Snake classification from images

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ABSTRACT

Incorrect snake identification from the observable visual traits is a major reason of death resulting from snake bites. So far no automatic classification method has been proposed to distinguish snakes by deciphering the taxonomy features of snake for the two major species of snakes i.e. *Elapidae* and *Viperidae*. We present a parallel processed inter-feature product similarity fusion based automatic classification of Spectacled Cobra, Russel's Viper, King Cobra, Common Krait, Saw Scaled Viper, Hump nosed Pit Viper. We identify 31 different taxonomically relevant features from snake images for automated snake classification studies. The scalability and real-time implementation of the classifier is analyzed through GPU enabled parallel computing environment. The developed systems finds application in wild life studies, analysis of snake bites and in management of snake population.

INTRODUCTION

The morbidity and mortality due to snakebite is high in many parts of the world even with the availability of anti-venoms. As a first-line treatment polyvalent anti-venom is injected to the snake bite victim (Warrell, 1999). The observational evidences of the patients are taken into account in identifying snakes, however, most doctors are not trained to identify the taxonomy of the snake, so accuracy of detection in practice is very low. There is an issue of serious misreporting, the extend of which is not studied. The injected polyvalent anti-venom contains antibodies raised against two or more species of snake that can neutralize the venom injected by a single snake bite (Calvete et al., 2007; Halim et al., 2011). The part of anit-venom that remain non-neutralized creates a further risk to the human health, making the correct identification of snakes an important problem (Halim et al., 2012).

In this paper, we propose an inter-feature product similarity fusion classifier that incorporates the fusion of histogram features representative of the taxonomy of the snake. As an example, we discuss here our results when the task was set to distinguish two major type of snake species (Elapidae and Viperidae) in real-time imaging conditions. The images used in our study are that of poisonous snakes collected over a period of 2 years from a recognized Serpentarium and are common specimens seen in the human habitat region.

In general, the automated classification of snakes from images is an open research problem. We present features that can be used for distinguishing two different types of snake species which is found commonly in India, where the data for this study was collected. The database for this study, the fusion classifier and the feature analysis methods are the main contributions reported in this work. In addition to the suitability of the method in real time imaging conditions, the proposed algorithm can be used on offline images of snakes for example in the application of detecting the snakes identified using the help of bite victim to recommend medical treatment to snake bite victims.

Background

The recognition of snake classes from images requires the development of a gallery of images of snakes belonging to given classes. The snake has several sets of taxonomy features that enable the identification of snake classes. Obtaining an extensive collection of snake image features for the gallery is a challenge making the snake classification attempted in this paper a small sample classification problem. It is well known that nearest neighbor classifiers are robust, simple and powerful technique under such conditions, and forms the basis for the classifier proposed in this paper. In this section, we provide the

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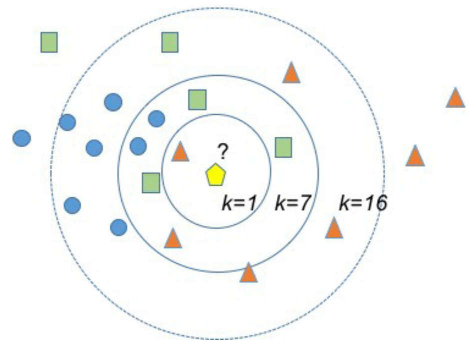

Figure 1. The illustration of feature distance space in a Nearest neighbour classifier.

necessary background on nearest neighbor classifier and in the preparation of snake database for setting the foundation for the further sections.

Nearest Neighbor Classfiers

In this paper, we use a subset of the well-known nearest-neighbor classifier. The nearest neighbor classifier (Cover and Hart, 1967) (kNN) identifies the class of unknown data sample from its nearest neighbor whose class is already known. Figure 1 shows the feature distance space of test sample to the known gallery samples. The set of samples that have its classes prior known is used to create the gallery set. The unknown sample belongs the test set and the distance from this sample to the gallery samples determined by a distance metric. The class of the sample in the gallery that has the closest distance to the test sample is assigned the class of the test sample. There are several ways of calculating the distances between the samples and also many different ways to include or exclude the distances to determine the class. When the closest distance is used for determining the class of test sample, i.e. when $k = 1$ as shown in Fig. 1, such a classifier is known as minimum distance nearest neighbor classifier. When $k > 1$, there are different ways of determining the class of the unknown test sample, such as voting for the largest number of class samples, or weighting and voting the sample distances, or having a learning scheme to determine the optimal value of k.

The popular variants of the nearest neighbour classifier include weighted kNN(Bailey and Jain, 1978), Condensed Nearest Neighbor(Gowda and Krishna, 1979), Reduced Nearest Neighbor(Gates, 1972), Model based k nearest neighbor(Guo et al., 2003), Rank nearest neighbor(Bagui et al., 2003), Modified k nearest neighbor(Parvin et al., 2008), Generalized Nearest Neighbor(Zeng et al., 2009), Clustered k nearest neighbor(Yong et al., 2009), Ball Tree k nearest neighbor(Liu et al., 2006), k-d tree nearest neighbor(Sproull, 1991), Nearest feature Line Neighbor(Li et al., 2000), Local Nearest Neighbor(Zheng et al., 2004), Tunable Nearest Neighbor(Zhou et al., 2004), Center based Nearest Neighbor(Gao and Wang, 2007), Principal Axis Tree Nearest Neighbor(McNames, 2001), and Orthogonal Search Tree Nearest Neighbor(Liaw et al., 2010).

The nearest neighbor classifiers are non-parametric and are suitable for small sample problems. Even when the number of sample per class is uneven or when they become as low as one(Raudys and Jain, 1990), the classifier provides a match based on the nearest distance. Further, limiting the value of k to lower values removes the impact of data outliers, and improves the robustness of classification. A lower value of k necessitates a distance metric that can remove the effect of outliers in features.

