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Indian sign language recognition using Krawtchouk moment-based local features

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ABSTRACT

In this paper, Krawtchouk moment-based shape features at lower orders are proposed for Indian sign language (ISL) recognition system which gives local information about the shape from a specific region of interest. The shape recognition capability of Krawtchouk moment-based local features is verified on two databases: the standard Jochen Triesch's database and 26 ISL alphabets which are collected from 72 different subjects, with variations in position, scale and rotation. Feature selection is performed to minimise redundancy. The effect of order and feature dimensionality for different classifiers is studied. Results show that Krawtchouk moment-based local features are found to exhibit user, scale, rotation and translation invariance. Moreover, they have shape identification capability.

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Correlation-based feature selection (CFS); human–computer interaction (HCI); Indian sign language (ISL); Krawtchouk moments; local features; orthogonal moments; region of interest (ROI); shape recognition

Introduction

In pattern recognition domain, moments have been identified to possess the capability to extract both global and local information of shape. For the first time, Hu proposed seven moments till third order, which were rotation, scale and translation invariant [1]. However, reconstruction of images with these moments was difficult as they were non-orthogonal in nature. To overcome this, the continuous orthogonal Zernike and Legendre moments were introduced. Because of their orthogonal nature, they had minimum information redundancy [2]. Moreover, such moments were independent to rotation, scale and position. However, they had certain drawbacks. The continuous orthogonal moments involved change of the image co-ordinate space into a different domain like, Zernike moments are defined in polar co-ordinate space. These also involved approximation of continuous integrals, which resulted in discretisation error, thus limiting the accuracy with the increase in order. Also, their complexity in terms of computation of moments increased with the increase in order. Due to these limitations, discrete orthogonal moments were introduced. Tchebichef moments come under this category. They do not require numerical approximation, as these are discrete in nature which means discretisation error does not exist. Also, they are defined in image co-ordinate space itself [3]. Krawtchouk moments come under the category of discrete orthogonal moments, based on classical Krawtchouk polynomials [4]. The discretisation error in case of Krawtchouk moments is nonexistent and does not involve co-ordinate space transformation. They extract both global and local information from a specific ROI of the image, which can be varied. Also, Krawtchouk moments are symmetrical in nature which results in lesser computational time when used for feature extraction [5].

Krawtchouk moments were first time used for object recognition by Yap et al. [6] on a database of seven English binary alphabets with variations in rotation and scale and they outperformed Hu moment. Sit et al. [7] collected a database of 9 English binary alphabets and grey-scale clip art images with Krawtchouk moments giving best results. Wang et al. [8] analysed the character recognition capability of Krawtchouk, Zernike and Legendre moments by using a database of 11,033 Chinese handwritten characters. Krawtchouk moments gave best recognition accuracy. Significant research work has been done in face recognition using Krawtchouk moments where a database consisting of 40 subjects with variations in expressions was used. It was concluded that Krawtchouk moments outperformed Zernike, Geometric and Tchebichef moments [9]. Rani and Devaraj [10] found that the combination of local and global features of Krawtchouk moments gave good classification accuracy, even with the addition of noise. Not much research work has been done in gesture recognition domain using

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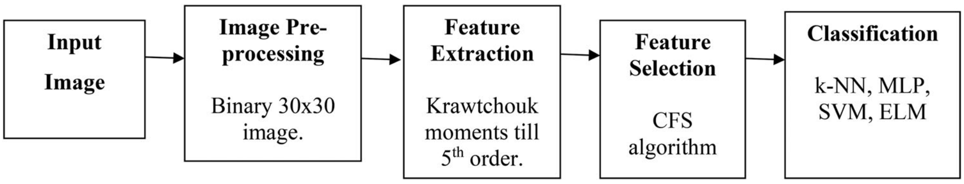


Figure 1. Proposed ISL recognition system.

