Empirical Analysis of Signature-Based Sign Language Recognition

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ABSTRACT

The significance of automated SLR (Sign Language Recognition) proved not only in the deaf community but in various other spheres of life. The automated SLR are mainly based on the machine learning methods. PSL (Pakistani Sign Language) is an emerging area in order to benefit a big community in this region of the world. This paper presents recognition of PSL using machine learning methods. We propose an efficient and invariant method of classification of signs of PSL. This paper also presents a thorough empirical analysis of signature-based classification methods. Six different signatures are analyzed for two distinct groups of signs having total of forty five signs. Signs of PSL are close enough in terms of inter-sign similarity distance therefore, it is a challenge to make the classification. Methodical empirical analysis proves that proposed method deals with these challenges adequately and effectively.

Key Words: **Sign Language Recognition, Shape Signature, Pakistani Sign Language.**

1. INTRODUCTION

The use of the gestures is very common practice for interaction and communication between human beings. SL (Sign Language) is a special type of gestures that is considered as the primary way of communication for the deaf community. All over the world, deaf people uses SL for the exchange of idea and for getting information. This is the reason that SLR is a focus of research in the recent years by many researchers. As SL is the most structured form of gestures therefore, it is considered as benchmark for the gesture recognition systems. Each and every member of the society have the fundamental rights to acquire the information in accessible format. It is a matter of fact that information itself is not accessible or inaccessible; rather the form in which it is represented or formulated. Due to this matter of fact, normally the deaf community remains deprived of the required information because the format of required information is not presented in an accessible format for them. So the solution is an SLR system that makes the information, in general accessible format. SLR systems can be very effective for deaf community for bridging up the gap between the deaf community and hearing society. This can be a facilitating tool for the deaf community to get integrated themselves with the mainstream. SLR system can be used in a very effective manner in industrial control, touch-free control systems, robot control, virtual reality, interactive learning and many other fields along with the services to deaf community.

SLR, just like verbal languages, are non-uniform throughout the world. Each country and region owns its SL. Chinese Sign Language [1-3], Arabic Sign

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Language [4-7] and American SL [8-11] have a very rich focus of the SL researchers. PSL is a visual-gestural language and it is a blend of national language of Pakistan (Urdu) and many other regional languages. There are 250,000 Pakistanis with hearing impairments and they use PSL as a mode of communication [12]. However, PSL has got unfortunately, a very small share of research. Very few researches have been done for PSL. Data gloves have been used by Alvi, et. al. [13] for the recognition of static one-handed signs of PSL. Kausar, et. al. [14] have used color-coded gloves to recognize the signs of PSL. However, the existing research on SL is still having many issues such as complexity of input module, complex settings for the system, multiple image processing is computationally inefficient, external instruments requirement, high cost, and limited size of dictionary. In this paper we proposed a method to address these problems. Consequently, the lives of the deaf community can be improved by integrating PSL with modern technologies.

The paper presents a robust, efficient and signer independent system for PSL recognition. The dataset used for the experimentation contains static one-handed signs of PSL. The paper puts more focus on the feature set for the recognition of PSL signs. First of all binary image of PSL sign is translated to1D (One Dimensional) signature, furthermore these signatures transformed to frequency domain. Then frequency features are extracted and fed into the classifier. Two different groups of signs are taken for analysis purpose. One of this group contains 35 signs of PSL alphabets and the other one contains only 9 signs of PSL numbers (1-9).

Section 2 critically analyzes some of the related work. Section 3 describes the detailed steps of methodology. After describing the method, in Section 4 results are analyzed. We discussed our research outcomes in Section 5 and closed our paper with conclusion in Section 6.

2. RELATED WORK

Researchers have paid due attention to the domain of SLR. This section critically enlists some of the latest researches in the domain of SLR. Elons, et. al. [4] and Philippe, et. al. [8] recognized SL while capturing the sign images with multiple cameras. Multiple view angles have been used by Elons, et. al. [4] to get the 3D features of sign by mounting cameras on varying angles. Krawtchouk moments are used as sign features by Padam, and Bora [15] for the recognition of static sign recognition and achieved viewer angle variation along with the signer independence. Portable ACC (Accelerometer) and sEMG (Surface Electromyography) sensors have been used for the recognition of Chinese SLR by Yun, et. al. [1]. The hand shape, hand orientation, and hand movement as basic components of sign have been used to achieve high accuracy rates. Xu, et. al. [16] and Tian, et. al. [17] have relied on data gloves for feature extraction to recognize SL. Colored gloves have been used for feature selection and extraction by Kausar, et. al. [14] and Rini, et. al. [18] for the purpose of SLR. Prime points of hand such as palm center and finger tips have been colored with specific colors and these points are used as features for SLR. Only four signs have been used for recognition by Ershaed, et. al. [5]. Just two signs of French SL are recognized by Wassnerr, [19] with their ANN (Artificial Neural Networks) based proposed system. Only six ASL signs have been used for recognition by Xing, et. al. [3], Ershaed, et. al. [5], Zahoor, et. al. [9] Helen, et. al. [20], and many other researcher have exploited the depth cameras utilizing 3D features of the sign for the recognition of SL. Depth cameras are expensive as compared to 2D cameras.

The preceding paragraph critically analyzed some of the researches in the area of SLR. These researches rely on different feature sets and classification methodologies and hence achieved different levels of accuracy and efficiency. These researches have some associated disadvantages such as multiple cameras dependence, complex settings for the system to get varying view angles, multiple images processing for one sign making it computationally inefficient, dependence upon external gadgetry, cost ineffectiveness and limited size of dictionary. This paper proposes a method that is an effort to overcome the above discussed challenges to SLR. The results of the proposed methodology are evident of its worth. The proposed method does not rely on depth camera or multiple cameras. Only a single camera is used, multiple cameras mean more cost in terms of time, money, complexity and hence performance. No dependence on any external gadgetry like data gloves or colored gloves. The proposed methodology is quite efficient and it can be implemented in real time systems because of its simple yet powerful features. Sign dictionary size is quite reasonable for the proposed system.

