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Research Article

Classification of Yoga Hand Mudras using SIFT and SURF Features

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Abstract

Yoga is a unique spiritual science of self-development and self-realization that teaches us how to live our lives to their greatest potential. Yoga's integrated method creates profound harmony and unwavering balance in the body and mind, allowing us to awaken our dormant ability for higher consciousness, which is the true purpose of human evolution. Yoga's various acknowledged physical and mental advantages have contributed significantly to the popularity of the practise. Due to a lack of datasets and the requirement to detect mudra in real time, recognising yoga hand mudras is a difficult undertaking. The yoga hand mudras are used as input in the proposed work, and the two features Scale Invariant Feature Transform (SIFT) and Speeded-Up Robust Features (SURF) are retrieved, followed by machine learning techniques namely Gaussian Naive Bayes (GNB) are used for classification. In the experimental results the performance of SIFT with GNB yields better results.

Keywords: SIFT, SURF, Gaussian Naive Bayes, Yoga hand Mudras.

INTRODUCTION

Today, yoga is a significant component of many people's lives. Although it is classified as a form of exercise, it has the ability to affect an individual's emotional and psychological well-being as well as their physical condition. Yoga has become a well-known practise for maintaining people in good physical and mental health all around the world (Trejo EW, 2018). Yoga is a Sanskrit word that means "to connect, synchronise, or energise," and it refers to the appropriate integration of body, mind, and spirit in order to reach one's full potential. Yoga helps us build awareness that transcends beyond our usual personal and human limitations by exponentially expanding our ordinary capacities (Frawley D, 2001). Yoga is a set of physical and mental exercises that aims to help the practitioner become more conscious of his or her own identity. Yoga can help with a variety of physical issues, but the ultimate objective of practising it is to find one's own truth. Asanas are just one part of an eight-part process that leads to enlightenment. They help the body prepare for meditation (Mittra D, 2003). Reduced blood pressure, anxiety alleviation, better flexibility, and reduced muscle and joint discomfort are among advantages of yoga. In recent years, yoga has become a way of life for many individuals all over the world. As a result, yoga poses must be studied scientifically (Agrawal Y, 2020). Mudras aid in the balance of the human body's five elements. Nature has created a self-sufficient, self-contained, and nearly flawless human body (Menen R, 2010). The elements are represented by the five fingers of the hand. The thumb is related with the element of Fire Agni, the index finger with the element of Air (Vayu), the middle finger with the element of Space Akash, the ring finger with the element of Earth Prithvi, and the little finger with the element of Water (Ganesan A, 2020). Mudras should be practised simultaneously with both hands. They can be done anywhere and at any time. For best effects, each mudra should be performed for fifteen to forty-five minutes, with a minimum of five minutes. The main element to remember is that mudras should be performed two hours after eating because they consume energy in the digestion process and divert energy focus. They are not total healers (Raghupathi KV, 2016). But they provide the best support when combined with Asanas and Pranayama.

Yoga hand mudras

Yoga Mudra is the science of employing hand gestures to alter or redirect energy flow throughout the body via acupuncture meridians, putting our energy body into perfect harmony or balance. Because the hands contain all of the acupuncture meridians, they are regarded as the body's control panel. The Pancha Mahabhutas, or five components of the body, are represented by the five fingers on a hand: fire, water, air, sky, and earth. Yoga Mudras are hand motions designed to improve the flow of energy, or Prana, in the body and mind for better health (Pullen P, 2018). Mudra is a Sanskrit word that roughly translates as 'hand gesture.' Mudras are used in many Hindu and Buddhist rituals, as well as many dance styles, to express deeper significance. This work classifies the most energising yoga mudras, which are Brahma, Chin, Chinmaya, Linga, Prana, Prithvi, Rudra, Surya, Varun, and Yoni, as shown in. Before extracting the features, the input images are pre-processed. The feature extraction techniques SIFT and SURF is utilized, and the machine learning model Gaussian Naive Bayes is used to categorize the features (Krishnan MMR, 2009). The suggested work's block diagram is shown in (Figures 1-2).