The features of snake images that we collect require a prior knowledge of the class and taxonomic significance to be selected as gallery samples. They are more generally referred to as gallery templates to recognize the overall classification as a template matching process. There are different possibilities and ways of creating gallery templates, such as by manual segmentation of the taxonomically relevant features or by automatic feature extraction methods. Its practically not possible to develop a fully automatic method of segmentation for creating the gallery of snake features as they have a large variability such as scaling, illumination changes, scars on the skin, aging, color changes, and pose changes. Therefore the gallery templates always require a manual validation before it can be incorporated into the snake database to be meaningfully used in the nearest neighbor classifier.

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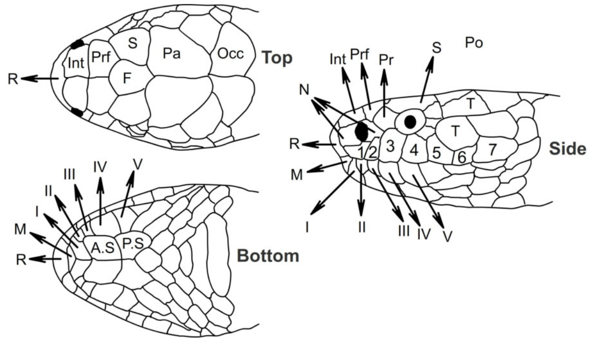

A.S Anterior sublinguals; F Frontal; Int Internasals; M Mental; N Nasals;
Occ Occipitals; Pa Parietals; Po Postoculars; Pr Preoculars; Prf Prefrontals;
P.S Posterior sublinguals; R Rostral; S Supraoculars; T Temporals;
1-7 Supralabials; I-V Infralabials;

Figure 2. Scale Diagram of Cobra

Snake Taxonomy

Snakes are legless, carnivorous reptiles of the suborder Serpentes which can be either venomous or non-venomous. In this section, we present the description of two major snake species for the proposed snake identification problem. The scale diagram of the two major snakes i.e. Spectacled cobra and Russell's viper is shown in Fig 2 and Fig 3[1].

Figure 2 shows the Spectacled cobra which is a well-known snake and is a species of genus *Naja*, native to the Indian subcontinent and has a Binomial name of *Naja naja*. It can be found in plains, jungles, open fields and in places populated by people. This species normally feed on rodents, toads, frogs, birds and other snakes for its survival. The Spectacled cobra has the following scientific classification; Kingdom: Animalia, Phylum: Chordata, Class: Reptilia, Order: Squamata, Suborder: Serpentes, Family: Elapidae, Genus: *Naja*, Species: *N. naja*.

Viper is a species of genus *Daboia*. The Binomial name of the viper is *Daboia russelii*. This species was named in honor of Patrick Russell (1726-1805), Scottish herpetologist, who first discovered this snake. The meaning of genus Daboia in Hindi is *"that hid lies"*. A common name of Daboia is Russell's Viper. The Scientific Classification of Russell's viper: Kingdom: Animalia, Phylum: Chordata, Subphylum: Vertebrata, Class: Reptilia, Order: Squamata, Suborder: Serpentes, Family: Viperidae, Subfamily: Viperinae, Genus: *Daboia*, Species: *D. russelii*.

Feature Differences In this paper, we are mainly concerned with identifying the difference in features between a Spectacled cobra and Russell's viper. The most unique and notable feature of the Indian cobra is its hood, which is absent in viper. When the snake is in danger, it forms hood by raising the front part of its body and spreading its ribs in its neck region. The hood contains two circular patterns, joined by a curved line, on the back of its hood which appears like spectacles. It has small nostril, which is placed in between two nasal scales.

The most important and distinctive feature in a viper is its triangular, flattened head, which is clearly broader than its neck. Usually, there is a presence of 'V' mark on its head. They have blunt and raised nose. Viper has a big nostril, which lies in the middle of a single large nasal scale. There is a crescent shaped supranasal scale and the lower part of nose touches the nasorostral scale.

[1] **Nasal:** These scales encloses the nostril. The nasal near the snout is called prenasal and the nasal near the eye is called postnasal. In vipers, nostril lies in center of single nasal. **Internasal:** These scales lie on top of snout and connects nasal on both side of head. **Rostral:** This scale lie on the tip of snout, in front of internasal. **Supraocular:** These scales form the crown of eye, and lie above the eye. **Preocular:** These scales lie towards the snout or in front of eye. **Postocular:** These scales lie towards the rear or back of eye. **Subocular:** These scales lie in rows below the eyes and above the supralabials. **Loreal:** These are 1-2 scales which are in between preocular and postnasal. **Labials:** These scales lie along the lip of the snake. Scales on upper lip is Supralabials and scales on the lower lip are called infralabials. **Frontal:** These scales lie in between both the supraocular. **Prefrontal:** These scales are in touch with frontal and lie behind the internasal. **Parietal:** These scales lie on back portion of head, which are connected to frontals. **Temporal:** These scales lie between the parietals above and supralabials below at the side of the back of the head. **Mental:** This is an anterior scale that lie underside the head, just like rostral on upper part. **Anterior Sublingual:** These scales are connected to the infralabials along the chin. **Posterior Sublingual:** These scales are next to anterior chin shield, further back along the chin. **Dorsal or Costal Scale:** These are scales on the body of snake. **Ventral Scale:** These are enlarged scales on the belly of snake. **Nasorostral Scale:** This is enlarged scale, just behind the rostral and infront of nasal.

