Implementation of Efficient Algorithm for Exact Hausdorff Distance

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Abstract— The Hausdorff distance is very important source in computer field. It is the very important source for the various image processing applications including image tonning stirringthe image, acknowledgement and track, shape recovery.However,there is no efficient algorithm has been report that compute the correct Hausdorff distance in the linear time for the compare two images. There are less number of methods that have been planned to compare the exact Hausdorff distance with higher estimate error. In this paper, we proposed a linear time algorithm for comparing the exact Hausdorff distance with less estimate error. The proposed method is helpful to decrese the time taken for processing, while minimizie the fault rate in content-based image processing and the examinaton. The Hausdorff distance is the evaluate of difference between two sets which is widely used in the variety of the applications. This has applicatios, for the example, in the image processing. In this paper we propose a novel efficient algorithm for comparing the approximate Hausdorff distance. The proposed algorithm is experienced against the HD algorithm of the generally used National Library of Medicine Insight Segmentation and Registration Toolkit (ITK) using the magnetic resonance volumes with the extremely large size. The proposed algorithm outperforms the ITK HD algorithm both in the rate and the memory essential. The Hausdorff Distance differ from number of other shape relationship methods in that no connections between the model and the image is resulting. The method is relatively broadminded of the less position faults such as those that happen with edge detectors and the other feature removal methods.

Key words: Hausdorff Distance, Early Breaking, Random Sampling in Place of Scanning, Excluding Intersection, Runtime Analysis,

I. INTRODUCTION

The Hausdorff distance (HD) is the quantify of the difference between two point sets. The HD is a very important metric that is mostly used in the many sources like the image processing and the pattern similarity as well as evaluate the excellence of clustering. It is also used in the applications like medical field for detecting Breast Cancer. Most of the practical writing is dedicated to the calculation for sets consisting of a limited number of points. This has applications, for example, in image processing. However, we would like to apply the Hausdorff distance to manage and calculate optimisation methods in level-set based shape optimisation. In this context, the involved sets are not limited point sets but characterised by level-set or signed distance functions. For example, we can calculate area or perimeter of any type of the shape like polygon. As polygon is not having a fixed shape that's why there is no such a formula to calculate the area or perimeter. But, by using this algorithm we can analyse the distance between two point sets.

There are variety of types of events used to evaluate two point clouds. Overlie based actions, e.g. the Dice coefficient, consider an imaginary grid on the union of the two point sets and calculate the overlap (intersection) between the point sets with respect to the grid. Points are assigned to subsets depending on whether they are or are not in the joint to build the uncertainty matrix.

Spatial distance based measures generally consider the pairwise distances between the computed point sets. Examples from same category are the total distance, i.e. the total of all pairwise distances and the Mahalanobis distance, which compare the estimate of the point sets as two hyper-ellipses. Both examples are also not sensitive to the positions of the individual points because in the case of the average distance, distances of far points are rewarded by other near points and in the case of the Mahalanobis distance, estimatine the point sets as hyper-ellipses mean ignore the details of the positions of the points. The HD is a max-min distance, and hence has the improvement that it takes into consideration of the spatial position of each single point, which makes it capable of considering the spatial properties in the measurement, e.g. the boundary of an object.

The directed Hausdorff distance ˇH between two point sets A and B is the maximum of distances between each point x 2 A to its nearest neighbour y 2 B.

That is:

H(A,B)= maxx2A{miny2B{||x, y||}}.... (1)

where ||., .|| is any norm e.g. the Euclidean distance function. Note that ˇH(A, B) 6= ˇH(B, A) and thus the directed Hausdorff distance is not symmetric. The Hausdorff distance H is the maximum of the directed Hausdorff distances in both directions and thus it is symmetric.

H is given by:

H(A, B) = max{ ˇH(A, B), ˇH(B, A)}

For a point set A, we define the point set size to be the number of elements in A. Images and image volumes are a special class of point sets, where the elements are pixels (or voxels for volumes) that are in pre-defined locations on a grid. For an image A, we define the point set size to be the number of pixels/voxels in A that are not in the background (non-zero pixels/voxels). Also we define the grid size to be the dimensions of the entire image including background (width x length x height). Note that the proposed algorithm is equivalently applicable on images and volumes, so we will not strictly differentiate between them. The same applies to pixel and voxel.

II. HAUSDORFF DISTANCE:

The Hausdorff distance, or the Hausdorff metric, also called the Pompeiu–Hausdorff distance, dealing how far two subsets of a metric space are from each other. It turns the set of non-empty compact subsets of a metric space into a metric space in its own right. It is named after Felix Hausdorff.