Krawtchouk moments. Priyal and Bora [11] concluded that Krawtchouk moments gave better results as compared to Geometric, Zernike and Tchebichef on a database of 10 gestures of digits from 23 users, which were rotated, translated and scaled. Kaur et al. [12] analysed the shape recognition capability of Krawtchouk moments on 5 gesture signs of digits collected from 21 different subjects with variations in illumination, rotation and scale. Krawtchouk moments were found to exhibit shape recognition capability with an accuracy of 91%. However, the role of Krawtchouk moments in gesture recognition domain was not deeply investigated.

Based on the literature survey, Krawtchouk moments are found to be one of the best shape descriptors. The proposed ISL recognition system is illustrated in Figure 1. The paper focuses on the following objectives:

(1) Krawtchouk moment-based features are extracted till 5th order for both Jochen Triesch and ISL databases by varying ROI.
(2) To select a minimum possible feature-set that gives good recognition accuracy using correlation-based feature selection (CFS) algorithm.
(3) To prove that Krawtchouk moment-based features have shape recognition capability and are user, position, rotation and scale invariant.

Krawtchouk moments

Krawtchouk moments are derived from classical Krawtchouk polynomials which are associated with binomial functions [4].

Krawtchouk polynomials

The rth order classical Krawtchouk polynomial

$$K_r(i;p,X) = \sum_{k=0}^{X} (a_{k,r,p} i^k) = {}_2F_1\left(-r, -i; -X; \frac{1}{p}\right) \quad (1)$$

where $i, r = 0,1,2 \ldots \ldots X, X > 0, p\varepsilon(0,1), a_{k,r,p}$ are Krawtchouk polynomial coefficients. ${}_2F_1$ is a hypergeometric function

$${}_2F_1(m,n;o;t) = \sum_{k=0}^{\infty} \frac{(m)_k \, (n)_k \, t^k}{(o)_k (k!)} \quad (2)$$

where $(m)_k$ is pochhammer symbol

$$(m)_k = m(m+1)\ldots\ldots(m+k-1) = \frac{(m+k)}{(m)}$$

Normalised Krawtchouk polynomials

$$\tilde{K}_r(i;p,X) = K_r(i;p,X)\sqrt{\frac{1}{\rho(r;p,X)}} \quad (3)$$

Weighted Krawtchouk polynomials:

$$\bar{K}_r(i;p,X) = K_r(i;p,X)\sqrt{\frac{w(i;p,X)}{\rho(r;p,X)}} \quad (4)$$

Weight function is

$$w(i;p,X) = \binom{X}{i} p^i (1-p)^{X-i} \quad (5)$$

$$\rho(r;p,X) = (-1)^r \left(\frac{1-p}{p}\right) r \frac{r!}{(-X)_r} \quad (6)$$

The weighted Krawtchouk polynomials were introduced to overcome the drawback of numerical instability with increase in order [6].

Krawtchouk moment invariants

The Krawtchouk moment invariants corresponding to (r, q)th order for an image intensity function $f(i,j)$ of X x Y is [6]

$$Q_{rq} = \sum_{i=0}^{X-1}\sum_{j=0}^{Y-1} \bar{K}_r\,(i;p_1,X-1)\bar{K}_q\,(j;p_2,Y-1)\,f(i,j) \quad (7)$$

p_1 and p_2 are used for varying ROI horizontally as well as vertically in an image for local feature extraction of that particular ROI. For $p_1 > 0.5$, ROI shifts towards positive x-direction and for $p_1 < 0.5$ towards negative x-direction. For $p_2 > 0.5$, ROI shifts towards negative y-direction and for $p_2 < 0.5$ towards positive y-direction. In this paper, parameters p_1 and p_2 are varied so that local features can be extracted from different ROIs in the image.

