GRAPH MODEL GENERATION FOR GRAY SCALE IMAGES

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Abstract:

The image is a visual representation of any object or we can say that the image or picture is created ,copied and stored in a electronics form Gray scale images, a kind of black and white or gray monochrome are composed exclusively of shades of gray, the contrast ranges from black at the weakest intensity to white at the strongest.

Mathematically image is the form of two dimensional signal define by 'f'. where f is the intensity property like brightness and contrast. Color information is made by RGB color format. Human has an ability to describe any type of colors and also identify colors but machine has no capacity to do those things like humans. Same problem will also arise in the gray scale images So we need a that type of system who can identify the gray scale information. In this paper generation of a graph model for the given grayscale image has been presented.

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1.1 INITIAL MODEL

This step represents the initial state of the system. It describes the state when the input Grayscale images are available and no processing has been performed on the Grayscale image. It describes basic information about the Grayscale image like its identification and its dimensions. The initial state of the system is represented using a null graph. The vertices of the graph describe the Grayscale images in the Grayscale image collection. This information is updated after more information about the Grayscale image characteristics are available after further analysis.

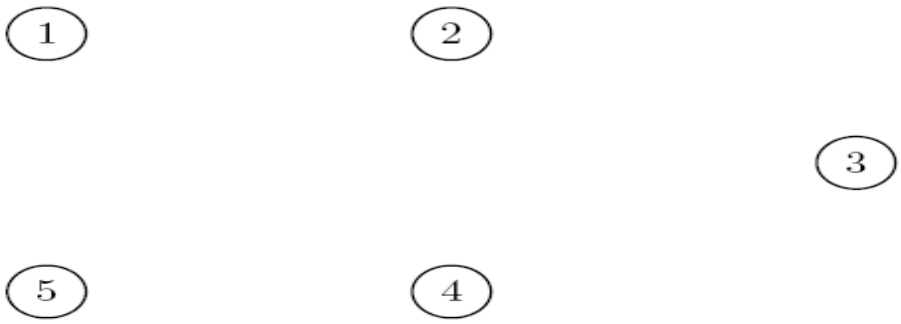

Figure 1.1: Initial Model

1.1.1 REFINED MODEL

The null graph representation used to represent the initial model is refined to represent additional information. This is done once all the features from the Gray scale image have been extracted and matched to determine the geometry. The initial model is augmented into a complete graph by adding an edge between every node in the null graph.

The nodes of the graph represent the Grayscale images and any other data associated with that Grayscale image. This data is available once the first step of the data extraction process is complete. The following are the data that are associated with a Grayscale image and hence stored in the node of the graph.

1. Gray scale image identifier
2. Gray scale image dimensions
3. Transformation matrix
4. List of feature descriptor describing the corners.

The edges of the graph store information about the relationship between the Grayscale images. The Gray scale images in the collection are compared with each other to obtain the above data which are then stored in the edges. The information about the feature matches obtained once the second step of data extraction is completed. These along with the information about the geometry computed from the matches are stored in the edges.

1. No. of feature matches.
2. List of feature descriptors describing the matches.
3. Feature descriptor for describing the fundamental matrix.
4. Feature descriptor for the epi pole.

