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IMPLEMENTATION OF 2-D IMAGES STITCHING USING ARTIFICIAL INTELLEGENCE

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***Abstract*—computer vision is a branch of Artificial Intelligence (A.I.) that allows computer and systems to retrieve useful information from the digital photos, videos and the other visual inputs and act or make suggestions based on that data. Image stitching is a technique for creating a panoramic view by combining several photographic images from various camera networks. In the proposed work, a method based on the invariant feature to realize an automatic image stitching. scale invariant feature transform (SIFT) is a computer vision algorithm for detecting and describing the local image features. It finds the spatial scale's extreme points and extracts its position, scale, and rotation invariants for feature descriptors. This technique is used in image stitching and image stitching by using local features. The proposed algorithm is Principal Compound Analysis (PCA)-SIFT algorithm. The proposed algorithm is implemented with the python 3.9 version. PCA-SIFT matching accuracy at the keypoint level is better compared to the standard SIFT and translates into a better retrieval result. PCA-SIFT is significantly faster in matching phase.**

***Keywords*— Computer Vision, Image Stitching, Image Features, Scale Invariant Feature Transform (Sift), Principal Compound Analysis (PCA), PCA-SIFT.**

I. INTRODUCTION

Image stitching is the process of combining two or more independent photographs with overlapping fields of view of same location to create a high-resolution image known as a panorama or mosaic. feature based method is one of the methods used in images stitching [1]. The methods basically consist of two things image matching and image blending [2]. Image matching means the process to find out the similarity in two or more images with the help of algorithms [3]. In the research process in the field of digital image processing. The key problems are the image feature extraction and image matching but it plays a vital role in the image registration, pattern detection and target detection [4]. Extraction and detection of feature plays a key role in the field of computer vision. Generally, the features are extracted from the initial set of a measured data and then the requires data is built. The informative and nonredundant that are obtained from the feature extraction are the functions of the measurement variables [5]. The feature extraction is widely used in the area where image classifications and pattern detection are required. The main aim of the feature extraction is to improve the efficiency and analysis and classification of the images.

To implement the image stitching or to construct the panorama the computer vision and image processing techniques utilized are as follows
1.Key point detection
2.Local invariant descriptors like SIFT, SURF.
3.Key point matching
4.Homography estimation of RANSAC
5.Perspective wrapping

- EXISTING METHOD : SIFT (Scale invarient reature transform)

Lowe (2004) presented SIFT for extracting distinctive invariant features from images that can be invariant to image scale and rotation. Then it was widely used in image mosaic, recognition retrieval etc. This technique is one of the most robust and mostly used in image matching algorithm based on local features. It ensures a good mosaic image and a reliable result. SIFT is a feature detection and description technique. SIFT produces key point descriptors which describe the image features. As shown in Fig. 1.

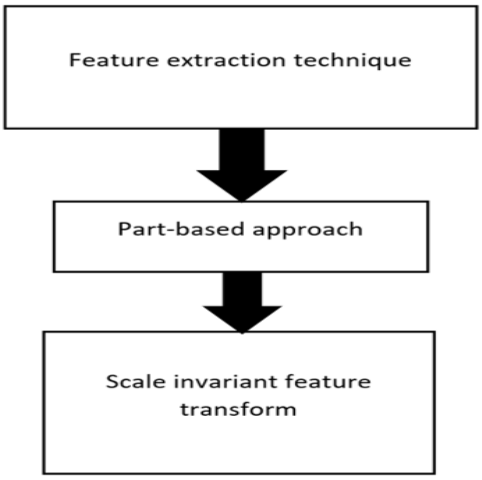

Fig.1. origin of SIFT algorithm

Sift Algorithm
SIFT consists of four major stages:
1) Scale-space peak selection
2) Keypoint localization
3) Orientation assignment
4) Keypoint descriptor