Behaviour of 2-D Krawtchouk polynomials

In weighted Krawtchouk polynomials as the orders increase, the number of zero crossings also increases with variations in both x and y-axis for image characterisation. Figure 2 shows the 2D weighted Krawtchouk polynomials plot at various orders with ROI focussed to the centre. With the increase in order, the oscillation of moment kernels increases, resulting in feature extraction with variation in kernels in both *x* and *y*-axis. For lower orders, local information is obtained with lesser kernel variations in contrast to global information with more number of variations at higher orders. Figure 3 shows the top view of 2D Krawtchouk moments with white colour showing positive peaks and black colour giving negative peaks of Krawtchouk moments. The lesser the order, the more localised will be the feature-set emphasising on local information particularly hand shape in this case. The higher the order, global information would be provided for the entire image as a whole. Thus, local features provide emphasis on the local information in the image which makes them best for shape description.

Pseudo code for calculation of Krawtchouk moments

```
Let f (i,j) be a binary image with size N × N after pre-processing
Wx = zeros (1, N); . . . . % Initialize weight vector
Wy = zeros (1, N);
p1 = 0.5; %Initialize ROI by setting parameters p1 and p2
p2 = 0.5; % ROI fixed at centre
r = 1; % Set orders
q = 1;
K = [ ]; %Initialize Krawtchouk matrix
for i = 0:N-1
for j = 0:N-1
%Calculation of weights
Wx (i) = (factorial(N)/factorial(i).* factorial (N-i)).*(p1^(i)).*(1-p1)^(N-i);
Wy (j) = (factorial (N)/factorial (j).*factorial (N-j)).*(p2^(j)).*(1-p2)^(N-j);
%Calculation of Krawtchouk features
K(i,j) = (hypergeom([-r,-i],-N,(1/p1)).*sqrt(Wx)).*(hypergeom([-q,-j],-N,(1/
  p2)).*sqrt(Wy)).*f(i,j);
end
end
```

Tools and techniques

Database

(1) The standard Jochen Triesch's database consisting of 10 static hand postures collected from 24 subjects in uniform dark, uniform light and complex background [13].
(2) The second database consists of 26 ISL alphabets from 'A' to 'Z'. Some alphabets have identical shapes like, 'A', 'B', 'P', 'Q', 'U', 'W', 'M', 'N', high occlusion as in 'M', 'N', 'W' and one gesture being subgesture of other as in 'I', 'K'. In most of the signs both hands are used, which leads to complexity. A total of 1865 gesture images are constructed which are taken from an average number of 72 subjects as shown in Figure 4. These are pre-processed. During pre-processing, each image is converted from RGB to binary. Edge detectors are used and each image is resized to form 30×30 binary images. Two datasets are prepared. The first group has gestures which are centre-resized, so that each sign is aligned to the centre of the image. The second group has gestures which vary in position, with a scale of 0.7 rotated at 90°. The performance analysis of Krawtchouk moment-based features in terms of recognition accuracy is done for this combined datasets. Samples of some of the ISL alphabets are shown in Figure 4.