3. PROPOSED METHOD

The proposed method for the PSL recognition comprises of four main modules: imaging, segmentation, feature extraction and classification. The signer's image is taken by a 2D digital camera and the captured image goes through the segmentation module, after segmentation binary image of signer's hand is passed to the feature extraction module. Feature extraction module translates this binary image into the corresponding 1D signature and this 1D signature is then transformed to FD (Fourier Descriptors) and these descriptors then goes to the classifier. Classifier finally classifies the PSL sign.

PSL is new emerging area of research for specific community so there exists no standard data set for PSL. Therefore, the dataset is developed by authors for this research. Sign dictionary used for this paper consists of two separate groups of signs named as Group-I and Group-II. Group-I contains 35 static signs of alphabets of PSL, and Group-II has got only 9 signs for the PSL numbers 1-9. Two groups of data sets are used to analyze the impact of the dictionary size on the recognition system for PSL. All signs in both groups of PSL dataset are one handed static signs. Training set used for the paper has total 389 examples from both sets and 10 different signers have posed for signs. Moreover the proposed method is investigated on the basis of this dataset. All modules of the proposed methods are explained further in the following sub-sections.

3.1 Imaging Module

Imaging module uses a 2D digital camera to capture the image of signer. The image contains only one hand of the signer that is used for signing. Some constraints for the imaging module are: (1) only the signer's hand should be captured, (2) signer background should be black or dark blue, and (3) signer should wear black or dark blue full sleeves. Although these constrains are needed to investigate to improve accessibility in everyday life however, we have easily implement these constraints in our research to make the segmentation process less complex and more efficient. In order to implement the proposed method there are no special illumination conditions required for imaging. In this research, it is important to note that no special camera is required, any ordinary digital camera can be used even a moderate quality webcam can be good enough for imaging.

3.2 Segmentation

Imaging module passes the digital image of sign to the segmentation module. For segmentation of signer's hand from the background, K-means clustering is used for the segmentation. This method is a machine learning method used for classification and adopted here for the classification of skin-color and non-skin-color classes. K-Means method is an obvious choice for segmentation as it is simple and numerical. Another reason for use of k-means clustering is that it is unsupervised, iterative and non-deterministic. It is well-tested technique for image segmentation [21-22]. The hand would get segmented from the background as a result of clustering. Three iterations of clustering were used for the segmentation phase of the proposed method.

K-means clustering can be mathematically defined with the Equation (1).

$$C_i = x_p : | x_p - m_i | \leq | x_p - m_j | \, \forall \, 1 \leq j \leq k \qquad (1)$$

C_i is the i^{th} cluster in the Equation (1) and total number of clusters is k. x_p is the point of image that needs to be assigned to a particular cluster and the mean of i^{th} cluster is m_i. x_p would be assigned to the minimum distant cluster. The distance is calculated from the point to the mean of the cluster. Each iteration requires to update the mean of every cluster. The mean is updated for each cluster with Equation (2):

$$m_i = \frac{1}{| c_i |} \sum x_{j \in c_i} x_j \qquad (2)$$

After three iterations, each point in the image would be allocated to either one of the two classes: signer's hand and the background. The foreground would get value one and the background would get 0. So the result of the segmentation process would be a binary image. To improve the quality of segmentation, the noise in the binary image is removed using the morphological operation. Noise here means small portions of background falsely segmented as foreground. Erosion as morphological operation is appropriate for our problem. The morphological operation used for this paper can be elaborated with the Equation (3).

$$G \theta S = \{ x \in I | S_x \subseteq G \} \qquad (3)$$

Where G is the segmented hand sign image, I is the integer grid and S is the structuring element. The binary segmented image "G" is in integer grid space I. Structuring element is a small binary image with pre-defined shape to probe the image. S={(-1,-1), (-1,0), (-1,1), (0,-1), (0,0), (0,1), (1,-1), (1,0), (1,1)} having all values equal to 1, so structuring element S is a 3*3 square. This structuring element would eliminate the small details in the image; whereas gaps and holes between objects become wider. Centre of S_x would be placed on the origin of E. S_x is the translation of S by the vector x and S_x is defined as:

$$S_x = \{s + x | s \in S\}, \forall x \in I \quad (4)$$

So this translation of structuring element moves the structuring element just like convolution mask. The new binary image f is produced by applying structuring element to I. This new image f would have zero-valued pixels (i.e. f(x,y) =0) where this structuring element would not have a fit and one-valued pixels (i.e. f(x,y) =1) elsewhere. This process is repeated for all the pixels of G. As a result of segmentation process, the binary image of the hand would be produced. Some results of segmentation with scaling, illumination and translation variations are shown in Fig. 1. This binary image would be the processed for feature extraction phase.

