

Analysis and Implementation of Hand Gesture Recognition System

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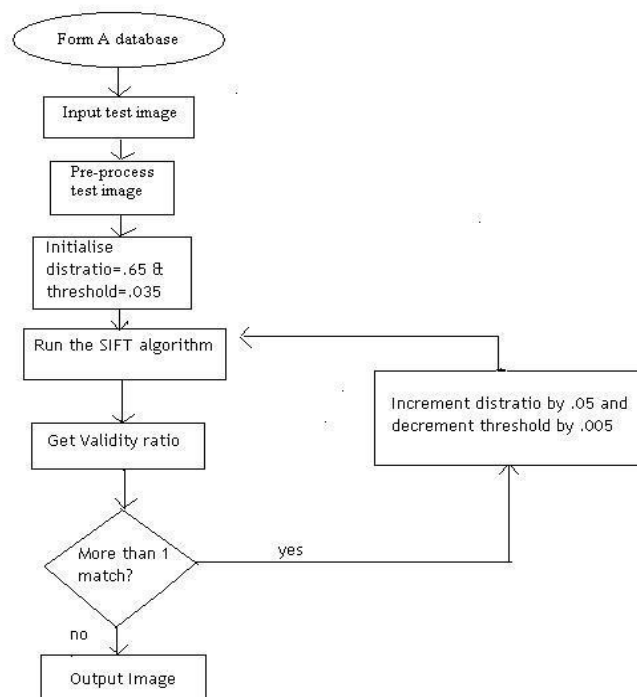
Abstract: Hand gestures recognition provides a natural way to interact and communicate with machines of different kinds. The process is known and referred to as static hand gesture recognition in which images of a hand gesture are stored in the database and analyzed in order to determine the meaning of the hand gesture. The implementation has been done using Scale Invariant Feature Transform (SIFT), Principal Component Analysis (PCA) which present an interface used to recognize hand gestures from the American Sign Language.

Keywords: Distance ratio, Threshold, convolution, Gaussian Filters, Eigen Vector.

I. INTRODUCTION

Gesture recognition can be termed as an approach in this direction. It is the process by which the gestures made by the user are recognized by the receiver. Gestures are expressive, meaningful body motions involving physical movements with the intent of conveying meaningful information and interacting with the environment. A gesture may also be perceived by the environment as a compression technique for the information to be transmitted elsewhere and subsequently reconstructed by the receiver.

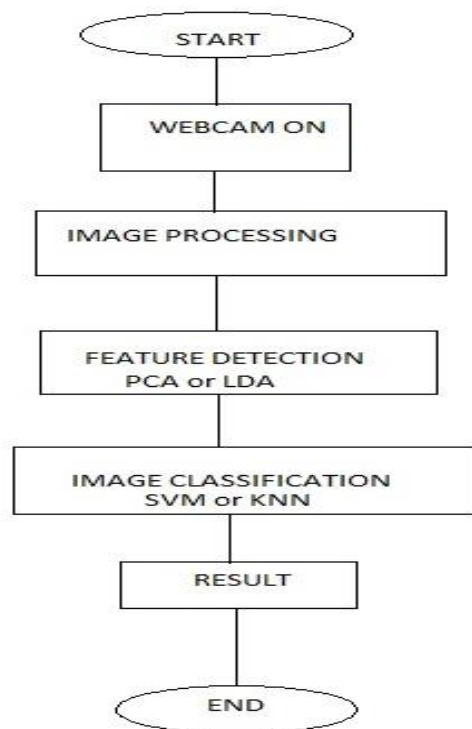
II. SCALE INVARIANT FEATURE TRANSFORM (SIFT)



Scale-invariant feature transform (SIFT) is an algorithm in computer vision to detect and describe local features in images. SIFT key points of objects are first extracted from a set of reference images and stored in a database. An object is recognized in a new image by individually comparing each feature from the new image to this database and finding candidate matching features based on Euclidean distance of their feature vectors.

III. PRINCIPLE COMPONENT ANALYSIS

Principal component analysis (PCA) is a mathematical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. The number of principal components is less than or equal to the number of original variables. Depending on the field of application, it can also be called as proper orthogonal decomposition (POD), Karhunen-Loève transform (KLT) or Hotelling transform.



SCALE-SPACE EXTREMA DETECTION:

This is the stage where the interest points, which are called key points in the SIFT framework, are detected. For this, the image is convolved with Gaussian filters at different scales, and then the difference of successive Gaussian-blurred images is taken. Key points are then taken as maxima/minima of the Difference of Gaussians (DoG) that occur at multiple scales. Specifically, a DoG image $D(x,y,\alpha)$ is given by

$$D(x, y, \alpha) = L(x, y, k_1\alpha) - L(x, y, k_2\alpha)$$

Where $L(x, y, k\alpha)$ is the convolution of the original image $I(x,y)$ with the Gaussian blur $G(x, y, \alpha)$ at scale $K\alpha$, i.e.

$$L(x, y, k\alpha) = G(x, y, \alpha) * I(x,y)$$

KEY POINT LOCALIZATION:

Scale-space extrema detection produces too many key point candidates, some of which are unstable. The next step in the algorithm is to perform a detailed fit to the nearby data for accurate location, scale, and ratio of principal curvatures. This information allows points to be rejected that have low contrast (and are therefore sensitive to noise) or are poorly localized along an edge.