Feature extraction

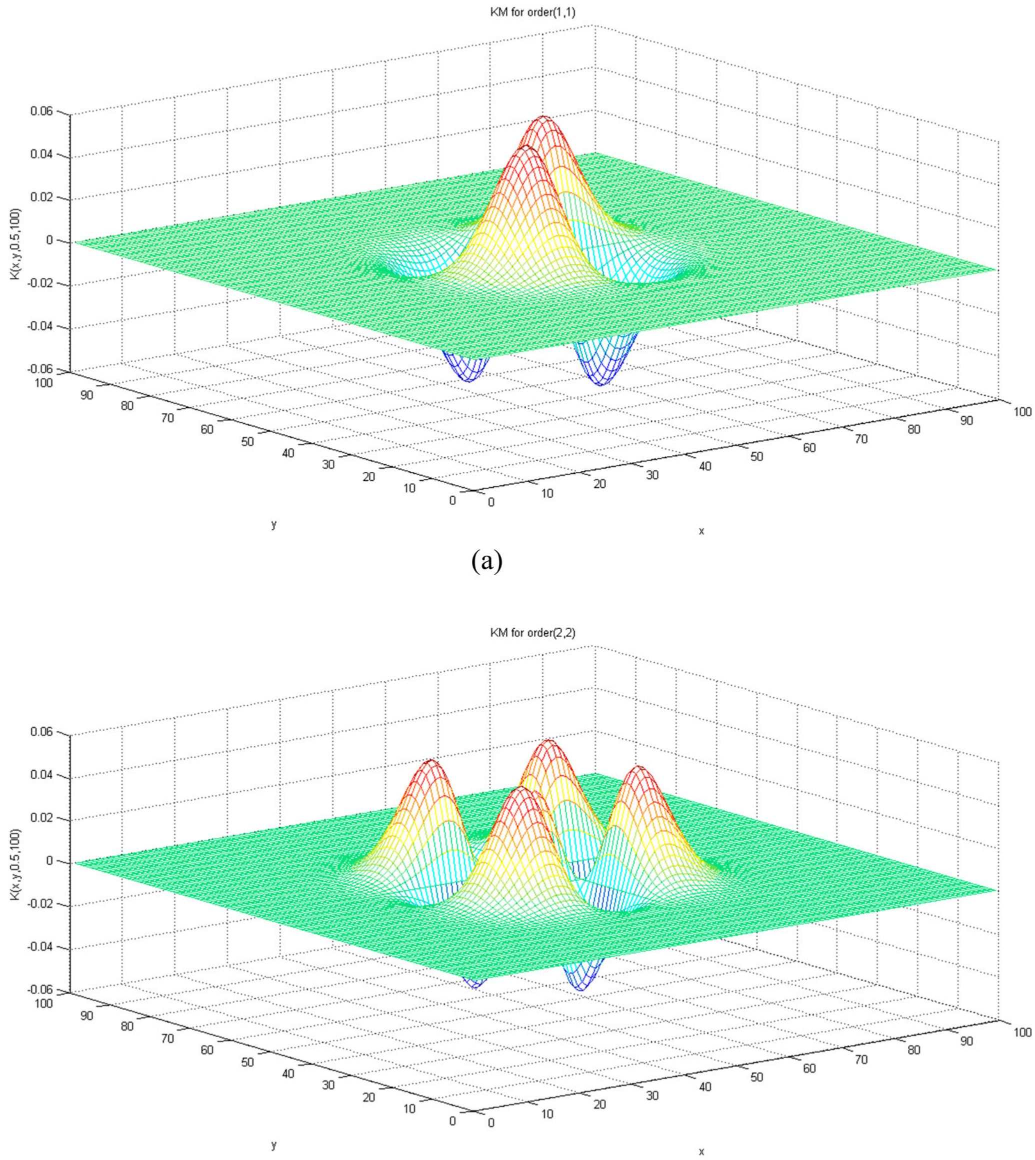
Figure 5 shows reconstructed images from orders 1–8. As can be seen, at lower orders finer details of the image are captured giving local information as compared to higher orders which extract global information of the image. ISL database contains 26 classes with both hands being used for different alphabets; therefore the feature vector size is increased by extracting Krawtchouk features at nine different ROIs in order to capture local features from different positions of the image, thus covering the entire image. For this, the values of p_1 and p_2 are varied such that features are extracted till 5th order at each of the nine different ROIs as shown in Figure 6. In this paper, the orders are taken with $r = q$. Thus, the feature vector size corresponding to (r,q)th order is $(r+1)^2$ with $r = q$. At each ROI the feature vector size obtained till 5th order is 36. Thus, at nine different ROIs the total feature vector size till 5th order is $36 \times 9 = 324$. Also, the lower orders take lesser computation time because as the orders increase, the Krawtchouk polynomial coefficients also increase, leading to large computational complexity.

Feature selection

Feature Selection removes irrelevant and redundant features. In this paper, CFS algorithm is used. It is considered as the most stable feature selection algorithm [14]. The CFS gives a feature-set which has higher correlation with the class and least correlation within one another. CFS uses Pearson correlation coefficient which is calculated as follows [15]:

$$M_s = \frac{k\,\bar{r}cf}{\sqrt{k + k(k-1)\bar{r}_{ff}}} \tag{8}$$

M_S is the merit of subset of features, k is the number of features, $\bar{r}_{cf}$ is the mean of correlations between each feature and class and $\bar{r}_{ff}$ is the mean of pairwise correlations between every two features. Feature sets are formed using greedy stepwise algorithm, in which useful features are added into an empty matrix and ranked on the basis of highest correlation coefficient (M_s). Out of all the feature subsets, the best feature subset is selected on the basis of the largest M_s.