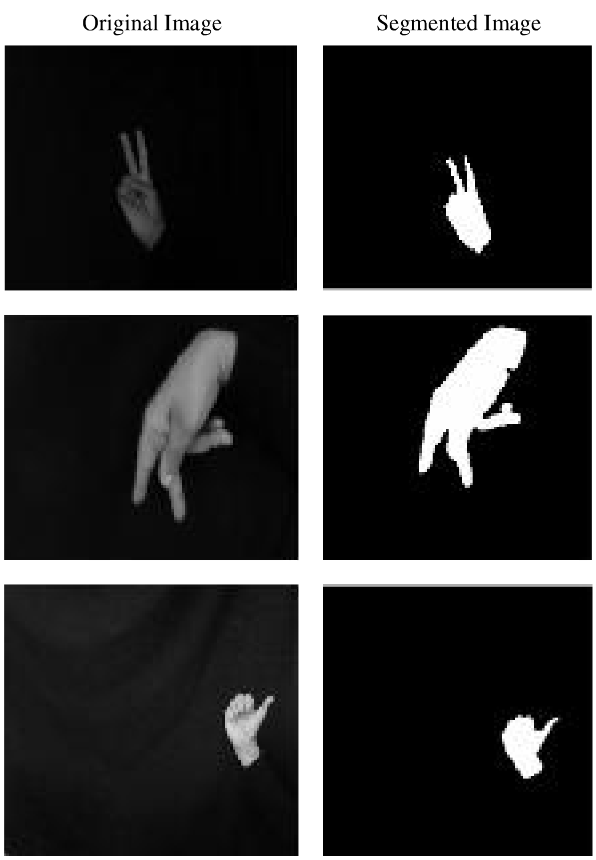


FIG. 1. SEGMENTATION RESULTS

3.1 Feature Extraction

The binary image, produced by segmentation is then processed by feature extraction module to get the sign features for the classification of signs. Transformation based descriptors are utilized as sign descriptors. These descriptors are calculated on the basis of 1D signature of the sign. Six different 1D signatures are analyzed for the paper and best among these is used for calculating the FD and these descriptors are then used for the PSL recognition. These six signature functions are the most commonly used signature functions. These are then methodically analyzed to get the most appropriate function. The result section in detail analyzes the inherent pros and cons of these signature functions. The following subsections elaborate these 6 1D signature functions and then the Fourier descriptors are explained.

3.1.1 Centroid Distance Function

Centroid distance is the most commonly used function for translating 2D structure to 1D signature. The segmented image defined with Equation (5) is used for calculating the centroid distance function.

$$f(x,y) = 1 \; if \; (x,y) \in I \quad (5)$$
$$f(x,y) = 0 \; otherwise$$

In Equation (5), 'I' is the domain of binary segmented image of sign. Centroid C(C(x), C(y)) of the segmented hand sign can be obtained with the Equations (6-7):

$$C(x) = \frac{1}{N}\sum_{i=1}^{N} x_i \quad (6)$$

$$C(y) = \frac{1}{N}\sum_{i=1}^{N} y_i \quad (7)$$

N= total number of points in the segmented sign. Only the point (x_i,y_i) would be considered for centroid equation that holds Equation (8):

$$(x_i, y_i) | f(x_i, y_i) = 1 \quad (8)$$

Once the centroid of the hand sign is extracted, the contour points of the hand sign are extracted. The distance between the contour points of hand and centroid distance is calculated using the Equation (9).

$$dist_i = | contp_i(x) - C(x), contp_i(y) - C(y) | \quad (9)$$

In Equation (9), $dist_i$ is the distance between centroid and i[th] contour point. The i[th] contour point is denoted with $contp_i$ and C(x) and C(y) are the x and y coordinates of the centroid point of the hand sign. Before extracting signature of the shape, sampling of the contour points is performed to make system more time efficient. To make the system efficient, periodic sampling is done on the contour points, so instead of calculating distance from each and every contour point, selective points are used for 1D signature. To counter the effect of scaling, adaptive step size is used for sampling. The adaptive step size is defined in Equation (10). For this paper 300 is used as the value of n. This value of n purely depends upon the dataset used depending upon the average size of the hand signs in the dictionary.

$$STEP = \frac{total\ No.\ of\ contourpoints}{n} \quad (10)$$

Centroid distance function based signature has invariance in terms of translation, rotation and scaling.

3.1.2 Complex Coordinates

Obtaining complex coordinates is another method to represent a shape into its 1D form. Complex coordinates $compc_i$ are obtained for the boundary point $comtp_i(x, y)$. Samples are taken with $STEP_i$ interval in boundary vector. Complex coordinate function can be defined as:

$$compc_i = [contp_i(x) - C(x)] + [contp_i(y) - C(y)]j \quad (11)$$

Where $C(x)$ is the x-coordinate and $C(y)$ is the y-coordinate of the centroid, which can be defined as follows:

$$C(x) = \frac{1}{N}\sum_{i=1}^{N} x_i \quad (12)$$

$$C(y) = \frac{1}{N}\sum_{i=1}^{N} y_i \quad (13)$$

Complex coordinates are translation invariant.

3.1.3 Tangent Angle

Tangent angle of a shape is another way to represent the shape in a 1D form. Tangent angles are calculated for the boundary points of the segmented sign. Tangent angle function θ_i can be represented as:

$$\theta_i = \frac{[contp_i(y) - contp_i(y - STEP)]}{[contp_i(x) - contp_i(x - STEP)]} \quad (14)$$

In Equation (14) function of tangent angle $contp_i(\,)$ is the point on the contour of the sign. Tangent angle contour is very sensitive to noise.

3.1.4 Curvature Function

Contour curvature is the natural way for human to discriminate shapes. So this strength of contours can be exploited for machines as well in computer vision applications. For this paper, contour curvature is used to transform binary sign to its signature. Contour curvature $contc_i$ can determined with following relation [23].

$$contc_i \frac{\dot{x}_i \dot{y}_i - \dot{y}_i \dot{x}_i}{\dot{x}_i^2 + \dot{y}_i^{2\,3/2}} \quad (15)$$

Contour curvature is invariant with respect to rotation and translation but it is scale variant.

3.1.5 Area Function

Area function is definition of signature in term of area of triangle, taking vertices from the contour and centroid of the shape. For this paper centroid is taken for PSL sign and contour is taken and then three vertices are taken to calculate area of the triangle, resultant of these three vertices. Three points to be considered are: $contp_i, contp_{i+1}, C$.