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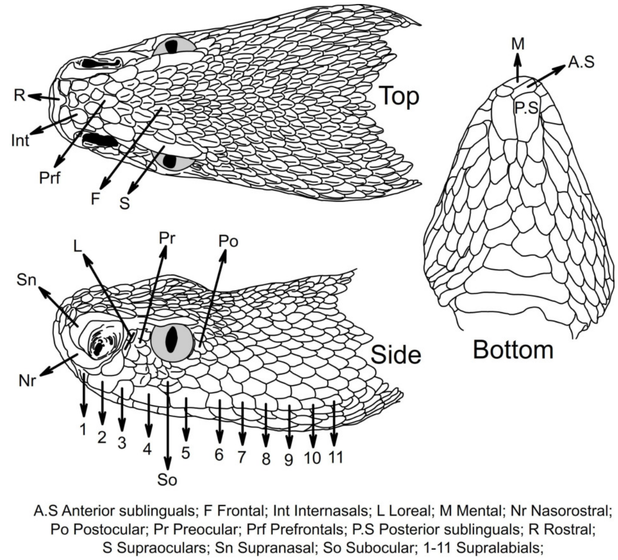
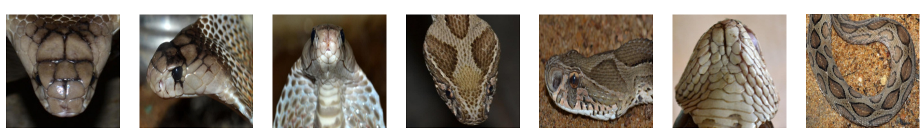


Figure 3. Scale Diagram of Viper. Note: In any view, only one example Prefrontals and Frontals scale is marked.

Scalation Differences The head scales of cobra shown in Fig. 2 is large compared to viper shown in Fig. 3. As can be seen from Fig. 2 there are rostral, 2 internasal, 2 prefrontal, 1 frontal, 2 parietals in the head part. There are generally 1-7 supralabial scales, which are placed along the upper lip of snake. There is 1 preocular and 3 postocular scale, which lies on front and back of the eye. The body scales i.e. the dorsal scale of the cobra is smooth.

The head scales of viper are small as compared to cobra. They contain small frontals and some parietals. The supraocular scale, which acts as the crown of the eye is narrow in comparison to cobra. The eyes are large in size with vertical pupil. There are 10-12 supralabials, out of which 4th and 5th are notably larger than the remaining. They also have preoculars, postocular, 3-4 rows of subocular scales below their eye and loreal scale between eye and nose. Loreal scales are absent in cobra. There are generally 6-9 scales between both the suproculars. There are two pairs of chin shields, out of which front one is larger.

The dorsal scales are strongly keeled. The dorsal scale has consecutive dark spots, which contain light brown spot that is intensified by thick dark brown line, which is again surrounded by light yellow or white line. The head has a pair of dark patches, which is situated on both the temples. Dark streaks are notable, behind or below the eye.



(a) Top (b) Side (c) Bottom (d) Top (e) Side (f) Bottom (g) Body

Figure 4. Images of cobra((a)-(d)) and viper((e)-(h)). The labels indicate the feature group to which the image belongs. Note: The images shown in this figure are resized to a common scale for display purposes.

MATERIALS AND METHOD

Snake Database

The snake images for the experiment were collected with the help of Pujappura Panchakarma Serpentarium, Trivandrum, India, through the close and long-term interaction with the subjects under study. These photographs don't require ethical clearance as we took photographs from a recognized Serpentarium and are common specimens seen in the human habitat region. The total number of images used for this

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experiment are obtained from 5-6 snakes of each species on different occasions and time under wild conditions. Sample images from the database are shown in Fig. 4. Obtaining photographs under realistic conditions are challenging due to the dangers involved with snake bites. The problem addressed in pattern recognition context is a highly challenging task of small sample classification under unconstraint recognition environments.

We started with a database of 88 images of cobra and 48 images of viper for the initial feature taxonomy analysis. Then for image based recognition the database with a total of 444 images; of which Spectacled Cobra (SC), Russel's Viper(RV), King Cobra(KC), Common Krait(CK), Saw Scaled Viper(SSV), Hump-nosed Pit Viper (HNPV) has 207, 76, 58, 24, 36 and 43 images were used.

Snake feature database

Table 1. Classification of the taxonomy features based on the observer view

Feature Table	
Top	F_1 Rostral; F_2 Internasal; F_3 Prefrontal, F_4 Supraocular, F_5 Frontal, F_6 Parietal, F_7 V mark on head, F_8 Triangular head, F_9 Dark patches on both sides of head, F_{10} No. of scales between supraocular
Side	F_{11} Small nostril, F_{12} Round pupil, F_{13} Big nostril, F_{14} Elliptical pupil, F_{15} Loreal, F_{16} Nasorostral, F_{17} Supranasal, F_{18} Triangular brown streaks behind or below eyes, F_{19} Subocular, F_{20} Nasal, F_{21} Preocular, F_{22} Postocular, F_{23} No. of Supralabial scale
Bottom	F_{24} Mental, F_{25} Asterior Sublingual, F_{26} Posterior Sublingual
Body	F_{27} Round Dorsal scale, F_{28} Hood, F_{29} Spectacled mark on hood, F_{30} Keeled Dorsal scale, F_{31} Spots on Dorsal scale

Table 1 shows the proposed grouping of taxonomy features based on the observer views of the snakes shown in Fig. 2 and Fig. 3. In total 31 taxonomy based features are identified for creation of the feature database from the 136 snake images collected. There is a total of 88 images of cobra and 48 images of a viper. For creating the feature database, each image is translated to samples with 31 features, totalling 136 samples for the database.