Causally, two sets are close in the Hausdorff distance if every point of either set is close to some point of the other set. The Hausdorff distance is the fastest distance you can be required to travel by an challenger who chooses a point in one of the two sets, from where you then must travel to the other set. In other words, it is the maximum of all the distances from a point in one set to the nearest point in the other set.

HD algorithm should take into kindness how these two charac-teristics differ in the relation to the following parameters:

A. Point Set Size:

For example, a brain MRI volume could reach a million vowels' and that of a whole body could reach 10 million vowels. The runtime of the algorithm should stay sensible when the set size increases extremely.

B. Grid Size:

It is attractive that the complication of the algorithm depend only on the point set size other than the grid size. For example, in brain tumor segmentations, the volume of the tumor is normally a small fraction of the grid size and the rest is background. The background should not be inclu0ded in the computation.

C. Density and Sparsity:

An algorithm could perform improved with sparse point sets like geographical lo-cations and worse with dense point sets like MRI segmentations and vice versa.

D. Generality:

Algorithms restricted to a special class of point sets cannot be useful in a general situation.

III. OBJECTIVE:

1) Our main goal is to calculate the exact Hausdorff Distance between two point sets.
2) To calculate the area or perimeter of any shape (polygon).

IV. FLOW OF SYSTEM:

Fig. 1 shows the flow of a system. In this system first user will brows the image from the set of images, after browsing the image our system will scan that image and read the pixel values. Once reading the pixel value is completed, user will enter any color code value which he/she wants to calculate the area of that color in the image. Then at the end, our system will show the result in the form of dimensions as well as in the image format.

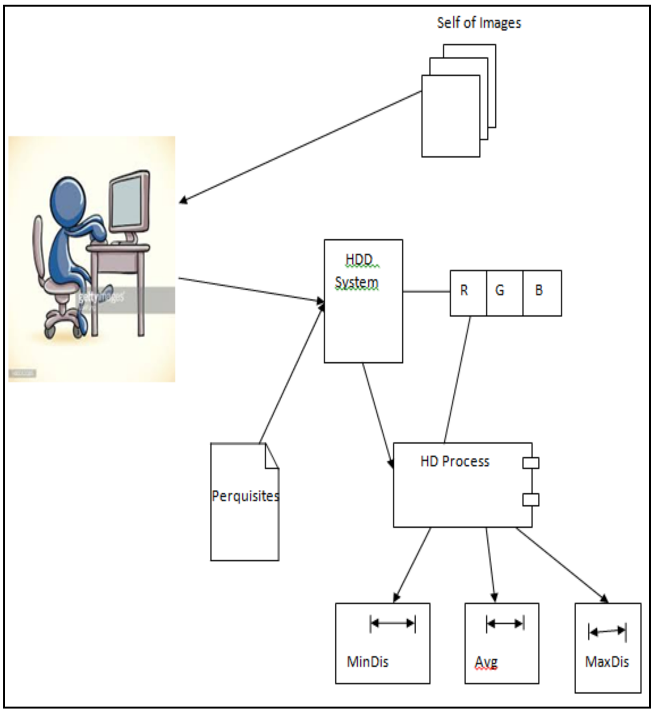


Fig. 1: System Flow

V. ALGORITHM

Input: Image (Color/Gray scale), Any color code.

Output: Minimun Distance, Maximum Distance, Area.

1. Scan image and read pixel values in (R,G,B) format and store it an array A.

2. Give any color code input (Ic) for calculating Hausdorff Distance.

3. for (i,j) (i=row, j=column)
{
Get Ic from A
{
If match found in i,j
get Superior $\sup_{x\to i, y\to j} (d(x,y))$

get Inferior $\inf_{x\to i, y\to j} (d(x,y))$
}

Calculate Hausdorff Distance:

$d_H(x,y) = \max\{\sup_{x\to i, y\to j} (\inf d(x,y)), \sup_{x\to i, y\to j} (\inf d(x,y))\}$

$d_H(x,y) = \min\{\sup_{x\to i, y\to j} (\inf d(x,y)), \sup_{x\to i, y\to j} (\inf d(x,y))\}$
}

4. Calculate area as:
min(i,j)*max(i,j)

VI. MATHEMATICAL MODEL:

System Description:
Input: Input I={I,O,P}
I=Input
O=Output

P=Process
Input I={Image,Pixel, Color code, Image Height, Image width, Specific color code on which Hausdorff distance is to be Calculate}
Output: Output O= {Minimum Hausdorff Distance, Maximum Hausdorff Distance, Average
Hausdorff Distance}
Functions: Mapping

1) All Function (Method) From
2) User parser color code Specification to calculate HD.
3) User get result HDMin, HDMax, HDAvg.