Distance between $contp_i,\ and\ contp_{i+1}$ is kept constant by taking a STEP size given as:

$$STEP = \frac{No.\ of\ contp_i}{n} \quad (16)$$

N=300 for this paper, this is carefully selected according to the average size of the image in the dataset, so important features may not get lost. Area function is invariant under rotation and translation and linear under affine transformation.

3.1.6 Triangle Area Representation

TAR (Triangle Area Representation) is another multi-aspect invariant function that can be used for transforming PSL segmented signs to 1D signature. It is based on area of triangles but unlike area function, it takes all three vertices for its triangle from the contour vector of the sign. TAR uses following three vertices:

$$contp_i,\ contp_i,\ contp_{i+1} \tag{17}$$

Again interval between these points is taken very carefully, to have in the signature all salient features of the sign. Interval is given by STEP.

$$STEP = \frac{No.\ of\ \ contp_i}{n} \tag{18}$$

Three types of areas can be obtained by TAR i.e. positive TAR, negative TAR and zero TAR for convex points, concave points and straight line points respectively.

3.1.7 Fourier Descriptors

Many image processing and machine vision researches have applied the Fourier transform. Fourier coefficients can also be utilized as shape descriptor. The worth of Fourier descriptors is analyzed by Kausar, et. al. [24]. The 1D signature is transformed to complex function z_i, to obtain Fourier descriptors.

$$z_i = x_i + jy_i \tag{19}$$

The Equation (20) holds true for i= 0……N-1 contour points. X and y in Equation (20) are the horizontal and vertical coordinates respectively of the 1D signature vector. The complex function z_i is transformed into Fourier transform F(x,y). The Fourier descriptors are the coefficients of this transform.

$$F(x,y) = \sum_{n=1}^{N} f(m,n) e^{-j2\pi\left[\frac{xn}{N}+\frac{ym}{M}\right]} \tag{20}$$

It is evident from the results that very few initial Fourier descriptors are enough to be used as an accurate sign descriptors, so making the whole system time efficient. If complex coordinates function is used for 1D signature, then Equation (19) is not required, rather signature can be directly used by Fourier transform. The FD are made translation invariant by ignoring the f_0 that is the first coefficient (DC component) of the Fourier transform. For having scale invariant descriptors, Equation (21) is used.

$$f_i = \frac{f_i}{f_0} \tag{21}$$

The Equation (21) holds true for i=0….N-1 for all Fourier coefficients of the sign. For making the shape descriptors, the starting point invariant, the phase of the Fourier coefficients are ignored and only the magnitude is used. The 1D signature is made starting point invariant, by taking the maximum distant point from the centroid point, as the starting point.

$$\max_{i-N}\,(dist\,(contp_i, C)) \tag{22}$$

Equation (22) shows the relation to define the starting point. In the equation, N is for the total number of contour points hand sign in the segmented image, as mentioned before that $contp_i$ is the ith contour point and C is the centroid point of the hand sign. FD have shown its worth for the recognition of PSL as by utilizing very few Fourier descriptors, quite high accuracy is achieved.

3.2 Classification

For classification, minimum distance metric is used. KNN (K Nearest Neighbour) method is used for classification of PSL recognition. KNN of classifier are varied to analyze accuracy for this paper. 3 different values of k (3,5,7) are used for the investigation of results.

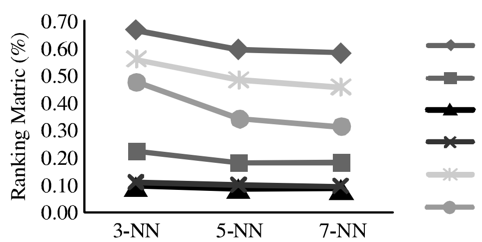
4. RESULTS

Our dataset contained the two groups named as Group-1 and Group-II (Discussed in Section 3). The test set contained 210 examples posed by 5 different signers. The analyses of 6 different types of 1D signatures, these 1D signatures constructs the feature sets for the recognition of PSL. The accuracy rates are computed for this analysis. RM (Ranking Metric) used for the paper is given by taking ratio of the summation of all the correctly recognized signs (ACC) and total number of signs tested (N).

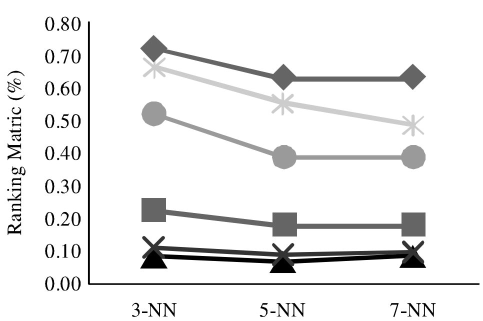
$$RM = \frac{\sum_{i=1}^{M} acc_i}{N} \tag{23}$$

Figs. 2-3 shows different variations in the parameters of classification for Group-I whereas Figs. 4-5 shows ranking metric analysis for Group-II. NN (Nearest Neigbour) of classifier are varied and it is observed that by tuning different parameters the accuracy obtained for Group-I goes above 88% and above 92% for Group-II. Six signatures are analyzed empirically, and results show that most consistent and best suitable signature function is centroid distance. Though triangular area representation function and area representation function for Group-II and area function for Group-I also gives high accuracy results but there is inconsistency, as if we change the distance measure or number of NN to be taken into account in the classification phase, accuracy rate may have substantial variations. But it is observed that, ranking metric does not show considerable fluctuation for centroid distance, while varying classification parameters.

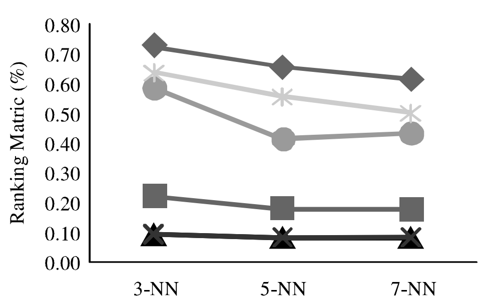
The maximum achieved accuracy of both groups are almost at same level. But by observing the results, it is obvious that for the smaller and simpler group i.e. Group-II, majority of the shape signatures consistently gives high accuracy as compared to the accuracy of the more complex and much larger group i.e. Group-I.