Snake image database

The taxonomical features can be used to construct an image only feature database from individual snake images. We use the taxonomical feature as outlined in Table 1, with the help of snake taxonomy to create image feature database. In the region of images with the specific features are cropped manually, so that each snake image sample can result in a maximum of 31 feature images corresponding to the taxonomical features as outlined in Table 1.

Figure 5 shows an example of taxonomically recognisable feature images extracted from an image of Cobra. In this example, the sample image of the cobra contain Internasal (F_2), Prefrontal (F_3), Supraocular (F_4), Frontal (F_5), Parietal (F_6), scales between supraocular (F_{10}) and Round Dorsal scale (F_{27}). These feature images collectively represent the taxonomically valid images representing the sample cobra image in Fig 5.

Issues with Automatic Classification

Missing features and lower number of gallery samples per class can significantly reduce the performance of conventional classifiers (Kotsiantis, 2007; Aha et al., 1991; Atkeson et al., 1997; Buhmann, 2003; III and Marcu, 2005; Demiroz and Guvenir, 1997). The practical difficulty in collecting well-featured snake images in real-time conditions makes automatic classification task challenging and difficult. Natural variabilities such as illumination changes, occlusions due to soil, skin ageing and environmental noise can impose further restrictions on the quality of features obtained in real-time imaging conditions. The summary of the proposed algorithm is shown in Fig. 6. In this paper, once the taxonomically relevant features are selected from the snake images they are normalized using mean-variance filtering. The histograms of gradients and orientation of these normalized features are used as feature vectors. These feature vectors are evaluated using a proposed minimum distance product similarity metric classifier.

Proposed Classifier

The proposed classifier is the modification of the traditional minimum distance classifier with gallery templates. The minimum distance classifier is a subclass of the nearest neighbor classifier (Cover and

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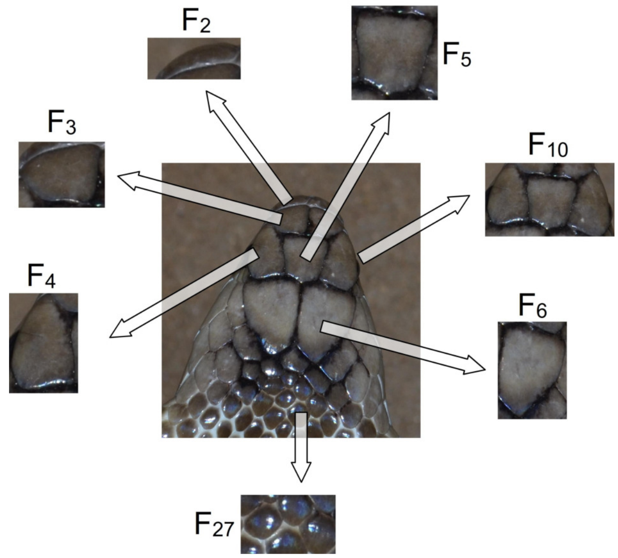

Figure 5. Taxonomically identifiable snake image features from a sample image in the presented snake image database.

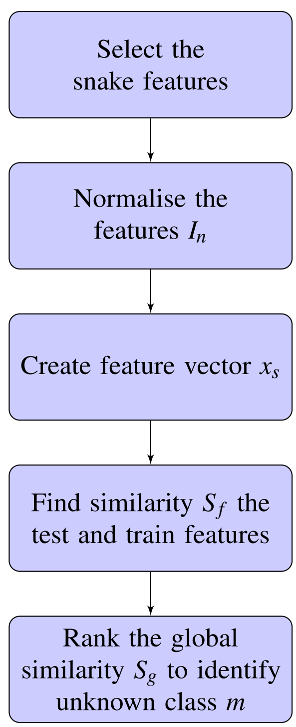

Figure 6. The summary of the stages of proposed algorithm. The features are selected either manually or through automatic extraction from the images. The image features are normalised using mean variance filtering. The feature vectors are created with histograms of gradients and orientation of normalised features. The resulting features are used in a min-distance classifier using a new product similarity metric.

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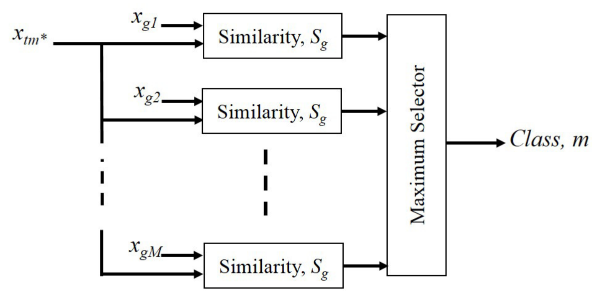

Figure 7. The proposed maximum similarity template matching classifier with the product similarity.

Hart, 1967). They one of the simplest yet most powerful of the classifiers suitable for small sample problems (Raudys and Jain, 1990). The template matching can be illustrated as shown in the Fig 7. The main difference with the conventional minimum distance classifier is in the use of a new similarity metric that changes the minimum selector to a maximum selector. The ability of the classifier to correctly discriminate snake classes depends on the availability of inter-class discriminating features in the samples. We propose to ignore the missing features and calculate global similarity based on remaining features in a sample using a product based inter-feature similarity measure.

