PERFORMANCE EVALUATION OF STATISTICAL CLASSIFIERS USING INDIAN SIGN LANGUAGE DATASETS

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ABSTRACT

Sign language is the key for communication between deaf people. The significance of sign language is accentuated by various research activities and the technical aspects will definitely improve the communication needs. General view based sign language recognition systems extract manual parameters by a single camera view because it seems to be user friendly and hardware complexity; however it needs a high accuracy classifier for classification and recognition purpose. The decision making of the system in this work employs Indian sign language datasets and the performance evaluation of the system is compared by deploying the K-NN, Naïve Bayes and PNN classifiers. Classification using an instance-based classifier can be a simple matter of locating the instance space and labelling the unknown instance with the same class label as that of the located (known) neighbour. Classifier always tries to improve the classification rate by pushing classifiers into an optimised structure. In each hand posture, a measure of properties like area, mean intensity, centroid, perimeter and diameter are taken; the classifier then uses these properties to determine the sign in different angles. They estimate the probability that a sign belongs to each of the target classes that is fixed. The impact of such study may reflect the exploration for using such algorithms in other similar applications such as text classification and the development of automated systems.

KEYWORDS

Sign Language, PNN, K-NN classifier, Navie Bayes, performance rate

1. INTRODUCTION

Sign language is important in humankind that is showing an increasing research interest in eradicating barriers faced by differently abled people in communicating and contributing to the society [1]. Automation over sign language recognition systems can greatly facilitate the vocal and the non-vocal communities which can be equivalently best and successive as speech-recognition systems [2]. Despite common misconceptions, sign languages are complete natural languages, with their own syntax and grammar. However, sign languages are not universal. As is the case in spoken language, every country has got its own sign language with high degree of grammatical variations. The sign language used in India is commonly known as Indian Sign Language (henceforth called ISL)[6].Linguistic studies on ISL were started around 1978 and it has been found that ISL is a complete natural language, instigated in India, having its own morphology, phonology, syntax, and grammar. ISL is not only used by the deaf people but also

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by the hearing parents of the deaf children, the hearing children of deaf adults and hearing deaf educators. Therefore the need to build a automation system that can associate signs to the words of spoken language, and which can further be used to learn ISL, is significant. This paper proposes a system for recognizing Indian sign language using the view based approach and the statistical classifier algorithm as a learning tool. These classifiers take the advantage of accuracy, ease of implementation and operational robustness. The paper is arranged as follows. Section 2 gives a brief overview of Indian sign language. Section 3 describes the feature extraction methodology, by using boundary detection techniques. Section 4 deals with the short description of classifiers used. Section 5 gives the performance evaluation of the classifiers using ISL datasets. Finally, section 6 summarizes the framework and future work that can be adopted.

2. OVERVIEW OF ISL CLASSIFICATION SYSTEM

Indian Sign languages are rich, faceted language, and their full complexity is beyond current gesture recognition technologies [6]. The interpersonal communication problem between signer and hearing community could be resolved by building up a new communication bridge integrating components for sign[5]. Several Significant problems specific to Automatic Sign Recognition are i) Distinguishing gestures from signs ii) Context dependency (directional, verbs, inflections, etc) iii) Basic unit modeling (how do we describe them?) iii) Transitions between signs (Movements) iv) Repetition (Cycles of movement). The ISL dictionary is been build by Sri Ramakrishna mission Vidyalaya College of Education, Coimbatore which as split the ISL into five parameters namely handshapes, locations, Orientation, Location, Movements and Facial Expression. Figure 1 explains the framework for classification system.