(b)

Figure 2. Plot of 2D weighted Krawtchouk polynomials at orders (a) (1,1), (b) (2,2), (c) (4,4), (d) (5,5).

Classification

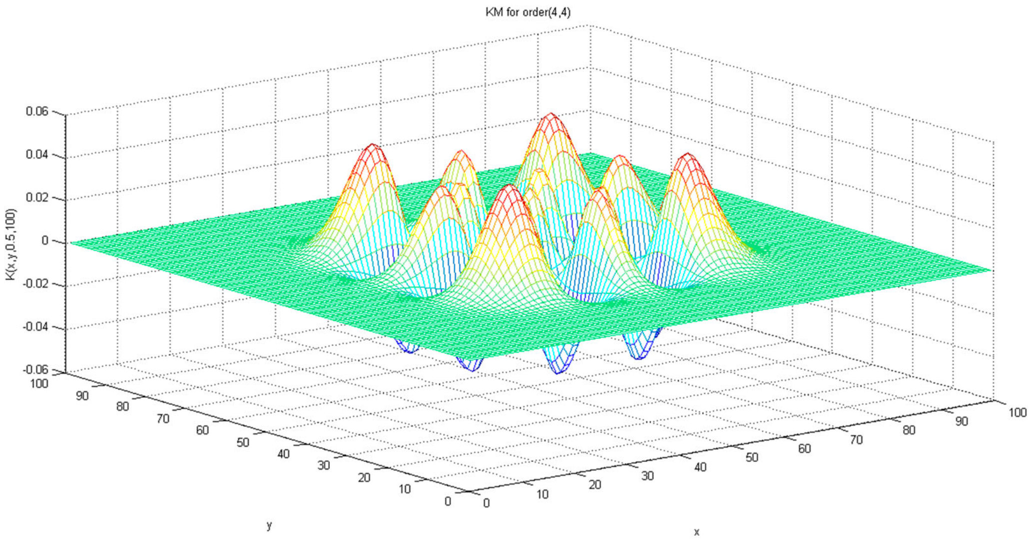
Features are classified by *k*-nearest neighbour (*k*-NN) using Manhattan and Euclidean distance, with $k = 1$, MLP, SVM with RBF, PUK (Pearson VIII Universal Kernel) and polynomial kernels and extreme learning machines (ELM) with Linear, RBF and polynomial kernels. SVM PUK shows better generalisation as compared to other kernel functions and classifiers [16]. ELM is used in various multiclass classification applications and gives generalisations at faster learning speed as compared to SVM which has high computational complexity [17].