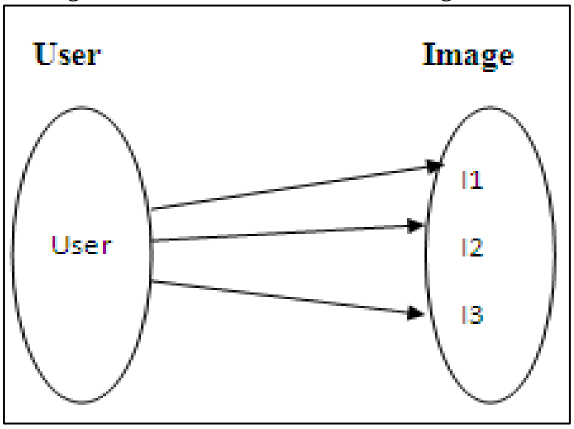


Fig. 2: Venn Diagram 1

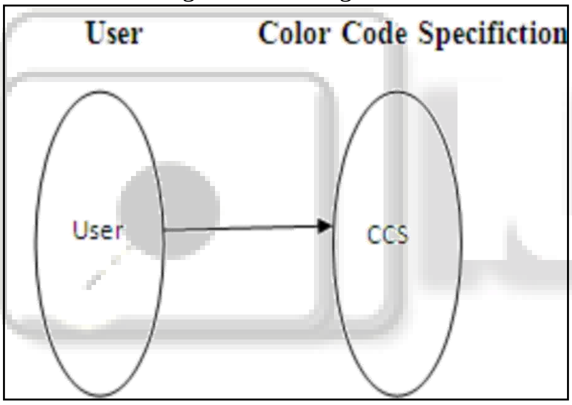


Fig. 3: venn Diagram 2

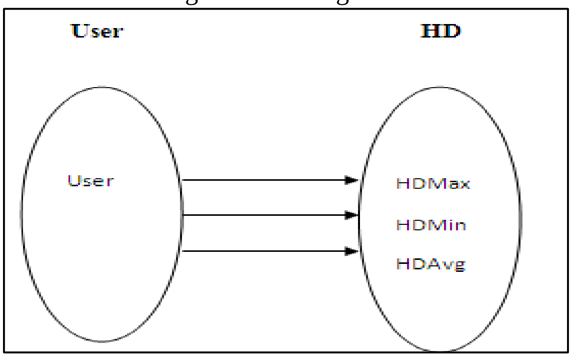


Fig. 4: Venn Diagram 3

Success Conditions: Desired output generated, If color found in image then Hausdorff Distance is achieved.

Failure Conditions: Desired output not generated, If color is not present in the image.

VII. Applications

1) Computed Tomography (CT scan):

Computed tomography (CT) is an imaging method that uses special x-ray equipment to generate detailed pictures, or scans, of areas inside the body. It is also called computerized tomography and computerized axial tomography (CAT). As X-ray CT is the most common form of CT in the medicine field and various other contexts, the term computed tomography alone (or CT) is often used to refer to X-ray CT, although other types exist (such as positron emission tomography [PET] and single-photon emission computed tomography [SPECT]).

2) Comparing images using hausdroff distance:

Automatic face recognition has newly received sig-nificant attention, particularlly during the past few years for the wide range of applications such as biometrics identification, security of information, law enforcement and surveil-lance, smart cards verification, access control, etc. Many face recognition approaches have been created. Classical face recognition approach include the pattern matching, principal component analysis(PCA), elastic graph matching, and neural nets.

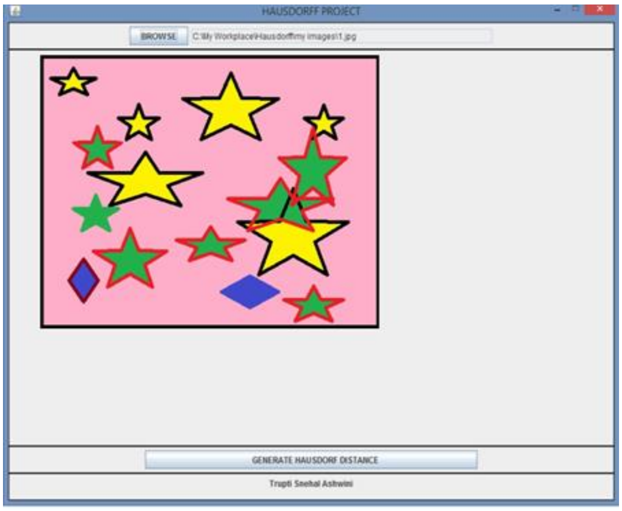
The Hausdorff distance estimates the level to which each point of a model set lies near some point of an image set and opposite to that. Thus, this distance can be used to verify the degree of similarity between two objects that are superimpose on the one another. Efficient algorithms for comparing the Hausdorff distance between all possible relative positions of a binary image and a model are presented. The focus is primarily on the case in which the model is only allowed to translate with respect to the image. The techniques are extended to strict motion. The Hausdorff distance calculation different from many other shape comparison methods in that no connection between the model and the image is derived. The method is relatively broadminded of small position errors such as those that occur with edge detectors and other feature extraction methods. It is shown that the method extend naturally to the problem of comparing a portion of a model against an image.