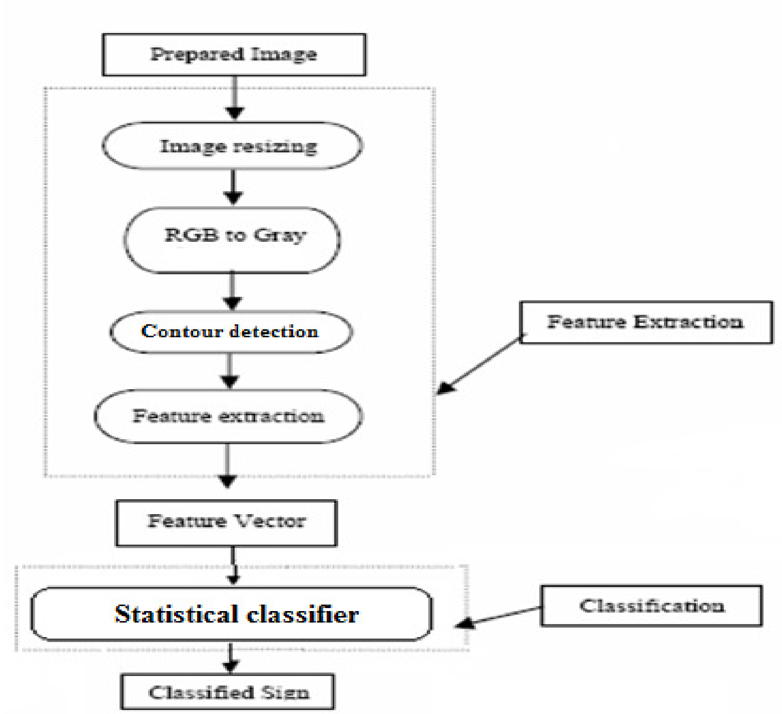

Figure 1: Steps involved for classification methodology for Indian sign datasets

3. FEATURE EXTRACTION METHODOLOGY

The great variability in gestures and signs, both in time, size, and position, as well as interpersonal differences, makes the recognition task difficult [11]. By extracting features from image processing sequence classification can be done by a discriminative classifier. Gestures, particularly in sign language, involve significant motion of the hands[5]. Thus, in developing a sign language recognition system, it is important to model both the motion (temporal characteristics) and shape (spatial characteristics) of the hand. In this research work only the spatial characteristics of the hand are of concern. Figure 2 shows the schematic view of gesture recognition process.

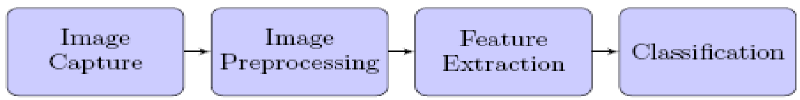

Figure 2: Schematic view of gesture recognition process

Feature extraction is the process of generating a set of descriptors or characteristic attributes from a binary image. Most of the features used in existing sign language recognition systems focus only on one aspect of the signing like hand movements or facial expressions. Figure 3 shows the feature extraction concept.

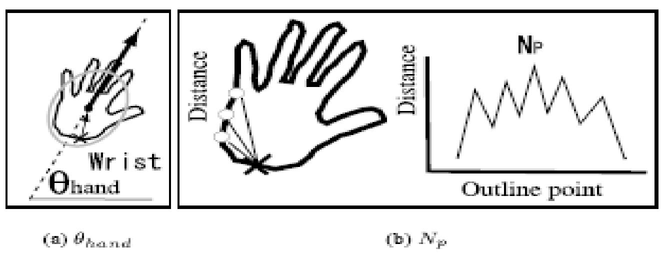

Figure 3: Hand feature extraction

The strategy used for segmentation is boundary segmentation method which traces the exterior boundaries of objects, as well as boundaries of holes inside these objects, in the binary image [3]. The two important need for this method of sign extraction is First, it keeps the overall complexity of the segmentation process low. Secondly, it eliminates candidates that may produce smooth continuations, but otherwise are inconsistent with the segments in the image. This simplifies the decisions made by the segmentation process and generally leads to more accurate segmentation[7]. The feature extracted from the database used is mean intensity, area, perimeter, diameter, centroid.

Mean Intensity: The mean intensity μ in the selected region of interest (ROI) is given in eqn (1):

$$\mu = \frac{1}{N}\int_{x,y} ROI(x,y)\,dx\,dy \quad \text{………………..(1)}$$

Area: The area of an object is a relatively noise-immune measure of object size, because every pixel in the object contributes towards the measurement. The area can be defined using eqn (2)

$$A(S) = \int\int I(x,y)\,dy\,dx \quad \text{………………………..(2)}$$

Where, I(x,y) = 1 if the pixel is within a shape,(x,y)$\in$ S, 0 otherwise.