Suppose $x_t(i)$ is the test sample and $x_g(i)$ is the gallery sample, and i represents the index of the ith feature in the respective samples, then, the similarity $S_f(i)$ represents the similarity between the features:

$$S_f(i) = x_t(i)x_g(i) \tag{1}$$

The missing features in the feature vector x_t is assigned a value 0 as this is indicative of the absence or non-detection of the feature. Which means that the even if the there exists a numerical measure of similarity between any missing features in x_t and x_g, the overall feature similarity S_f would not have the effect of missing features. The absence of a feature in a test would not result in similarity between the test and gallery. The global similarity of a test sample with a class m containing J gallery samples with each sample having N features can be represented as:

$$S_g(m) = \sum_{i=1}^{N} \left(\frac{1}{J} \sum_{j=1}^{J} S_f(j,i) \right) \tag{2}$$

Suppose there are M classes and $\{c_{m1}, c_{m2}.., c_{mk}\}$ gallery samples per each class, then there will be $\{c_{m1}, c_{m2}.., c_{mk}\}$ number of similarity values, S_g, for determining the class of the unknown test sample x_t. The class with the maximum number of high scores can be considered to be the most similar class to which the test sample belongs. If m represents the class label, then the class of the unknown test sample can be identified by:

$$m^* = \arg\max_m S_g(m) \tag{3}$$

Implementation in CUDA

Because the similarity S_f is calculated at the feature level, and a global similarity S_g is calculated as an additive fusion of feature similarities at the class level, can be realised as a parallel processed algorithm in CUDA (Garland et al., 2008; Cook, 2012) as shown in Listing 1.

```
__global__ void kernelProductSimilarity(float* j, float* Sf, float* Sm,
    int* indf, int featSize, int J)
{
//J=Total number of samples per class
//Sf=Product similarity
//Sm=Mean product similarity per feature in a class
//featSize=Total number of features
```