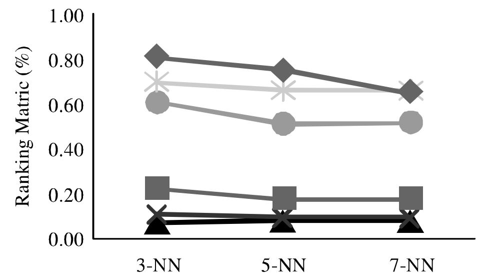
(a) CORRELATION WITH 5 FOURIER DESCRIPTORS



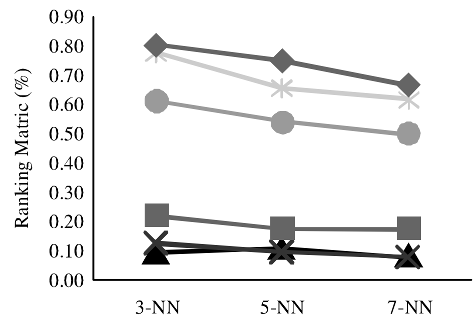
(b) EUCLIDEAN WITH 5 FOURIER DESCRIPTORS



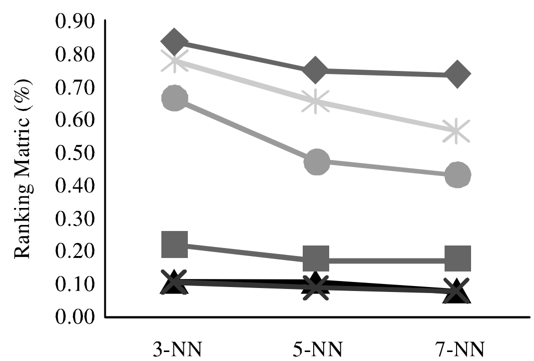
(c) CITY-BLOCK WITH 5 FOURIER DESCRIPTORS