Figure 1: Types of Mudras.

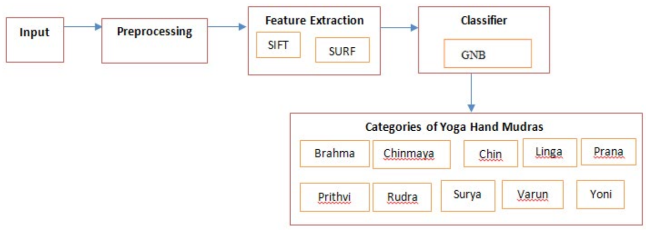

Figure 2: Being sent into feature extraction. Before classification, RGB images are transformed to HSV color space

LITERATURE REVIEW

The yoga participants conducted the research. The data was gathered from yoga studios. In this study, 100 observations were collected from yoga participants in Ammapet, Salem. The significance of the independent variable is determined using maximum likelihood estimation (MLE). The effect of improvement in practising yoga in the dependent variable was divided into two categories no improvement and improvement. Then, using a logistic regression model to match these data, four independent variables were discovered to have a substantial impact on the improvement achieved by practising yoga. For example, the variables that are changed when practising yoga on a regular basis, the motivation for continuing to practise yoga, health problems, and yoga style. For the development of home and clinical yoga therapy for hard-to-reach populations, gesture analysis for yoga alignment training was implemented in (Panchal PM, 2013). The experimental exergame proposed here is a tool that scores yoga posture performance and provides improvement metrics. In this study, statistical metrics were used to track improvements in yoga posture learning in young adults over a 10-week period. The research data was collected from yoga teachers for evaluation, and Kinect Studio was utilized to capture the yoga postures, which were then processed using KS Convert.

Color Space

A color space is defined as a one to four-dimensional spatial model of color representation in terms of intensity values.

One of the dimensions is a color module, often known as a color network. During pre-processing, RGB color is converted to HSV color space.

HSV Color Space

Hue, Saturation, and Value (HSV) are an acronym for Hue, Saturation, and Value. The value represents the color's intensity, which is independent of the image's color information. The hue and saturation components are directly tied to how the human eye sees color, leading in physiologically based image processing algorithms (Krishnan MM, 2012). As the hue value changes from 0 to 1.0, the associated colors go from red through yellow, green, cyan, blue, and magenta before returning to red, therefore there are red values at both 0 and 1.0. Colors (hues) vary from unsaturated (shades of grey) to fully saturated as saturation goes from 0 to 1.0. (no white component). The associated hues increase brighter as the value, or brightness, varies from 0 to 1.0.

Color Conversion: In order to use a good color space, conversion of color is needed between color spaces which preserve the perceived color differences.

RGB to HSV Conversion

Initially, the R, G, B values are divided by 255 to change the range from 0...255 to 0...1:

R'= R/255, G'= G/255, B'= B/255, $C_{min} =$ min (R', G', B'), Δ= C_{max}-C_{min}

In the proposed work, the RGB yoga hand mudra images are taken and converted into the HSV conversion. The value images (intensity) are taken for processing. The preprocessing screenshot of an image is shown in (Figure 3).

FEATURE EXTRACTION

The feature extraction techniques namely, Scale Invariant Feature Transform and Speeded-up Robust Features are used to extract the features from the input image.