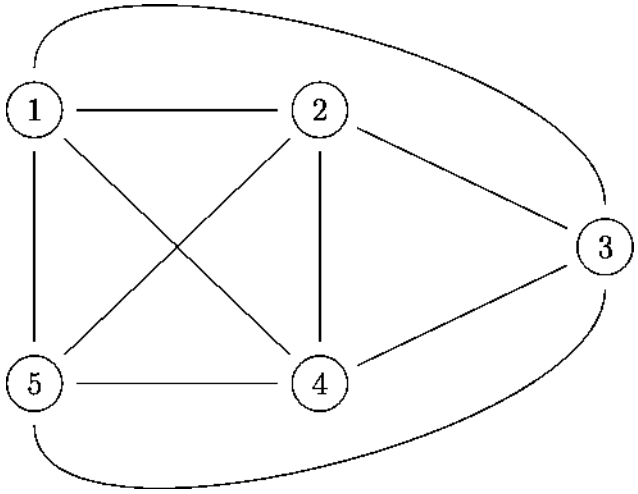

Figure 1.2: Graph based Data Representation

1.2 ANALYSIS

The refined model is analyzed to estimate additional parameters and compute weighted measures based on these parameters. The measures obtained are weights that describe the various characteristics of the matches obtained. The aim is to determine the validity and match strength between the Gray scale images to generate a final model. This is done by traversing the graph and analyzing each edge and its corresponding vertices to infer statistical information from the store data. These are used to assert whether the Gray scale images are connected or not connected. It also gives an indication about the strength of the connections in case the Gray scale images are connected.

Computed Parameters

1. Correspondence information
   (a) Maximum possible matches (max Matches)
   (b) No. of feature matches(num Matches)
2. NCC distribution
   (a) No. of matches with very high correlation (v high NCC)
   (b) No. of matches with high correlation (high NCC)
   (c) No. of matches with average correlation (avg NCC)

3. Inlier information
   (a) No. of inliers (num Inliers)
   Correspondence information : The maximum possible feature matches is the minimum number of corner features between the concerned Gray scale image pair.

$$max\ Matches=Minimum(NumCorners(I_1),Numcorners(I_2))$$

where Num Corners(I) denotes the number of corners features in Gray scale image I.

The number of feature matches is given by the number of matches in the feature match list

$$num\ Matches=Count(FD_{match})$$

NCC distribution : The NCC distribution gives an indication about the correlation characteristics of the selected feature matches. They are classified into matches with very high correlation, high correlation and average correlation. The threshold for these parametersare given below:

$$Vhigh\ NCC=\ Count(\ FD_{match}[i].NCCScore \geq \tau_{vhigh}NCC)$$

$$high\ NCC =\ Count(\ FD_{match}[i].NCCScore \geq \tau_{vhigh}NCC)$$

$$avg\ NCC =\ Count(\ FD_{match}[i].NCCScore \geq \tau_{vhigh}NCC)$$

where FD[i] denotes the feature descriptor for the ith match and τ_{vhigh} NCC, τ_{high} NCC, τ_{avg} NCC are the corresponding threshold values.

Inlier information The number of inliers is given by the total number of matches in the feature descriptor for inliers FDinliers.

$$num\ inliers=Count(FDinliers)$$

1.3 COMPATIBILITY MEASUREMENTS

Compatibility Measurements are obtained from the computed parameters. They are described below:

FEATURE RATIO: This is the ratio of the number of features between the two Gray scale images.

MATCH PERCENTAGE: This is the percentage of obtained matches. It is obtained as follows:

$$pctMatches = \frac{numMatches}{maxMatches} \times 100$$

In lier Percentage: This is the percentage of inliers out of the obtained matches. The threshold for a match to be an in lier is 1pixel. It is given by the ratio between the number of inliers and the number of matches.

$$pctInliers = \frac{numInliers}{numMatches} \times 100$$

1.3.1 COMPATIBILITY MEASURES

The following are the weighted compatibility measures that are computed from the compatibility measurements and the computed parameters which are then used to determine the connection strength between the Gray scale images.

1. wtMatches(Wm) - Indicates percentage of correspondences,
2. wtCorrelation(Wc) - Indicates correlation, and
3. wtInliers (Wi) - Indicates percentage of inliers.

The weighted measures are scaled values and the lower and the upper values used for scaling each of these measures are given by L_{Value} and U_{Value} respectively.

The weighted measure for the percentage matches is a scaled value between 0 and 1. It is denoted by Wm.

$$Wm = \frac{numMatches - Lvalue}{Uvalue - Lvalue}$$

The weighed measure for indicating the correlation of the correspondences is obtained as a scaled value between 0 and 2, denoted by Wc_1 The correspondences which have very high correlation values are given more weightage and is denoted by Wc_2.

$$Wc, = \frac{(highNCC + VhighNCC) - Lvalue}{Uvalue - Lvalue}$$

$$Wc_2 = \frac{VhighNCC - Lvalue}{Uvalue - Lvalue}$$

$Wc = Wc_1 + Wc_2$

The weighed measure for indicating the percentage of inliers is a scaled value between 0 and 2 and is denoted by W_i.

$$W_i = \frac{numInliers - Lvalue}{Uvalue - Lvalue}$$

The final weighted measure is obtained as a sum of all the measures obtained above.