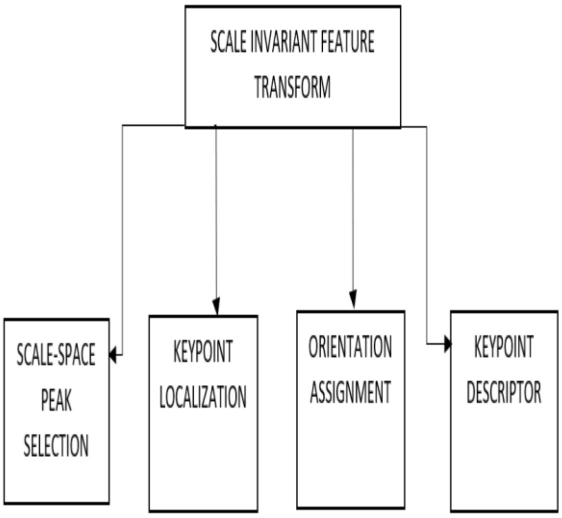

Fig. 2. SIFT algorithm steps

- **Scale-space peak selection:**

In the first stage, potential interest points are identified by scanning the image over location and scale. This is done quickly by building a gaussian pyramid and examining a succession of difference of gaussian (DOG)image for local peak called keypoints.

- **Keypoint Localization:**

In the second stage, candidate keypoints are localized to sub-pixel accuracy and eliminated if found to be unstable.

- **Orientation Assignment:**

The third stage, identifies the dominant orientations for each keypoint based on its local image patch. SIFT is able to generate a conical view for each keypoint that is invariant to similarity transform because to give orientation scale and placement.

- **Keypoint Descriptor:**

The final stage builds a local image descriptor for each keypoint, based upon the image gradients in its local neighborhood. The patch that has been previously centered about the keypoints location, rotated on the basis of its dominant orientation and scaled to the appropriate size. The goal is to create a descriptor for the patch that is compact, highly distinctive (i.e., patches from different keypoints map to different representations) and yet robust to changes in illuminations and camera viewpoint (i.e., the same keypoint in different images maps to similar representations). As illustrated in Fig. 2.

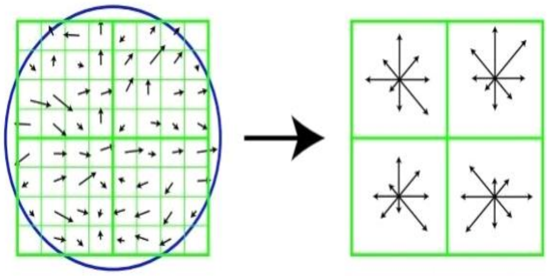

Fig. 3. Gradient to key descriptor formation

Keypoint matching: After we have the information of feature matching of all pictures, we can use this useful information to do image matching. In the image matching step, we are going to find the correct feature matching set we need for the next step of all feature matching sets.

Homography estimation using RANSAC: RANSAC (Random Sample Consensus) is a Nondeterministic algorithm, because it doesn't ensure return acceptable results. It is used to estimate parameters for Homography of a mathematical model from a set of observed data which contains outliers iteratively. RANSAC loop involves selecting four feature pairs (at random); compute Homography H (extract); compute inliers, keep the largest set of inliers, and finally it is a re-compute least squares H estimate on all of the inliers.

Perspective wrapping: Once we have estimated Homography, we need to warp one of the images to a common plane. Here, we are going to apply a perspective transform may combine one or more operations like rotation, scale, translation, or shear. The idea is to transform one of the images so that both images merge as one. An image and the homography is taken as an input. Then it warps the source image to the destination based on the homography, as in Fig. 3.

- proposed method principal compound analysis (pca) - sift.

PCA (Principal Components Analysis) is a mathematical procedure for the reducing the number of dimensions in data. Thus, the PCA technique allows the identification standards in data and their expression in such a way that their similarities and differences are emphasized. Once patterns are found, they can be compressed, i.e., their dimensions can be reduced without much loss of information. The PCA formulation may be reduced without much loss of low level of loss.

The information in a collection of data is stored in a computational structure with reduced dimensions using the integral protection optimum system of the PCA technique. by using the Eigenvalues Decomposition (EVD) method. The reduced dimension computational frame work is chosen to identify relevant data properties with minimal information loss. Such a representation, calculation reduction necessary in subsequent processing,

Steps involved in the PCA:

Step-1: Standardization

This phase is used to normalize the range of continuous beginning variables so that they all contribute equally to the analysis. The importance of standardization prior to PCA is due to the latter's sensitivity to the variances of the initial variables. That is, if the ranges of starting variables differ significantly, the variables with high ranges will outnumber those with smaller ranges. (For example, the variable which ranges between 0 and 100 will dominate over a variable that ranges between 0 and 1), which will lead to biased results. So, the solution for this problem is the transforming the data to comparable scales.

Subtracting the mean and dividing by the standard deviation for each value of each variable can be done mathematically. All of the variables will be changed to the same scale once the standardization is completed.