Scale invariant feature transform

Scale Invariant Feature Transform (SIFT) algorithm proposed by to solve the image rotation, scaling, and affine deformation, viewpoint change, noise, illumination changes, also has strong robustness. The SIFT algorithm has four main steps:

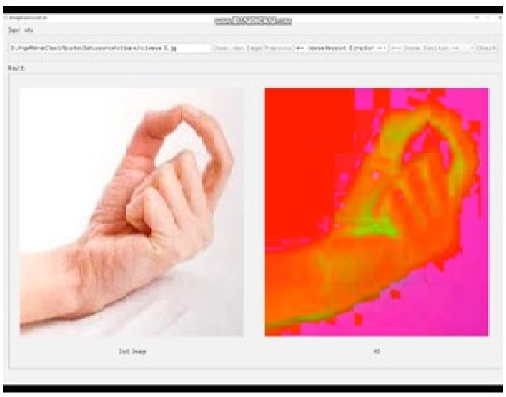

Figure 3: Preprocessing of input image.

Scale space extrema detection: Interest points can be detected at several scales, partially because finding correspondences sometimes necessitates comparing images at various scales. Using scale space extrema in DoG (Difference-of- Gaussian) functions with varying values of, the DoG function is convolved of image in scale space separated by a constant factor k as in the following equation:

$D(x, y, \sigma) = (G(x, y, k\sigma) - G(x, y, \sigma) \times I(x, y)$

Where, G is the Gaussian function and I is the image. Now the Gaussian images are subtracted to produce a DoG, after that the Gaussian image subsample by factor 2 and produce DoG for sampled image. A pixel compared of 3×3 neighborhood to detect the local maxima and minima of D(x, y, σ).

SIFT Descriptor Construction: The image gradient magnitudes and orientations are sampled around the key point position, and the image's amount of Gaussian blur is determined by the scale of the key point (Anuradha K, 2013). To achieve orientation invariance, the descriptor's coordinates are rotated relative to the key point orientation, and then the gradient orientations are rotated. On the left side of. Little arrows indicate each sample location. On the right side of Fig. 3, the key point descriptor is shown. By constructing orientation histograms spanning 4x4 sample sections, it allows for substantial shifts in gradient positions. While contributing to the same histogram on the right, a gradient sample on the left can shift up to four sample places. Each sample has a 44 array location grid and 8 orientation bins. The key point descriptor has a 128-element dimension. The SIFT features are shown in (Figures 4-5).

Speeded-Up Robust Features

The Speeded-Up Robust Features (SURF) algorithm is based on the same principles and steps as SIFT; but details in each step are different. The algorithm has three main parts: interest point detection, local neighbourhood description and matching.

Detection: SURF uses square-shaped filters as an approximation of Gaussian smoothing. Filtering the image with a square is much faster if the integral image is used.

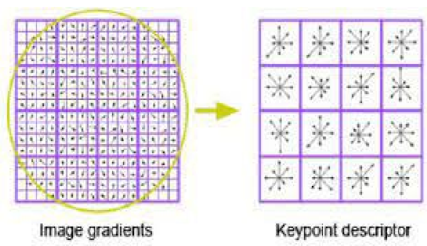

Figure 4: Key point Descriptor.

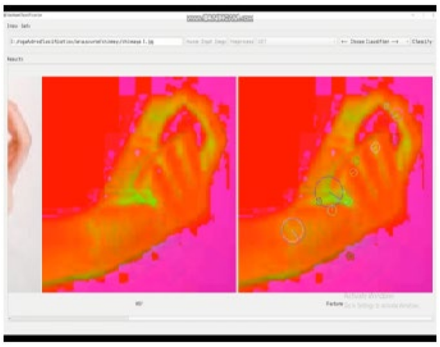

Figure 5: SIFT feature extraction.

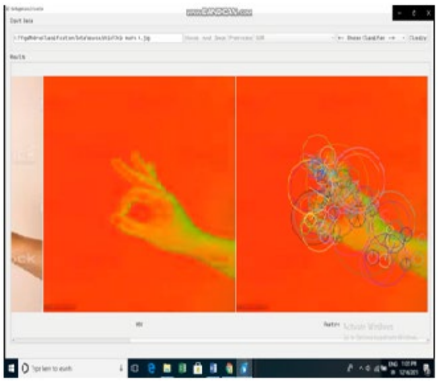

Figure 6: SURF feature extraction.