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```
//j=Index of the gallery samples
//indf=Index of the feature in a sample
//x,y are coordinates of the two dimensional grid used for parallel
    computation
unsigned int x = blockIdx.x*blockDim.x + threadIdx.x;
unsigned int y = blockIdx.y*blockDim.y + threadIdx.y;
Sm[y*featSize+x]=0;
Sf[y*featSize+x]=0;
indf[y*featSize+x]=0;
for (j[y*featSize+ x]=1;j[y*featSize+ x]<J; j[y*featSize+x]++)
   {
   indf[y*featSize+x]=indf[y*featSize+x]
                      +featSize;
   Sf[y*featSize+x]= Sf[y*featSize+x]+ feature_x[y*featSize+x]*
       feature_x[(y*featSize+x)+ indf[y*featSize+x]];
    }
Sm[y*featSize+x]= Sf[y*featSize+x]/(J-1);
}
```

Listing 1. Product similarity implemented as CUDA kernel code

The CUDA kernel code when tested for a similarity calculation on 10000 gallery samples with 31 features and 10000 features has an execution time of 0.0013s and 0.14s, respectively. All the classification experiments reported in this paper is performed on Tesla 2070 GPU processor, and coding is done in C language.

Table 2. Example of proposed classification of snake data using 4 features

		Features				Local Similarity				Global Similarly score
Class	Sample	F_7	F_{12}	F_{14}	F_1	$S_f(7)$	$S_f(12)$	$S_f(14)$	$S_f(1)$	S_g
Cobra	1	0	1	0	1	0	1	0	1	**1.5**
	2	0	1	0	0	0	1	0	0	
Viper	1	1	0	1	0	0	0	0	0	0.0
	2	1	0	1	0	0	0	0	0	
Unknown X_t		0	1	0	1	-	-	-	-	-

Classification with Feature Database

The feature database consists of 31 taxonomically distinct observable snake features. The similarity calculation between the test and gallery is performed using S_f. The global similarity S_g is calculated and the class of the sample under test is identified using m^*.

0.0.1 Example on Feature Database

Consider the example in Table 2, where two samples from each class (ie Cobra and Viper) is used as gallery x_g while unknown sample x_t is used as a test. To make the understanding clear, the x_t originally belongs to the class Cobra. The task is to identify the class of the x_t using the 4 example features F_7, F_{12}, F_{14} and F_1.

In this simple example, we calculate the local similarity $S_f(i)$ between the test and gallery features. Because the features F_7 and F_{14} are absent in x_t, it can be seen that they do not contribute to the positive similarity values of S_f, which means that the global similarity S_g is formed of the local similarities from features F_{12} and F_1. It can be seen that for the given example, the Viper class has a similarity score of 0.0 against the Cobra class that has a similarity score of 1.5. The class of the test sample x_t is identified as Cobra.

Classification with Image Database

The images in the gallery set can be used to create a template of features describing the snake. While a feature sample based database can be used, a more practical approach in a real-time situation is to have a technique that can automatically process the images directly for classification. Images are usually affected by natural variabilities such as illumination, noise and occlusions. In order to reduce the natural

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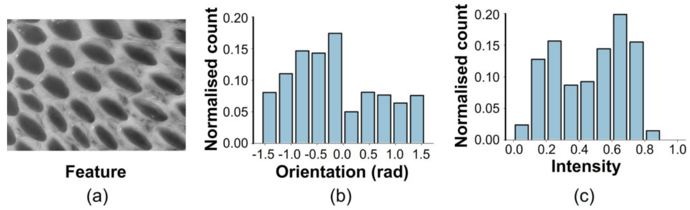

Figure 8. An example of the taxonomically identifiable feature F_{27} of cobra is shown in (a), and its corresponding normalised orientation and magnitude histograms $hist_n(\theta)$ and $hist_n(a)$ is shown in (b) and (c), respectively.

variability, it is important to normalise the intensity values. The reduction in natural variability would result in reduced intra-class image distances and improved classification accuracies. The image I can be normalised using mean-variance moving window operation:

$$I_n(k_x,k_y) = \frac{\sum_{i=-m1}^{m1}\sum_{j=-n1}^{n1}\left(I(k_x-i,k_y-j)-I_\mu\right)}{I_\sigma} \tag{4}$$

where, the window has a size of $(2m+1)\times(2n+1)$, I_μ is the mean and I_σ is the standard deviation of the pixels in the image window. The normalised image I_n is converted into a feature vector, consisting of orientation of gradients and magnitudes of the image pixel intensities. The gradient orientation θ and magnitude a of I_n is computed at each point (k_x,k_y), given $dy = I_n(k_x,k_y+1)-I_n(k_x,k_y-1)$ and $dx = I_n(k_x+1,k_y)-I_n(k_x-1,k_y)$ is calculated as:

$$\theta(k_x,k_y) = \arctan\left(\frac{dy}{dx}\right) \tag{5}$$

and

$$a(k_x,k_y) = \sqrt{dx^2+dy^2} \tag{6}$$

The orientations θ is quantised in N bins of a histogram, and magnitude a is quantised into M bins of the histogram. The count of the histogram is normalised by dividing the counts in the individual bins by the overall area of the individual histograms. The normalised histograms $hist_n(\theta)$ and $hist_n(a)$ is concatenated to obtain the feature vector for a snake image. An example of the normalised histogram features from the images are shown in Fig. 8.

In the context of *snake image database*, we have a maximum of 31 feature images resulting from a single sample of snake image. Suppose, I_f is the normalised feature image, and $hist_n(\theta_f)$ and $hist_n(a_f)$ its corresponding orientation and magnitude features. Then, we can represent the overall fused feature vector x_s for any sample image s as:

$$x_s = \Xi_{i=1}^{31} hist_n(\theta_f)\Xi hist_n(a_f) \tag{7}$$

where Ξ represent the concatenation operator. The test images and gallery images are converted to feature vectors using x_s.

The similarity calculation between the test and gallery samples is performed, the global similarity S_g is calculated using Eq. 2 and the class of the sample under test is identified.

RESULTS

The *feature database* and *image database* of the snakes is used for analysing the classification performance of this two class small sample classification problem. The feature database contains 31 features, while image database consists of a total 1364 histogram features. Each of $hist_n(\theta)$ and $hist_n(a)$ histogram feature consisted of 33 orientation features and 11 intensity features respectively, that resulted in a total of $31\times33\times11$ features. The experiments for classifier performance analysis were repeated 50 times by a random split for test and galley set to ensure statistical correctness.

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Table 3. Comparison of the proposed method with other classifiers when 5% of the class samples are used as gallery and remaining 95% of sample are used as test on *snake feature database*.

Method	% Correct	F - Score	AUC	Precision (%)	Recall (%)