ORIENTATION ASSIGNMENT:

Consistent orientations based on local image properties are assigned to each key point. Representing the following key point descriptor relative to the orientation assignment is a motivating factor to help achieve invariance to image rotation. The scale of the key point is used to select the Gaussian smoothed image, L with the closest scale, so that all computations are performed in a scale invariant manner. For each image sample, $L(x; y)$ at a particular scale the gradient magnitude, $m(x; y)$, and orientation, $\mu(x; y)$, is computed:

$$M(x,y) = [(L(x+1, y) - L(x-1, y))^2 + (L(x, y+1) - L(x, y-1))^2]^{1/2}$$

$$\Theta(x, y) = \text{atan2}(L(x, y+1) - L(x, y-1), L(x+1, y) - L(x-1, y))$$

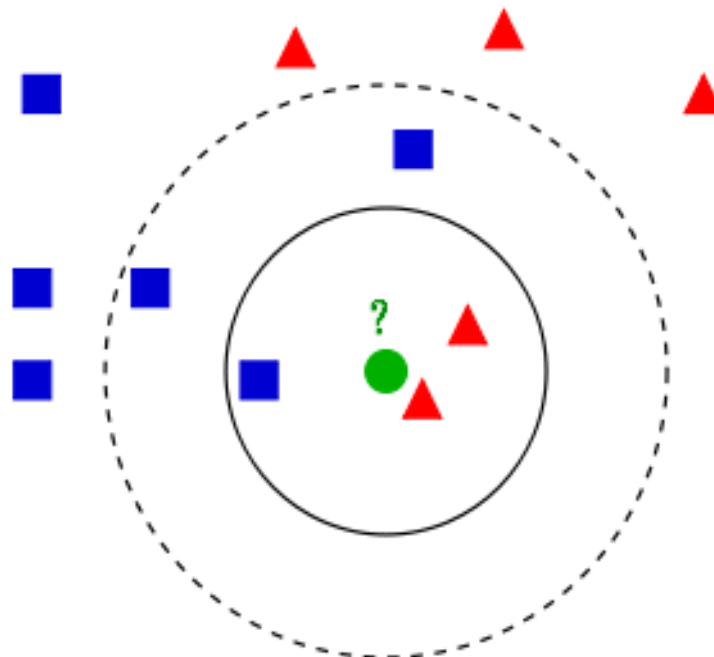
KEY POINT DESCRIPTOR:

After image location, scale, and orientation have been assigned to each key point, it is possible to impose a two dimensional coordinate system to describe the local image region and provide invariance with respect to these parameters. The next step is to compute a descriptor for the local image region that is distinct yet invariant to additional variations such as change in illumination and three dimensional pose.

SUPPORT VECTOR MACHINES:

A support vector machine (SVM) is a non-probabilistic linear binary classifier which can analyze input data and predict which of the two classes it belongs to. It works by building a hyper plane separating the two classes which is of a high dimension. A good separation is obtained by a hyper plane that is very far from any data point of each class, since further the separation of the data, better the performance. The vectors defining the hyper planes can be chosen to be linear combinations with parameters α_i of images of feature vectors that occur in the data base. With this choice of a hyper plane, the points x in the feature space that are mapped into the hyper plane are defined by the relation:

$$\sum \alpha_i K(x_i, x) = \text{constant}$$

IV. K- NEAREST NEIGHBOURS

The k-nearest neighbor algorithm (k-NN) is an classifying method which classifies an object into the type which majority of its neighbors belong to. The choice of the number of neighbors is discretionary and up to the choice of the users. If k is 1 then it is classified whichever class of neighbor is nearest. Usually Euclidean distance is used as the distance metric; however this is only applicable to continuous variables. Hence, the various algorithms have been studied.

V. RESULTS AND CONCLUSION

FEATURE VECTOR TECHNIQUES	CLASSIFICATION TECHNIQUES	TOTAL INPUTS	CORRECT RESULT	EFFICIENCY
PCA	SVM	20	09	45%
	KNN	20	04	20%

Four number of samples were taken for each of the five gestures (A, B, C, V, Five, Point)

The analysis of the algorithm namely PCA has been shown in the tabular form as above. Primarily 20 inputs of the alphabets A, B, C, V, Five, Point were taken each to form the image database. In the PCA algorithm, 09 correct results of the images were obtained out of 20 images using SVM technique with an efficiency of 45% and 04 correct results of the images were obtained using KNN technique giving an efficiency of 20%.

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