Scale-space representation and location of points of interest: Interest points can be found at a variety of scales, in part because detecting correspondences frequently demands comparing images at different scales. In other feature detection approaches, the scale space is usually represented as an image pyramid. Before being sub sampled to generate the next higher level of the pyramid, images are smoothed with a Gaussian filter many times. As a result, many levels or stairwells are calculated, each with its own mask measurements. Each octave corresponds to a collection of response maps that covers a scale doubling, and the scale space is divided into a number of octaves. The lowest level of the scale space in SURF is produced by the output of the 99 filters. As a result, unlike earlier approaches, SURF uses boxing to implement scale spaces.

Descriptor: A descriptor's purpose is to provide a unique and reliable description of an image feature, such as the intensity distribution of pixels in the vicinity of the place of interest. Most descriptors are thus generated locally, resulting in a description for each point of interest already specified. The first stage is to establish a repeatable orientation using data from a circular zone surrounding the interest point. The SURF descriptor is then extracted from a square region aligned to the specified orientation.

Orientation assignment: The orientation of the point of interest must be determined in order to achieve rotational invariance. Within a circular neighborhoods of radius 6s around the point of interest, the Haar wavelet responses in both x and y directions are computed, where is the scale at which the point of interest was discovered.

Matching: By comparing the descriptors obtained from different images, matching pairs can be found. (Figure.6).

CLASSIFIERS

Gaussian Naive Bayes are the machine learning algorithms used to classify the features in the proposed work.

Gaussian Naive Bayes

Gaussian Naive Bayes (GNB) is a supervised machine learning classification technique that is a subset of the Naive Bayes algorithm. It is a simple classification technique with high functionality. It can also be used to solve complex classification tasks. It is specifically used when the features have continuous values and also assumes that all the features are following a Gaussian distribution (i.e.) normal distribution. When working with continuous data, an assumption often taken is that the continuous values associated with each class are distributed according to a normal (or Gaussian) distribution. GNB is useful when working with continuous values whose probabilities can be modeled using Gaussian distributions whose means and variances are associated with each specific class.

$$P(x_i \mid y) = \frac{1}{\sqrt{2\pi\sigma_y^2}} \exp\left(-\frac{(x_i - \mu_y)^2}{2\sigma_y^2}\right)$$

Where μ and σ are the mean and variance of the continuous x computed for a given class y (Figure 7).

EXPERIMENTAL RESULTS

Datasets

A real time data was collected from, Center for Yoga Studies, Annamalai University, Chidambaram, and Tamilnadu, India. A total of 1000 yoga hand mudra images were gathered, 75% used for training and 25% used for testing. Brahma, Chin, Chinmaya, Linga, Prana, Prithvi, Rudra, Surya, Varun, and Yoni are represented by 100 images.

Classification using SIFTS and SURFS with GNB

The SIFT and SURF features are extracted from the images in the proposed study, and the classifier GNB is employed to

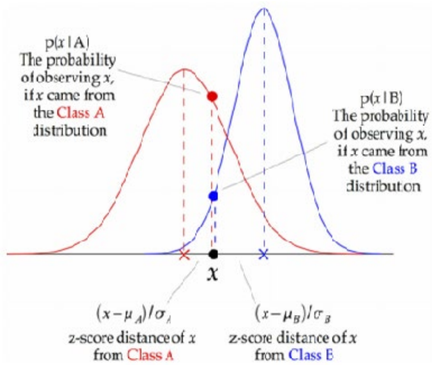

Figure 7: Working of Gaussian Naive Bayes.

categorize the features. To classify the Yoga hand mudras, 128 dimensional SIFT features and 64 dimensional SURF features were recovered, and the classifier GNB was utilized. The system has a SIFT feature accuracy of 71.15% and an SURF feature accuracy of 45.51%. The classification of yoga hand mudras using SIFT and SURF with GNB is shown in (Figures 8-11).