Proposed	**94.27± 6.34**	**0.959±0.062**	**0.937±0.005**	92.11 ± 14.4	93.03 ± 10.4
J48(Quinlan, 1993)	90.00 ± 6.70	0.922 ± 0.057	0.914 ± 0.007	97.17 ± 6.7	88.25 ± 8.3
IB1(Aha and Kibler, 1991)	93.24 ± 3.16	0.947 ± 0.024	0.923 ± 0.004	94.6 ± 5.4	**95.46±5.5**
IBK(Aha and Kibler, 1991)	93.49 ± 3.20	0.949 ± 0.024	0.933 ± 0.004	94.61 ± 5.4	95.86 ± 5.3
LWL(Frank et al., 2003)	92.42 ± 5.34	0.940 ± 0.045	0.919 ± 0.060	94.78 ± 5.7	93.75 ± 7.0
RBF(Scholkopf et al., 1997)	89.94 ± 7.04	0.916 ± 0.065	0.874 ± 0.073	95.82 ± 6.6	89.20 ± 11.9
Voted Perceptron(Freund and Schapire, 1998)	79.79 ± 13.13	0.850 ± 0.093	0.846 ± 0.132	85.19 ± 14.4	88.63 ± 15.2
VF1(Demiröz and Güvenir, 1997)	80.28 ± 11.74	0.829 ± 0.105	0.749 ± 0.204	92.22 ± 11.6	77.44 ± 15.6
AdaBoost M1 (Freund and Schapire, 1996)	90.50 ± 6.71	0.921 ± 0.057	0.914 ± 0.072	**97.11±6.8**	88.25 ± 8.3

Table 4. The performance of proposed classifier with other classifiers when 5% of the class samples are used as gallery and remaining 95% of sample are used as test on *snake image database*

Method	% Correct	F - Score	AUC	Precision (%)	Recall (%)
Proposed	**85.20 ±7.10**	**0.91± 0.03**	**0.920 ± 0.06**	**89.95 ± 12.6**	83.2 ± 18.9
J48(Quinlan, 1993)	72.65 ± 14.37	0.78 ± 0.15	0.676 ± 0.11	75.5 ± 7.8	84.8 ± 24.1
IBI(Aha and Kibler, 1991)	81.21 ± 5.29	0.86 ± 0.04	0.762 ± 0.06	81.3 ± 5.2	**93.3±9.9**
IBK(Aha and Kibler, 1991)	81.21 ± 5.29	0.86 ± 0.04	0.762 ± 0.06	81.3 ± 5.2	93.3 ± 9.9
LWL(Frank et al., 2003)	73.61 ± 11.11	0.78 ± 0.12	0.712 ± 0.10	78.3 ± 6.4	82.5 ± 20.0
RBF(Scholkopf et al., 1997)	84.08 ± 7.43	0.89 ± 0.06	0.823 ± 0.09	88.0 ± 6.5	91.8 ± 11.7
Voted Perceptron(Freund and Schapire, 1998)	71.65 ± 8.28	0.80 ± 0.06	0.772 ± 0.08	74.8 ± 10.3	90.8 ± 14.1
VF1(Demiröz and Güvenir, 1997)	83.40 ± 8.25	0.86 ± 0.07	0.911 ± 0.05	89.1 ± 6	85.3 ± 12.6
AdaBoost M1(Freund and Schapire, 1996)	70.89 ± 12.92	0.74 ± 0.15	0.716 ± 0.15	80.8 ± 9.7	73.9 ± 23.3

The samples in the database are randomly split into gallery and test, where 5% of total samples are used in the gallery while remaining 95% samples are used for the test. Table 3 and Table 4 shows the performance of the snake classifier problem using the presented product similarity classifier and several of the common classification methods. The performances indicated are percentage accuracy of correct classification, F-score value, the Area under the receiver operator characteristic curve, precision and recall rates. In comparison with other classifiers, the proposed classifier show performance improvements in

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accuracy, F-score and area under the curves, that are practical measures for robust classification. While the precision and recall fairs near to the best methods when tested on feature and image snake databases. The large standard deviations on the precision and recall makes drawing the differences between the methods inconclusive.

Figure 9 shows the recognition accuracies and area under the receiver operator characteristic curve for the proposed classifier when tested on *feature database* and *image database* of snakes. In this experiment, an equal number of samples in cobra and viper classes are selected from the database to form the gallery and the remaining samples in the database are used as a test. It can be seen that, the performance results shows even on one gallery sample per class more than 70% of the test samples are correctly identified for both *feature* and *image* databases. A higher standard deviation with a low number of gallery samples results from the variability associated with availability of feature in a gallery image sample. With the increase in the number of samples per gallery to just 10, the standard deviations reduce to stable levels resulting in robust classification performances.

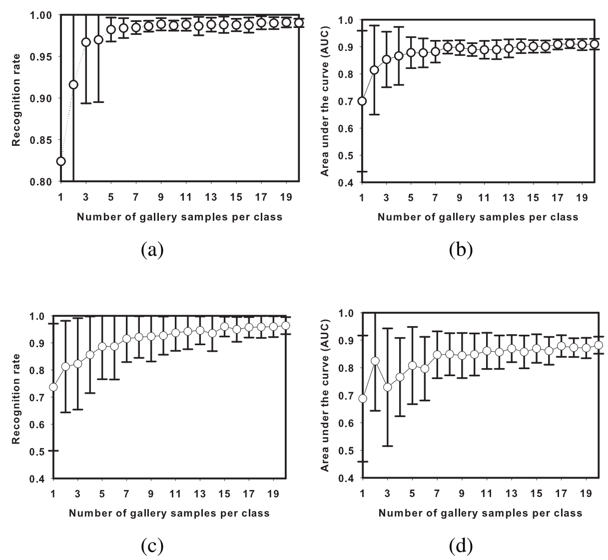

Figure 9. The variation of performance measures with increase in percentage of samples used for training from the *snake feature database* is shown in (a) and (b), while that done using *snake image database* is shown in (c) and (d). The recognition rates obtained using the proposed classifier is shown in (a) and (c), and area under the curve that is representative of receiver operator characteristic is shown in (b) and (d).

The classification time for the proposed classifier implementation in CUDA for 31 features when tested on a large number of duplicated gallery samples are shown in Fig. 10. It can be noted that the presented parallel processing classifier shows only marginal increase in the classification times even with 20 times increase in the number of samples per gallery.

Automating Feature Detection The manual processing of features as explained in the previous sections can be a tedious and time-consuming job with growing number of samples. A purely automated approach would need the features to be automatically identified followed by an automated process of matching the test image features with that in the training images. In a view to addressing this, we use the scale invariant feature transforms for the detection of the features, as the features extracted by this transform operation is known to be robust against the variations in object size, which is one of the common issues in snake features.

The matching process using *Scale-Invariant Feature Transform (SIFT)* consists of detection of features followed by description of the region of interest that can be used to represent uniquely during the comparison. The spatial difference between multiple resolutions of the images is explored in SIFT using Gaussian filtering and inter-pixel difference calculations (Lowe, 2004; Zhao et al., 2013).

The SIFT algorithm can be broken down into four stages: (1) Scale-space extreme detection: Using

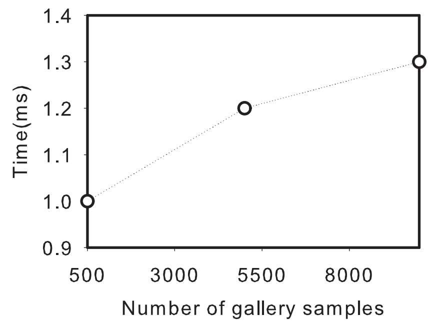

Figure 10. The classification time in CUDA using 31 features.

the Gaussian difference at various scale and sigma values the original image is used to generate images of different spatial resolutions and the difference between them to identify the most prominent feature areas in the image; (2) Keypoint localization: The feature specific details on individual identified areas based on the image size is located and mapped as regions of interest reflective of discriminative to object characteristics; (3) Orientation assignment: Once the region of interest is chosen, the gradient orientation is associated with this area is computed. This orientation assignment provides the properties of invariance to scale, angle and location; and (4) Keypoint descriptor: Finally, the keypoint that is found to have discriminative information about the object in a region of interest is retained as the feature vector of the object. This resulting feature vector is expected to be robust against natural variabilities resulting from shape shifting and illumination variation.