Step-2: Covariance Matrix Computation

The aim of this step is to understand how the variables of this input data set are varying from the mean with respect to each other, or in other words, to see if there is any relationship between them. Because sometimes, variables are highly correlated in such a way that they contain reductant information. So, in order to identify these correlations, we compute the covariance matrix. The covariance matrix is a p x p symmetric matrix (where p is the number of dimensions) that has as entries the covariances associated with all possible pairs of the initial variables.

In the main diagonal (Top left to bottom right) we actually have the variances of each initial variable. And since the covariance is commutative (Cov (a, b) = Cov (b, a)), the entries of the covariance matrix are symmetric with respect to the main diagonal

It's actually the sign of the covariance that matters: If positive then the two variables increase or decrease together if negative then, one increases when other decreases, inversely correlated. The covariance matrix is symmetric with summaries the correlations between all the possible pairs of variables.

Step-3: Compute The Eigenvectors And Eigenvalues Of The Covariance Matrix To Identify The Principal Components

We need to compute Eigenvalues and Eigenvectors from the covariance matrix in order to determine the principal components of the data.

Principal components are new variables that are constructed as linear combinations or mixtures of the initial variables. These combinations are done in such a way that the new variables (i.e., principal components) are uncorrelated and most of the information within the initial variables is squeezed or compressed into the first components. So, the idea is 10-dimensional data gives you 10 principal components, but PCA tries to put maximum possible information in the second and so on. Organizing information in principal components this way, will allow you to reduce dimensionality without losing much information, and this by discarding the components with low information and considering the remaining components as directions of the data that explain a maximal amount of variance, that is to say, the lines that capture most information of the data.

The relationship between variance and information in this case is that the greater the variance carried by a line, the greater the dispersion of data points along it, and the greater the dispersion along a line, the more information it contains. The directions of the axis with the largest variance (information), which we name principal components, are the eigenvectors of the covariance matrix. Eigenvalues are simply the coefficients attached to eigenvectors, which give the amount of variance carried in each Principal Component. By ranking your eigenvectors in order of significance. After knowing the principal components, to find the percentage of variance (information) accounted for by each component, we divide the eigenvalue of each component by the sum of eigenvalues of variance

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(information) accounted for by each component, we divide the eigenvalue of each component by the sum of eigenvalues.

Step-4: Feature Vector

In this step, we need to choose whether to keep all these components or discard those of lesser significance (of low eigenvalues), and form with the remaining ones a matrix of vectors that we call a feature vector So, the feature vector is simply a matrix that has as columns the eigenvectors of the components that we decide to keep. This makes it the first step towards dimensionality reduction, because if we choose to keep only p eigenvectors (components) out of n, the final data will have only p dimensions.

Step-5: Transform The Original Data:

In this step, which is the last one, the main is to use the feature vector formed using the eigenvectors of the covariance matrix, to reorient the data from the original axes to the ones represented by the principal components.
Final Data Set = Feature Vector ^T *Standardization Original Data Set^T
Finally, PCA enables us to linearly project high dimensional samples onto a low dimensional feature space. More importantly, projecting the gradient patch onto the low dimensional the distortions induced by other effects.

PCA-SIFT:

The use of PCA in the SIFT can be summarized in the following steps
1.pre-compute an eigenspace to express the gradient images of local patches.
2.Given a patch, compute its local image gradient.
3.project the gradient image vector(or)keypoint descriptor using the eigenspace to derive a compact feature vector.
This feature vector is significantly smaller than the standard SIFT feature vector, and can be used with the same matching algorithms. The Euclidean distance between two feature vectors is used to determine whether the two vectors correspond to the same keypoint in different images.
This alternative representation of the keypoint descriptors in SIFT using PCA was theoretically simpler, more compact, faster and more accurate than the standard SIFT descriptor. To ensure that results are an accurate reflection of reality, the original SIFT source code was used and restrict the changes to the fourth stage, i.e., keypoint descriptor.
PCA-SIFT's matching accuracy can be attributed to several factors. First, using the gradient patch rather than the raw patch around the keypoint makes the representation robust to illumination changes, and reduces the variances that PCA needs to model. Second, the pre-processing performed by the first three stages of SIFT simplifies the modeling problem for PCA since the remainder of the variation is due to keypoint identity and perspective distortions. Third, discarding the lower components in PCA improves accuracy by eliminating the variances due to unmodeled distortions. Finally, using a small number of dimensions provides significant benefits in storage space and matching speed.