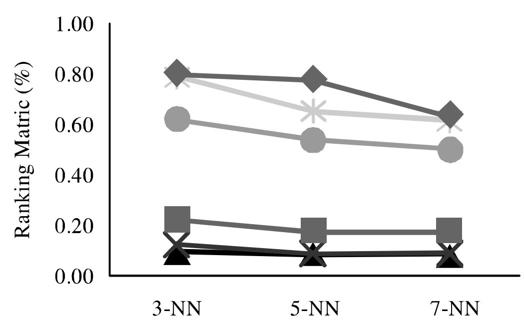
(d) COSINE WITH 5 FOURIER DESCRIPTORS



(e) CORRELATION WITH 10 FOURIER DESCRIPTORS

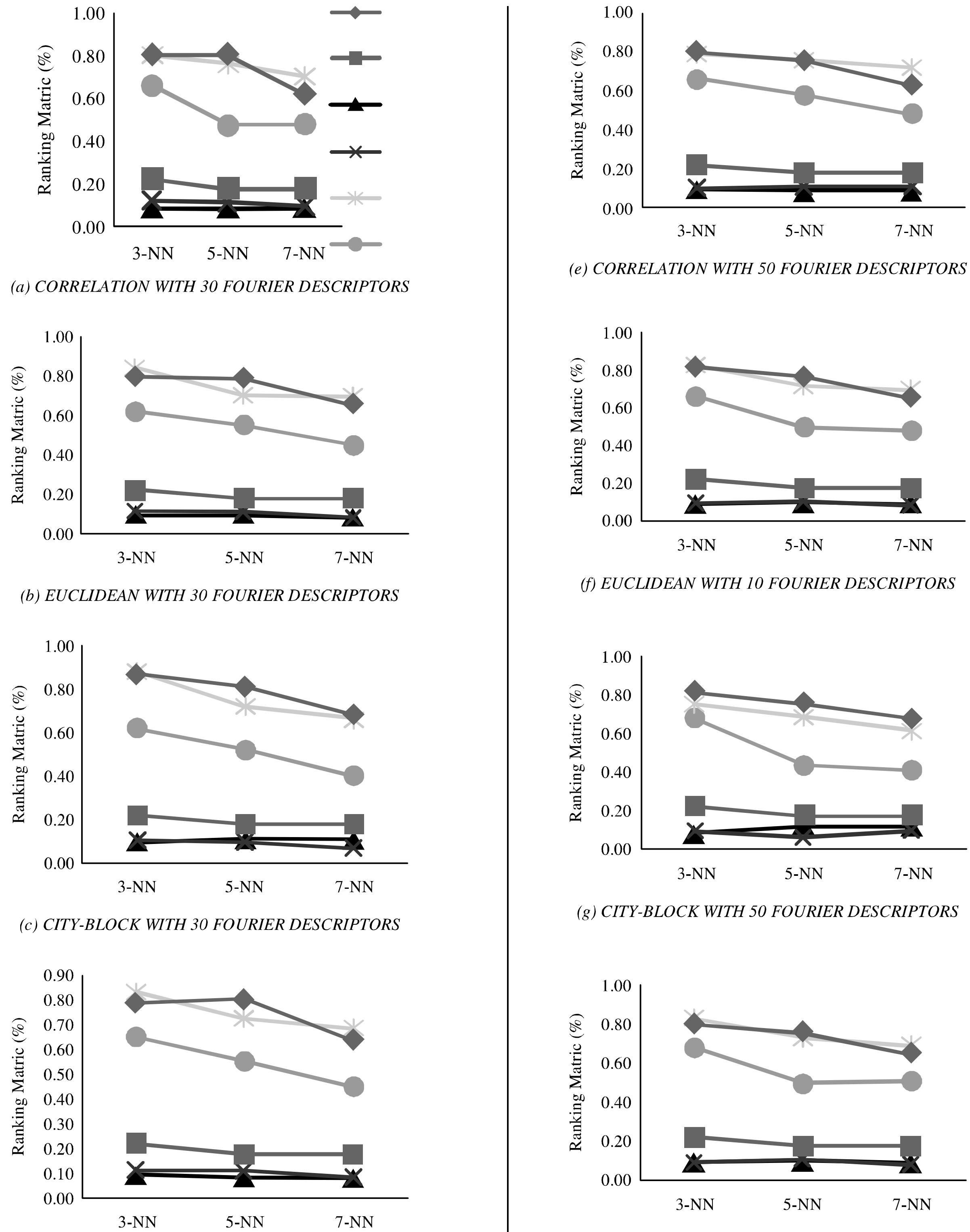


(f) EUCLIDEAN WITH 10 FOURIER DESCRIPTORS



(g) CITY-BLOCK WITH 10 FOURIER DESCRIPTORS

FIG. 2. ANALYSIS OF DIFFERENT SHAPE SIGNATURES FOR DIFFERENT NUMBER OF FOURIER DESCRIPTORS ALONG WITH TUNING OF CLASSIFICATION PARAMETERS (DISTANCE MEASURE AND NEAREST NEIGHBOURS FOR GROUP-I



(a) CORRELATION WITH 30 FOURIER DESCRIPTORS

(b) EUCLIDEAN WITH 30 FOURIER DESCRIPTORS

(c) CITY-BLOCK WITH 30 FOURIER DESCRIPTORS

(d) COSINE WITH 30 FOURIER DESCRIPTORS

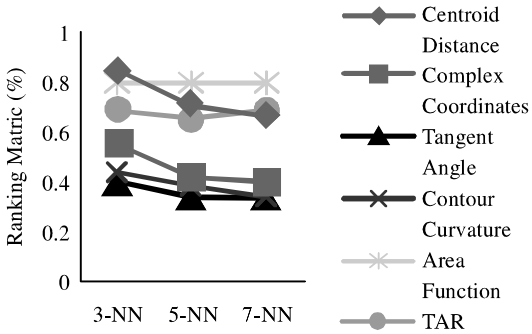
(e) CORRELATION WITH 50 FOURIER DESCRIPTORS

(f) EUCLIDEAN WITH 10 FOURIER DESCRIPTORS

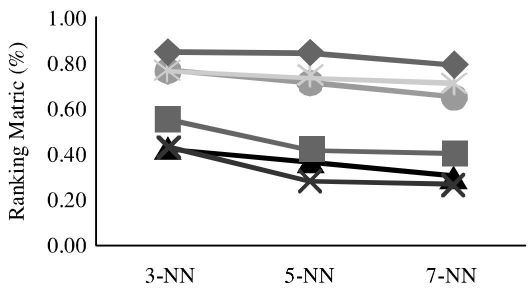
(g) CITY-BLOCK WITH 50 FOURIER DESCRIPTORS

(h) COSINE WITH 50 FOURIER DESCRIPTORS

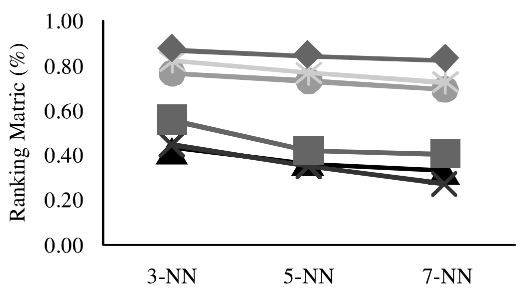
FIG. 3. ANALYSIS OF DIFFERENT SHAPE SIGNATURES FOR DIFFERENT NUMBER OF FOURIER DESCRIPTORS ALONG WITH TUNING OF CLASSIFICATION PARAMETERS (DISTANCE MEASURE AND NEAREST NEIGHBOURS FOR GROUP-I



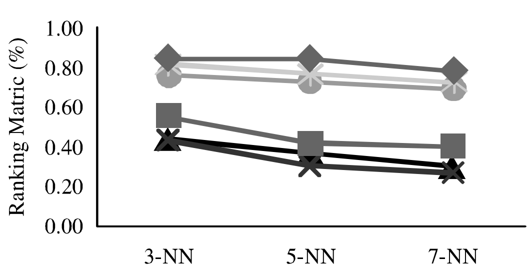
(a) CORRELATION WITH 5 FOURIER DESCRIPTORS



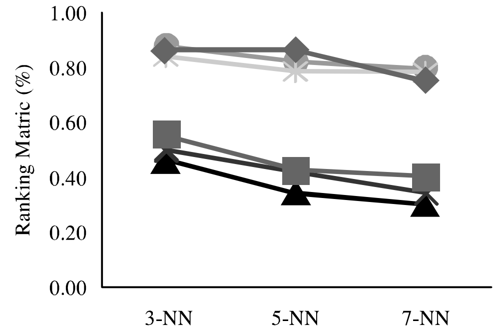
(b) EUCLIDEAN WITH 5 FOURIER DESCRIPTORS



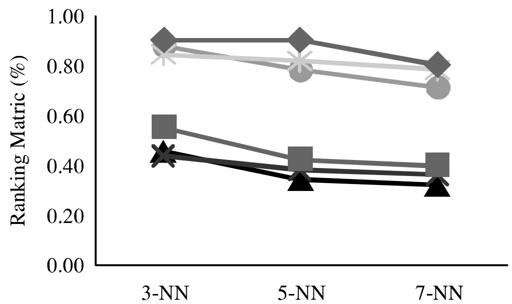
(c) CITY-BLOCK WITH 5 FOURIER DESCRIPTORS