Perimeter: The perimeter measurement gives the smooth relative boundaries and the perimeter of the region is defined as by the eqn (3)

$$P(S) = \int_t \sqrt{x^2(t) + y^2(t)dt} \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots(3)$$

Diameter: The distance around a selected region is called the circumference**.** The distance across a circle through the center is called the diameter**.** π is the radius of the circumference of a circle.. Thus, for any circle, if you divide the circumference by the diameter, you get a value close to π. This relationship is expressed in the following eqn (4):

$$c/d=\pi \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(4)$$

where,C is circumference and d is diameter

Centroid: It specifies the center of mass of the region. Centroid is the horizontal coordinate (or *x*-coordinate) of the center of mass, and the second element is the vertical coordinate (or *y*-coordinate) and it is written as given in eqn (5)

$$C = \frac{\int xg(x)dx}{\int g(x)dx} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(5)$$

4. SHORT DESCRIPTION ON CLASSIFIERS

Classification (generalization) using an instance-based classifier can be a simple matter of locating the nearest neighbour in *instance space* and labelling the unknown instance with the same class label as that of the located (known) neighbour [4]. This approach is often referred to as a neighbour classifier. Classifier always tries to improve the classification rate by pushing classifiers into an optimised structure[10].

4.1 K-NN Classifier

The K-Nearest Neighbor classifier is a supervised learning algorithm where the result of a new instance query is classified based on majority of the K-nearest neighbor category. The purpose of this algorithm is to classify a new object based on attributes and training samples[8]. The Nearest neighbor classifier is based on learning by analogy. The training samples are described by n-dimensional numeric attributes. Each sample represents a point in an n-dimensional pattern space. More robust models can be achieved by locating k, where $k > 1$, neighbours and letting the majority vote decide the outcome of the class labelling. A higher value of k results in a smoother, less locally sensitive, function. The Nearest Neighbor classifier can be regarded as a special case of the more general K-Nearest Neighbors classifier, hereafter referred to as a K-NN classifier.

The data for KNN algorithm consists of several multivariate attributes names X_i that will be used to classify the object Y. The data of KNN can have any measurement scale from ordinal, nominal, to quantitative scale, this study deals only with quantitative X_i and binary (nominal) Y. All training samples are included as nearest neighbors if the distance of this training sample to the query is less than or equal to the K^{th} smallest distance. In other words, the distances are sorted of all training samples to the query and determine the K^{th} minimum distance. The unknown sample is assigned the most common class among its K-Nearest Neighbors. These K training samples are the closest k nearest neighbors for the unknown sample. Closeness is defined in terms of Euclidean distance, where the Euclidean between two points, $X = (x_1, x_2, \ldots x_n)$ and $Y= (y_1, y_2, \ldots y_n)$ is given in eqn (6)

$$d(X,Y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \dots\dots\dots\dots\dots (6)$$

The drawback of increasing the value of *k* is when *k* approaches *n*, where *n* is the size of the instance base, the performance of the classifier will approach that of the most straightforward statistical baseline, the assumption that all unknown instances belong to the class most frequently represented in the training data. The high degree of local sensitivity makes nearest neighbor classifiers highly susceptible to noise in the training data.

4.2 Naive bayesian classifier

A Naive Bayes classifier assigns a new observation to the most probable class, assuming the features are conditionally independent given the class value [9]. It can outperform more sophisticated classification methods by categorizing incoming objects to their appropriate class. The Naive Bayesian classifiers can handle a random number of independent variables whether continuous or categorical.

It classifies data in two steps:

1. Training step: Using the training samples, the method estimates the parameters of a probability distribution, assuming features are conditionally independent given the class.

2. Prediction step: For any unseen test sample, the method computes the posterior probability of that sample belonging to each class. The method then classifies the test sample according the largest posterior probability.

Bayes theorem used, takes the eqn as given in (7) and (8)

$$P(H|X) = P(X|H)\,P(H) / P(X) \dots\dots\dots(7)$$

It can also be expressed as $P(C_i|X) = \frac{P(X|C_i)P(C_i)}{P(X)}$…………………(8)

Where P(X) is constant for all classes, only $P(X|C_i)P(C_i)$ need be maximized.
The class-conditional independence assumption greatly simplifies the training step since estimation can be done using one-dimensional class-conditional density for each feature individually. This assumption of class independence allows the Naive Bayes classifier to better estimate the parameters required for accurate classification while using less training data than many other classifiers. This makes it particularly effective for datasets containing many predictors or features. Since the build process for Naive Bayes is parallelized it can be used for both binary and multiclass classification problems.

