : m=0,+1,-1,+∞,-∞}.The slope subsets {-1},{1}represent the forward counts and backward counts denoted by n(f)and n(b) respectively and similarly the slope subset {0,- ∞,+ ∞}represent the n(f) and n(b) respectively and so on. These counts vary with the sharpness of the curvature type. The membership values of the forward and backward directions associated to the pixel(P)have the attributes of exponential decay as such these can be represented by $\mu f(P)=\beta*\exp(-s)$,where $s=1/nf$ and $\mu b(P) = \beta*\exp(-t)$,$t=1/nb$ corresponding to some scalar multiplier β.

Here corresponding to finite counts of n(f) and n(b) of the image the values of $\mu f(P)$ or $\mu b(P)$ should lie between 0 and 1.Thus from the above vertex testing we select the edge pixel P which can represent the three dimensional feature Fi: where

$$Fi = [\mu(P),\mu f(P),\mu b(P)] \quad (9)$$

We detect the fuzzy edge associated to equal intensity vertices (pixels) with equal or nearly equal intensity in the two domains of G1 and G2 with the fuzzy edge map $\mu(ed)=\{P,\mu(P)\}$.

Initially a suitable threshold value of the gradient membership has to be decided to select a subset of E(ed) and only those points of the two domains will be used for computation of $\mu f(P)$ and $\mu b(P)$ that detect fuzzy edge for detection of equal strength of the vertices in the two images to give IND.. To locate points from significant portions on the image, a contrast transformation is used as a pre- processing step as shown by the following :

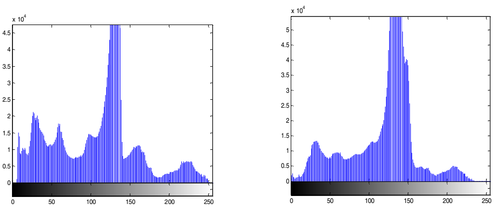

Fig. 8(a). Pixel Contrast Histogram ratio of Fig.1(a)

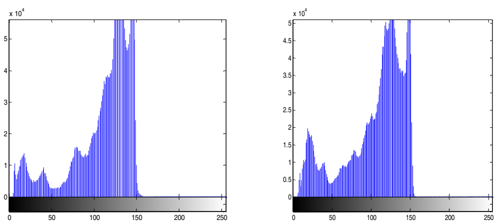

Fig. 8(b). Pixel Contrast Histogram ratio of Fig.1(b)

Then the extraction of probable edges of the images is achieved by thresholding through non- linear transformation of membership values as associated to γ function as above.

Here we set β=0.9 , α=0.7 its membership function then is the corresponding γ function given by fig. 4 which can be written as :

$$\mu d(P) = 1, \quad a > 0.9, \\ =(10\,\mu P-7)/2\,, \quad 0.7<b<0.9 \\ = 0, \quad b<0.7 \qquad (10a)$$

Thus the above pixel contrast transformation operation can alternatively be also given as:

$$\mu d(P)=(10\,(\mu P)-7)/2, \quad 0.7<\mu P\leq 0.9, \\ = 1\,, \quad \mu P>0.9 \qquad (10b)$$

The following figures **9(a) and 9(b)** result from the membership values of μ(dp) before and after the transformation associated to equation(2a).

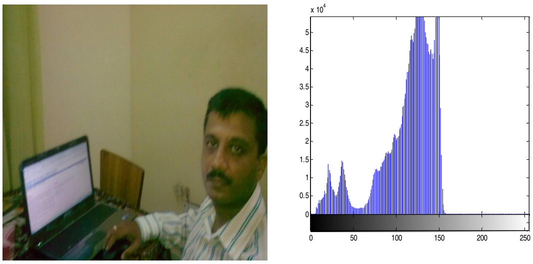

Fig. 9(a). Threshold points

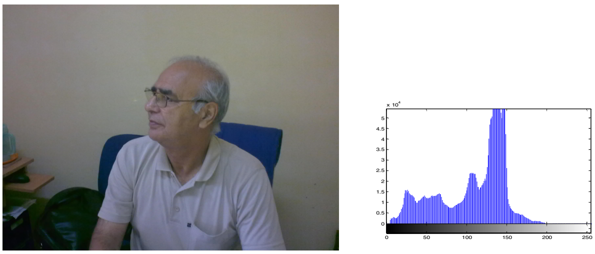

Fig. 9(b). Threshold points

We further notice that the number of insignificant vertices under discussion are reduced at the same threshold value in G1 and G2. Let Ed={P,μd(P)}denote the transformed edge map from source image to target image then the thresholding above the different membership values may be obtained by the use of proper alpha cuts[15] as discussed in section 2 .Due to this process we are able to obtain the edge of equivalent strength of pixels connecting G1 and G2 given by Ed(alpha) and denoting by Edf and given by

Edf=Ed(alpha)={P€Edf:μd(P)≥alpha}, 0≤alpha≤1.0 where Ed(alpha) is represented by the local features

$$Fi = [\mu d(P),\mu f(p),\mu b(P)].$$

Multilevel fuzzy edge map may be generated by the thresholding of Ed in which case the corresponding pixels of G1 and G2 will be segregated as strong , moderate and weak edge pixels based on their gradient membership values of corresponding values of μd(P).

Analysis of images related to the fuzzy membership is given by the following table:

The values of the edge points of G1 and G2 corresponding to respective μd(P) are closer to each other than if the local contrast of a region is very poor and on the other hand if the membership value of the edge joining nearly equal strength of the intensity of vertex pixels of G1 and G2 are separated above the crossover points of each μd(P) ≥0.75 then the similarity is stronger. Thus in view of edges associated to vertices with membership μd(P)≥0.75 will represent the relative comparison of the images strongly in accordance of the strength of pixels in G1 and G2.

4 Experimental Results

We have extended the performance of detectors on various images so as to extract the edge map with the help of membership function with respect to the threshold so that μd(P) is strong, moderate or weak. The region could not be extracted where contrast ratio is poor and threshold is less than or equal to0.75.Our method of detection of vertices compare very well with the methods of detectors using Harris and SUSAN methods.

We notice here that there are large variations of distinct gray values with high threshold values corresponding to μd(P) to reduce the no. of weak and noisy vertices. Though their detections are more general however, IND images based on our algorithm works reasonably well. Our proposed detector of near duplicate images is able to extract most of the significant vertices of nearly equal strength images of the two domains G1 and G2 under different imaging conditions .This is mainly because of the reason that the slope of the fuzzy property plane is obtained from the dynamic range. From the above results we therefore confirm using ARBG the near image duplicate detection working satisfactorily based on our algorithm.

5 Conclusion

We present fuzzy framework for calculating the similarity of two attributed relational bipartite graphs (ARBG) in grey level vertex matching. However, we applied fuzzy set theoretic approach for the detection of the vertices of near duplicate images. The algorithm in this approach does not require computation of chain codes or complex differential geometric operators or the complex partition function as used in the ARG matching for Stochastic frame -work since in such cases similarity is based on EM scheme which is based on two learning phases firstly on the application of supervised vertex learning and secondly on graph level learning which is complex[1]. Using fuzzy approach, our experiments have been performed on various types of twenty images and the algorithm performs reasonably well. However, we shall explore the possibility to improve the algorithm so that the parameters may be selected adaptively for thresholding.

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