II. RESULTS AND DISCUSSION

Fig. 4. Input image #1

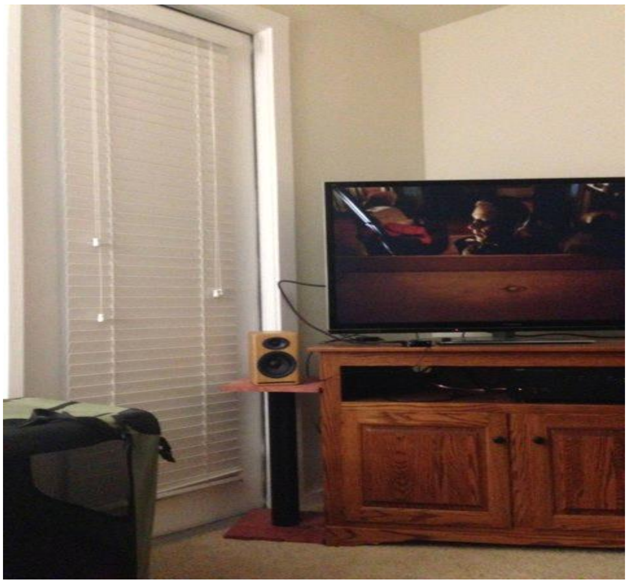

Fig. 5. input image #2

Fig. 6. PCA-SIFT key points in input image #1

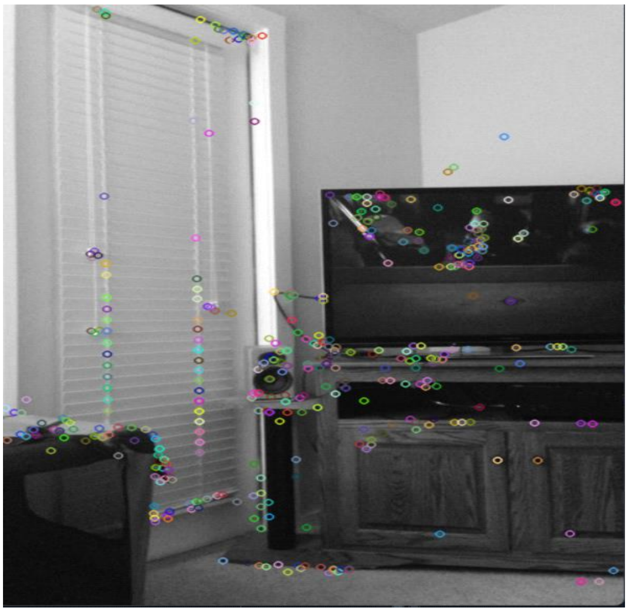

Fig.7. PCA-SIFT key points in input image# 2

Fig.8 PCA-SIFT key points matching between the give two input images.

Fig.9.output after stitching the give input images.

The fig-4 is the first input image with dimensions of 480X640 pixels and with resolution of 72x72 dpi. The fig-5 is the second input image with dimensions of 480X640 pixels and with resolution of 72x72 dpi. Now the fig-6,7,8 describes the main operation of key points generation and key points matching respectively to obtain the output stitched image as shown in fig-9 with dimensions of 960X640 pixels and with resolution of 96x96 dpi. As given inputs are of RGB color representation, the output obtained is also generated in RGB color representation

III. CONCLUSION

PCA-SIFT's matching accuracy at the key point level is better compared to the standard SIFT and translates into better retrieval results. time needed to compute the representation is comparable. PCA-SIFT is significantly faster in the matching phase. PCA-SIFT was both significantly more accurate and much faster than the standard SIFT local descriptor. In PCASIFT increasing the dimensionality of the feature vector results in better accuracy, since the representation is able to capture the structure of the gradient patch with better fidelity. As we continue adding dimensions to the feature vector, the marginal benefits lows. PCA-SIFT is dramatically better at handling noisy images. The standard SIFT representation outperforms PCA-SIFT only when very high false positives rates can be tolerated. PCA-SIFT is both more distinctive and more compact leading to significant improvements in matching accuracy and speed for real- world conditions compared to the standard SIFT algorithm. Although PCA is ill-suited for representing the general class of image patches, it is very well-suited for capturing the variation in the gradient image of key point that has been localized in scale, space and orientation.

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