4.3 Probabilistic Neural Network

Probabilistic neural networks are forward feed networks built with three layers. They train quickly since the training is done in one pass of each training vector, rather than several. Probabilistic neural networks estimate the probability density function for each class based on the training samples. The probabilistic neural network uses Parzen or a similar probability density function. This is calculated for each test vector. This is what is used in the dot product against the input vector as described below. Usually a spherical Gaussian basis function is used, although many other functions work equally well. Vectors must be normalized prior to input into the network. There is an input unit for each dimension in the vector. The input layer is fully connected to the hidden layer. The hidden layer has a node for each classification. Each hidden node calculates the dot product of the input vector with a test vector subtracts 1 from it and divides the result by the standard deviation squared. The output layer has a node for each pattern classification. The sum for each hidden node is sent to the output layer and the highest values wins.The Probabilistic neural network trains immediately but execution time is slow and it requires a large amount of space in memory. It really only works for classifying data. The training set must be a thorough representation of the data. Probabilistic neural networks handle data that has spikes and points outside the norm better than other neural nets. PNN has proven to be more time efficient than conventional back propagation based networks. In order to classify a feature pattern vector x $\in R^m$ that is to assign the pattern to one among k predefined classes, the conditional density $P\ (x|C_k)$ of each class C_k is estimated since it represents the uncertainty associated by the rule of bayes that allow making optimal decision[12]. One possible way of looking at this technique is to build sphere of influence p(s,x) around each training sample s and to add them up for each of k classes.

$$P(x|C_k) = \sum_{x \in C_k} p(s,x) \qquad (9)$$

5. PERFORMANCE EVALUATION

The proposed classifier Navie bayes is used to justify the objects using new methods to get a maximum accuracy comparing to K-NN and PNN classifier. The features are the parameters extracted from the sign images which are taken from normal camera. In each image, a measure of properties is taken to determine the sign in different position. They estimate the probability that a sign belongs to each of the target classes that is predetermined. In the training phase, the training set is used to decide how the parameters must be weighted and combined in order to separate the various classes of signs. The classifier used for classification is validated using sensitivity, specificity error rate, predictive value, likelihood value, plotting the classification and misclassification error rate according to the sample datasets.

Table 1 : Performance evaluation of NB ,KNN and PNN Classifiers

S.No	Performance Measures	NB	KNN	PNN
1.	Classified rate	1.0000	0.9500	1.0000
2.	Sensitivity	0.7143	0.5714	0.5000
3.	Specificity	0.8571	0.6857	1
4.	Error rate	0.3429	0.6857	0.4000
5.	Inconclusive rate	0	0	0
6.	Positive predictive value	0.5556	0.3077	1
7.	Negative Predictive Value	0.9231	0.8636	0.7500
8.	Negative likelihood	0.3333	0.6316	0.5000
9.	Positive Likelihood	5.000	1.7778	1.8650
10.	Prevalence	0.2000	0.2000	0.4000

To keep track of the performance during the validation of classifiers Table 1 mentioned values are the measures taken into consideration. Conducted experiments with Indian sign language datasets shows that the Navie bayes classifier has better performance than K-NN, PNN and the current implementation for both classifiers yield good results when compared to other implementations by other researchers.