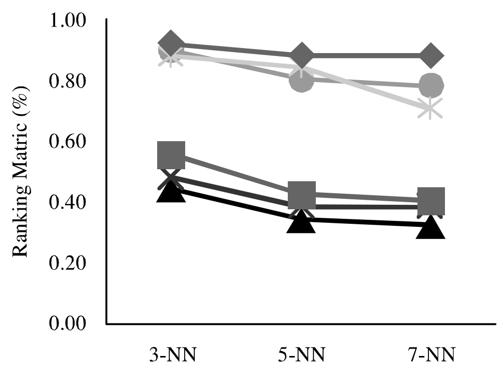
(d) COSINE WITH 5 FOURIER DESCRIPTORS



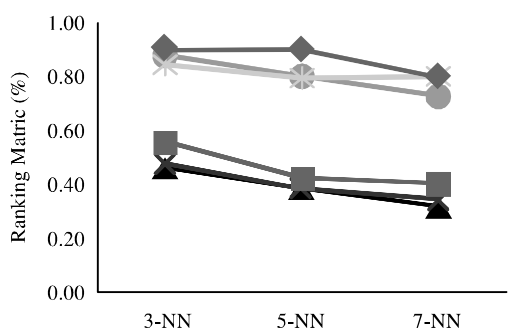
(e) CORRELATION WITH 10 FOURIER DESCRIPTORS



(f) EUCLIDEAN WITH 10 FOURIER DESCRIPTORS

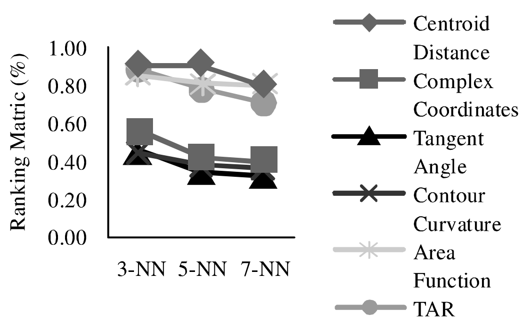


(g) CITY-BLOCK WITH 10 FOURIER DESCRIPTORS

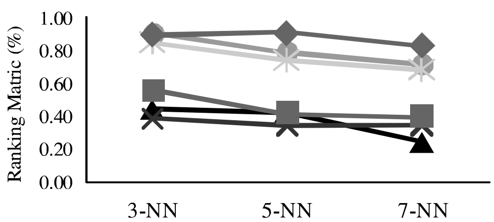


(h) COSINE WITH 10 FOURIER DESCRIPTORS

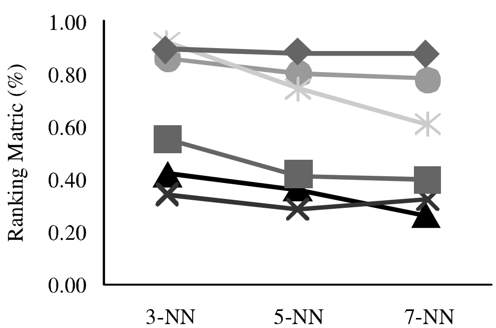
FIG. 4. ANALYSIS OF DIFFERENT SHAPE SIGNATURES FOR DIFFERENT NUMBER OF FOURIER DESCRIPTORS ALONG WITH TUNING OF CLASSIFICATION PARAMETERS (DISTANCE MEASURE AND NEAREST NEIGHBOURS FOR GROUP-II



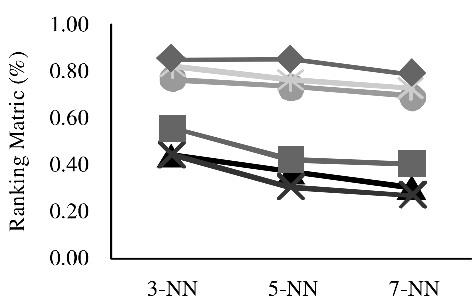
(a) CORRELATION WITH 30 FOURIER DESCRIPTORS



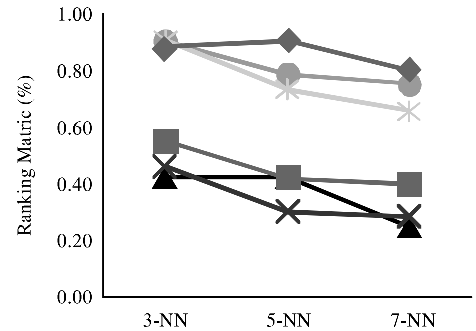
(b) EUCLIDEAN WITH 30 FOURIER DESCRIPTORS



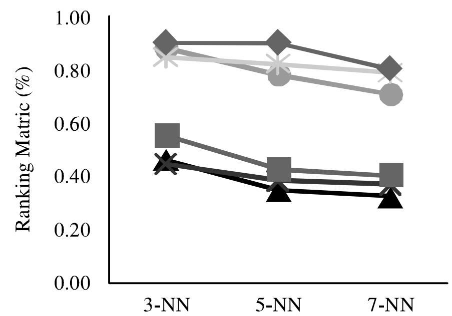
(c) CITY-BLOCK WITH 30 FOURIER DESCRIPTORS