PERFORMANCE MEASURES

The overall performance of F-Score, precision, and recall of yoga hand mudras are classified. (Table 1) shows the overall accuracy. The confusion matrix is used to calculate the accuracy of each hand mudra. The data can be properly trained and tested; the proposed work's precision, recall, F-Score, and accuracy are all acceptable.

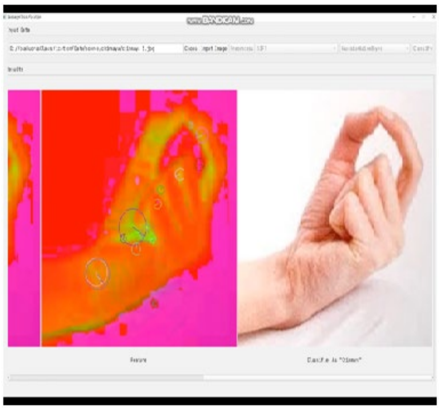

Figure 8: Classification of Yoga hand mudras.

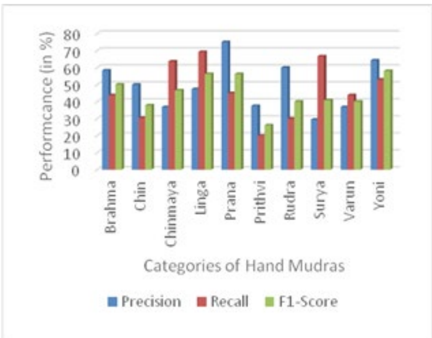

Figure 9: Performance of GNB using SIFT features.

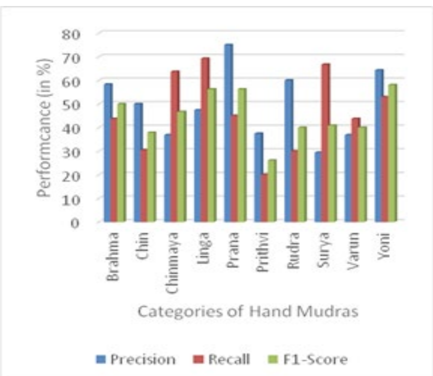

Figure 10: Performance of GNB using SURF features.

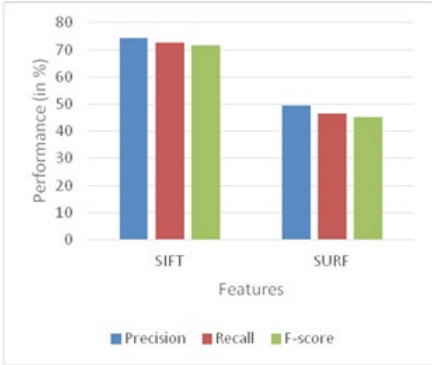

Figure 11: Comparison of SIFT and SURF using GNB.

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$\text{Accuracy} = \frac{(TP + TN)}{TP + TN + FP + FN}$$

The performance of SIFT with GNB and SURF with GNB are shown in Fig. 9 and 10. The performance of SIFT with GNB gives better performance when compared to SURF with GNB models. The comparison of precision, recall and f-score are shown in Fig. 11. The overall accuracy of the proposed work is shown in (Table 1).

Table 1. Overall Accuracy.

Features	Classifiers	Accuracy
SIFT	GNB	71.15
SURF	GNB	45.51

CONCLUSION

This paper, the classification of yoga hand mudras has been proposed using the machine learning techniques GNB, where SIFT and SURF as features to classify. Experimental results show that, the real time Yoga Hand Mudra images were collected. In this research, the performance of GNB with SIFT features gives the highest accuracy of 71.15% when compared to other model. In future, the Yoga hand mudras and yoga asana will classify using deep learning models.

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