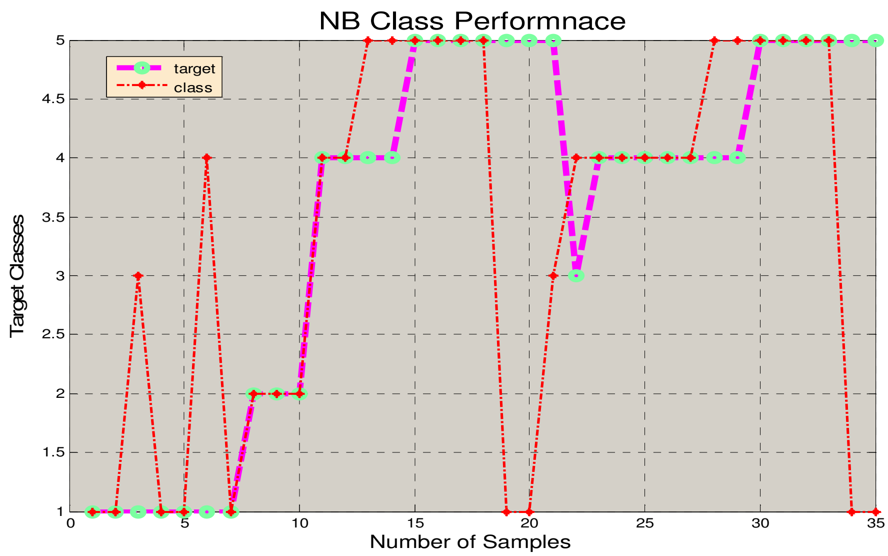

Figure 4: Navie Bayes class Performance

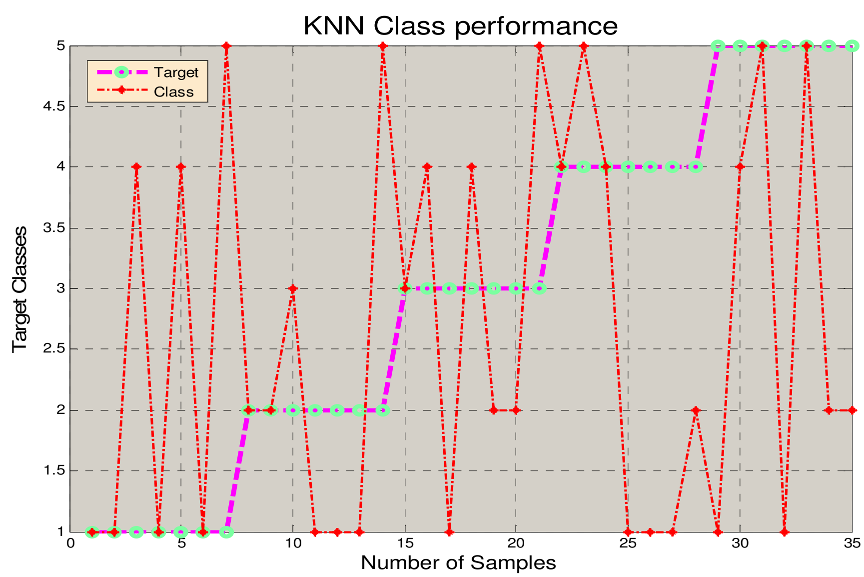

Figure 5: KNN class Performance

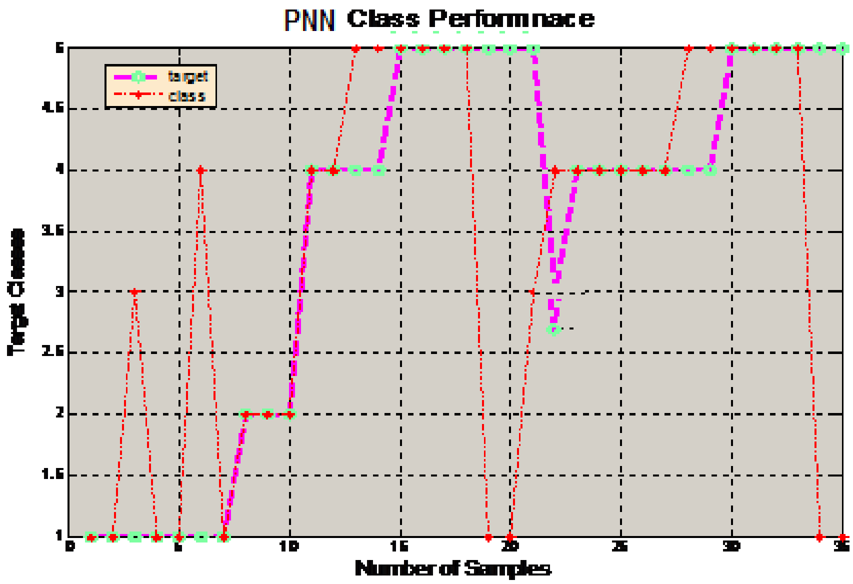

Figure 6 : PNN class Performance

Figure 4,5 and 6 depicts the classifier performance based on the datasets taken and the target class is less achieved by K-NN and PNN classifier than the proposed Navie bayes classifier.

6. CONCLUSION

An analysis of different classifiers is done in which the Navie bayes approach is proved to be better for sign language classification system. This help in understanding the current state of knowledge in Indian sign language research area. And therefore, identifying the directions lead towards the standardised procedure of classifier system design. However, the results in this work are biased by the size of the database: on the one hand, the lack of training data and the large amount of singletons leads to a very difficult task. The methods used in this work are focused towards good recognition accuracy and not toward real-time performance and thus it meets the sample experimental requirements. This research result developed here is a principled technique that will enable their use, not only in sign language or hand gesture recognition but also in other related areas of computer vision.

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