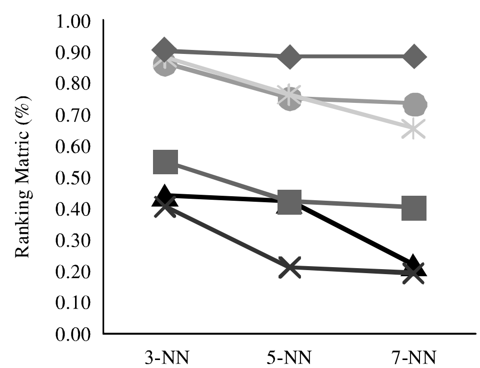
(d) COSINE WITH 30 FOURIER DESCRIPTORS



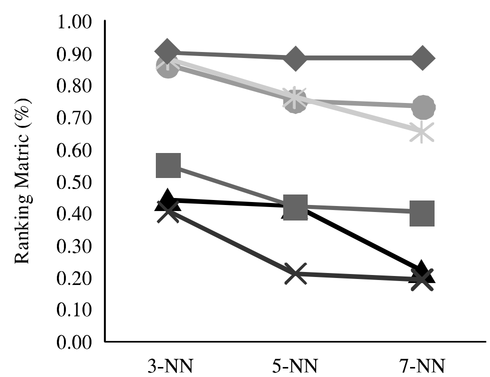
(e) CORRELATION WITH 50 FOURIER DESCRIPTORS



(f) EUCLIDEAN WITH 10 FOURIER DESCRIPTORS



(g) CITY-BLOCK WITH 50 FOURIER DESCRIPTORS



(h) COSINE WITH 50 FOURIER DESCRIPTORS

FIG. 5. ANALYSIS OF DIFFERENT SHAPE SIGNATURES FOR DIFFERENT NUMBER OF FOURIER DESCRIPTORS ALONG WITH TUNING OF CLASSIFICATION PARAMETERS (DISTANCE MEASURE AND NEAREST NEIGHBOURS FOR GROUP-II

5. DISCUSSION

We have proposed a novel method for PSL recognition that has shown very encouraging results on the provided dataset. We have developed a dataset for PSL and successfully used it in our analysis. Shape signatures are empirically evaluated and analyzed in the context of sign language. The analysis presented, is robust in terms of its applicability for other sign languages. The analysis is also helpful for other related fields, which are based on shape descriptors. Quite reasonable size of the sign dictionary is used in the paper. The proposed methodology is purely vision based and hence requires no dependence on cumbersome and expensive data gloves. Rather skin color properties are exploited for segmentation and the segmented hand features are used to get the sign descriptors. We have achieved high accuracy rate by using single camera in a simple setting for imaging. Our proposed method is easy and low cost method for PSL recognition.

The results for the proposed method are further discussed as: Centroid distance is invariant in terms of rotation, translation and scaling. Invariance in terms of translation and scaling is very useful for the recognition of PSL but as far as rotation invariance is concerned; it is a negative instead of positive point for PSL recognition system. There are many examples in Group-I and few in Group-II, where same sign with different orientation in PSL is considered as different sign. So a good shape descriptor for PSL is that, which is orientation sensitive rather than being rotation invariant. For example “daal” and “ain”, “zaal” and “ghain”, “no” and “chay” are some of the examples of PSL of same sign with different orientation means different sign. There are other such examples in PSL as well. Fig. 6 shows some examples those are different signs just on the basis of their orientation. Contour curvature is translation and rotation invariant but scale variant. As mentioned, rotation invariance is negatively affecting PSL recognition rate. Low accuracy rates are evident of the fact that scale variance and rotation invariance are negative factors for the proposed method. As sign dataset cannot be scale-consistent as size of the hand varies and distance from the camera is not kept constant. Rotation invariance of area function is catered for to some extent, by not taking very dense boundary samples.

Tangent angle function is very sensitive to noise and that is the main reason of its low accuracy rates for PSL classification system. Complex coordinate function has invariance in terms of translation and that is not good enough for high accuracy rates for PSL recognition system. FD are used for this paper as feature set for the recognition of PSL. FD proved to be quite reasonable choice for both groups of signs. Analysis according to the RM is shown in Figs. 3-6. These results are achieved while using only magnitude of the FD to make it starting point invariant. If phase information is also included in the feature set accuracy goes down 40-50% on average. Figs. 3-6 show results of 5,10,30 and 50 FD. There was no further improvement in results for more than 30 descriptors. Even only 10 FD are enough to give good results, thus making a very small yet powerful feature set, that leads to an efficient classification process. Distance measure city-block gives best result with three nearest neighbors for classification. More than three neighbors are having negative effect on accuracy due to low inter-sign distance in the feature space.

6. CONCLUSION

The paper presents a signer independent, efficient and robust methodology for the recognition of one-handed static PSL signs. The paper investigates the accuracy of six different sign descriptors for PSL recognition system. The 1D signature then transformed to frequency domain to obtain the FD and these Fourier descriptors as shape descriptor. Two distinct groups of signs are used to analyze. It is observed that Group-II that has less complex signs and less no. of signs, gives better result as compared to more complex and larger Group-I. The presented method has given very encouraging accuracy rates. For future research work, further signs can be added to the PSL recognition.

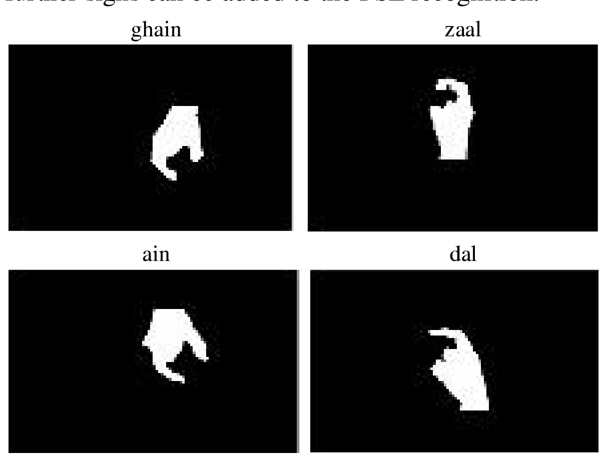


FIG. 6. DIFFERENT SIGNS ON THE BASIS OF ORIENTATION

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