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$$W = W_m + W_c + W_i$$

1.4 MODEL GENERATION

This is the last stage of the system and is concerned with generating a model to represent the connectivity information between the Grayscale images. The results obtained from analysis is used to this model. The model used here is a weighted, undirected graph.

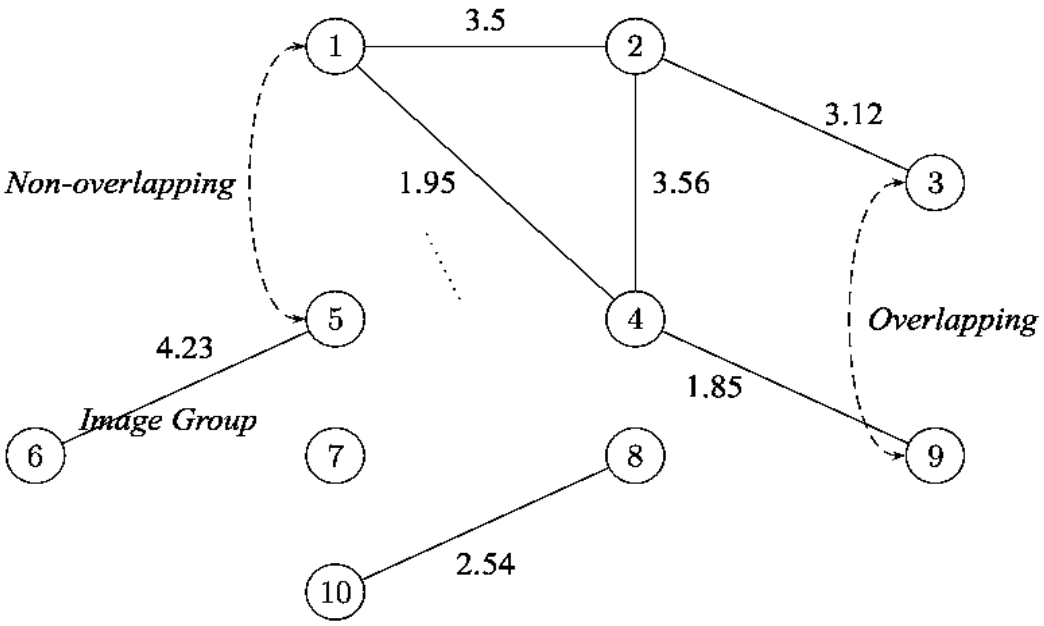

Figure 1.3: Final Model

The reason for using a graph model is that it is a simple and effective method for storing connectivity information and grouping them into distinct scenes. A measure of the connectivity strength is also determined and stored in the model.

The model is generated by creating nodes representing all the Grayscale images in the collection. The results obtained from each Grayscale image pair are then used to determine the connectivity between them by checking the weighted quantities. A Grayscale image pair is considered to be connected if the total weighted quantity (W) has a positive value. The strength of the matches is described by this value which is a positive real value (0 - 5) if the Grayscale images match.

1.5 OBSERVATION

The overlapping Grayscale images are denoted by the presence of an edge between the nodes which represents the Grayscale images. It basically indicates that the two Grayscale images match. The Gray scale image groups are represented by the sub graphs in the graph. A Gray scale image group comprises of overlapping Grayscale images and other Grayscale images that are part of the same scene. All the Grayscale images in the group may not have an edge between them but they are connected with each other through other Grayscale images or views of the scene. Non-overlapping Grayscale images do not belong to the same group. The nodes representing the Grayscale images are in different sub graphs.

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