3) Robust face detection using hausdorff distance:

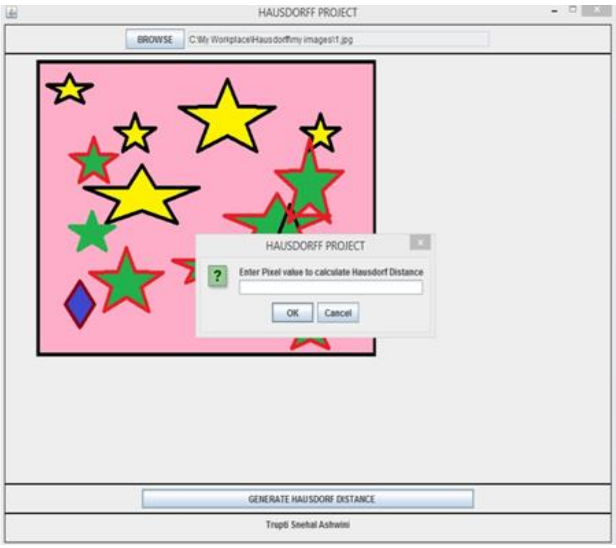
Regular face detection has newly expected significant attention, specially during the past few years for the large range of application such as biometrics identification, information safety, law enforcement and surveillance, smart card verification, access control, etc. Many face detection approaches have been developed. Classical face detection application include the pattern matching, principal component analysis(PCA), elastic graph match-ing, and neural nets. These applications have provided good performances under the certain conditions. But in most systems, searching and matching are done on gray-level face images and these systems are computationally expensive due to the large number of images available in the database.

VIII. RESULT

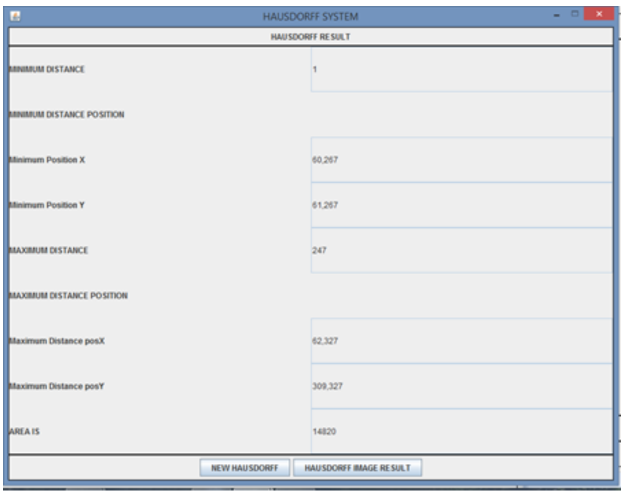
A. Browse The Image:



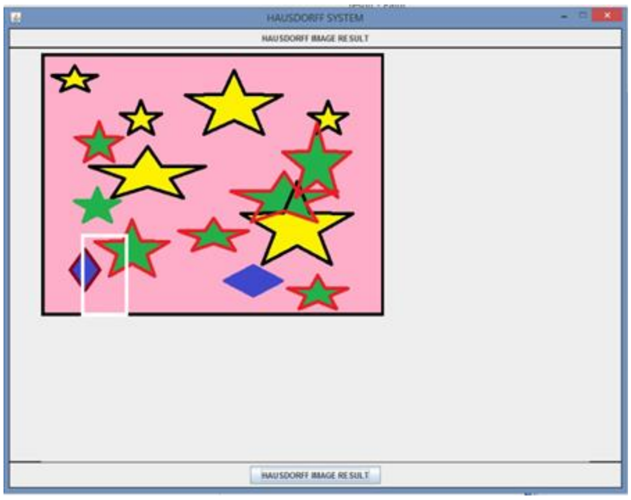
B. Scan The Image and Read The Pixel Values:



C. Hausdorff Distance:



D. HD in The Form of Image:



IX. CONCLUSION

We propose an efficient algorithm for computing the approximate Hausdorff distance. We officially show that the proposed algorithm has a nearly-linear runtime in the regularly average case. The proposed algorithm does not require the any limits on the input data, and is hence generalizable to all applications. Moreover, it does not require a complex setup phase needing high computational effort and extensive storage space.

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