The SIFT feature vector can be used further in the classification of the snakes through the matching of the features between the training set and a given test snake image. The matching algorithm proposed in this paper is that governed by the steps followed in Section 0.0.1. Consider I_1 and I_2 to be two images of the same object or region of interest that are representative of intra-class objects. Each descriptor in I_1 image is compared with all descriptors in I_2 image by calculating the difference between them using the Euclidean distance. The difference in the ratio between first and second best distance of the descriptor is used to control the similarity between the regions of interest. The standard ratio of 1.5 is used as found to work in most situations (Lowe, 2004).

Any gradient information in an image that has significant change across different scales of Gaussian filter is considered to be valuable for detection of those particular objects. This information would give better results for a database containing snake images under the ideal condition and could lead to poor recognition performance in databases containing natural features (complex shadows, trees, branches etc.) as shown in (Picard et al., 2009). In our database, the features under natural condition include those of resulting from the images of live snakes having movements, and wild snakes having different carve marks, variation in snake skin as it shed their skin (scale) 4 times in a year on an average, intra-class variations in snake scales and snake scales containing shades (or change of gradient) that are not unique

These characteristics can contribute towards poor discrimination of snake species from digital images using scale invariant feature transform technique. The non-separability of the SIFT features between the two classes can be seen in Fig. 11(a).

A number of SIFT features extracted from the original image of average size 2000×2000 pixels had an average number of 2500 features identified. Using nearest neighbour classification, we used 50 percent of data in the training set selected randomly each time, and a recognition accuracy of 87.5% was obtained.

Analysis on multiple species The sub-species of the viper and cobra has different variants to its features. The feature within the same species of snakes are similar and hence the discrimination of this is challenging task. Table 5 shows the confusion matrix depicting classification accuracy of classifying Spectacled Cobra (SC), Russel's Viper(RV), King Cobra(KC), Common Krait(CK), Saw Scaled Viper(SSV), and Hump-nosed Pit Viper (HNPV) having 207, 76, 58, 24, 36 and 43 images respectively. They are obtained after running the nearest neighbor for 50 times with random split of 66% training and remaining 34% as test images in the dataset.

To better understand the classification performance of SIFT features in identifying the type of snake

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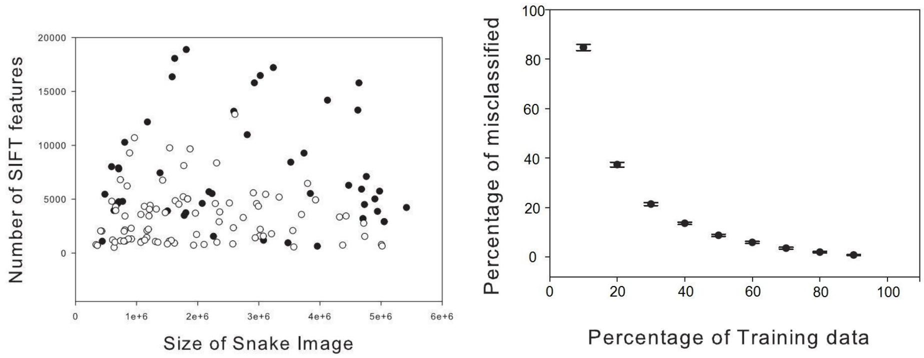


(a) (b)

Figure 11. (a)Number of SIFT features extracted from snake images. (b)The classification performance of SIFT features for different percentage of training images.

Table 5. Confusion matrix on different types of snakes using SIFT.

Method	SC	RV	KC	CK	SSV	HNPV
SC	**86.46**	00.71	01.11	00.06	00.05	11.20
RV	06.15	**66.00**	06.46	00.00	00.15	21.23
KC	06.40	04.70	**64.10**	02.10	00.90	21.80
CK	05.00	06.00	13.00	**58.75**	08.75	08.50
SSV	16.67	02.33	03.83	07.00	**51.00**	19.17
HNPV	17.20	03.20	05.067	00.13	00.13	**74.27**

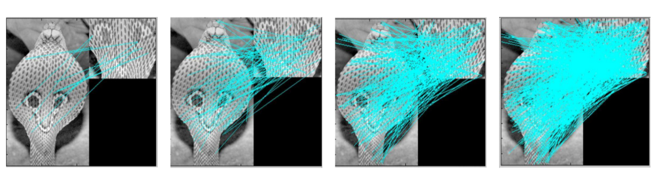
images, we varied the number of training and testing image used for classification. From Fig. 11(b) it can be seen that on the best accuracies for each sample size with increase in training samples per class the misclassified data reached to zero. It can also be noticed that the standard deviation is very less even in less number of training sample, proving that snake images of similar poses contribute to similarity match.

From Fig. 12 shows that by varying the Euclidean distance ratio the number of features that get matched can be controlled. However, the classification of feature vectors obtained from SIFT technique can become a difficult task when the variability between the test and training samples are high. This makes the automated recognition of snakes in real-time imaging environments a challenging task.

CONCLUSIONS

In this paper, we demonstrated the use of taxonomy features in classification of snakes by developing a product similarity nearest neighbor classifier. Further, a database of snake images is collected, and converted to extract the taxonomy based *feature* and *image* snake database for our study.

The knowledge base for the snake taxonomy can enhance the accuracy of information to administer correct medication and treatment in life threatening situation. The taxonomy based *snake feature database* can be used as a reference data for the classifier to utilize and compare the observations of the bite victim or the witness in realistic conditions. This can be further extended to other applications such



(a) (b) (c) (d)

Figure 12. Matching SIFT feature descriptor by varying the distance measure in Nearest neighbour. (a) ratio used is 0.7 and 11 features matched, (b) ratio used is 0.8 and 86 features matched, (c) ratio used is 0.85 and 225 features matched(a) ratio uses is 0.9 and 634 features matched.

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as monitoring and preservation of snake population and diversity. The automatic classification using *snake image database* can help with the analysis of snake images captured remotely with minimal human intervention.

There are several open problems that make snake recognition with images a challenging topic such as various natural variability and motion artefacts in realistic conditions. The automatic identification of snakes using taxonomy features offers better understanding of snake characteristics, and can provide insights into feature dependencies, distinctiveness and importance. The computerised analysis of snake taxonomy features can generate a wider interest between the computing specialist, taxonomist and medical professionals.

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