Results and discussions

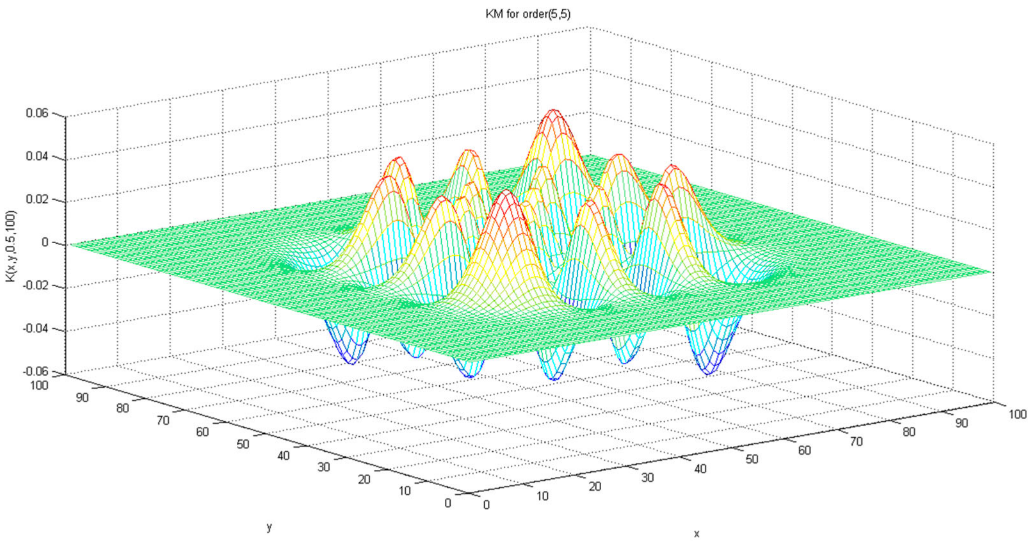
To ensure the recognition capability of Krawtchouk moments for a smaller feature vector, the comparison of its accuracy is done with Hu and Zernike moments for centre-aligned ISL database in Table 1. It is found that Krawtchouk moments outperform with an accuracy of 86.6% at SVM PUK. For the same feature vector size, Zernike moments show 82.6% at SVM PUK while for Hu moments at most 70.9% accuracy is observed at ELM Polynomial and SVM RBF.

A comparison of recognition accuracy is done till 8th order using Krawtchouk moments for centre-aligned images. Figure 7 shows a significant increase in accuracy from 1st to 5th order after which the accuracy stabilises at 6th, 7th and 8th orders.

Table 2 shows the comparative analysis of the recognition accuracies using Jochen Triesch's database. Raw features are normalised to map the feature values in the range of $[-1, 1]$, thus improving the recognition accuracy [18]. SVM PUK performs best with 91.5 and 92.4% accuracy for raw and normalised feature-set. However, ELM RBF also shows comparable accuracies of 90.9 and 91.8% for raw and normalised feature-set, respectively.



(c)



(d)

Figure 2. Continued

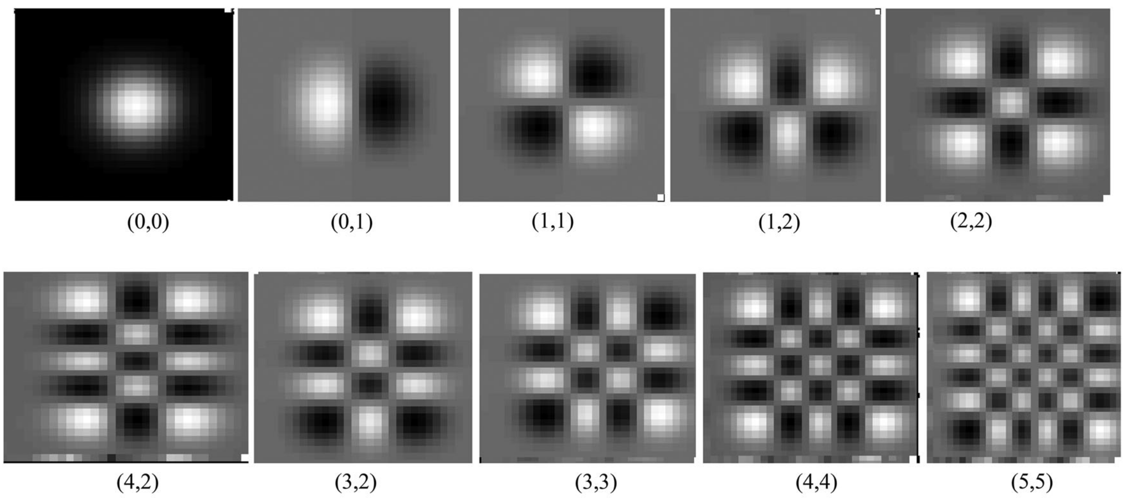


Figure 3. 2D Krawtchouk plots for $X = Y = 30$, $p_1 = p_2 = 0.5$.

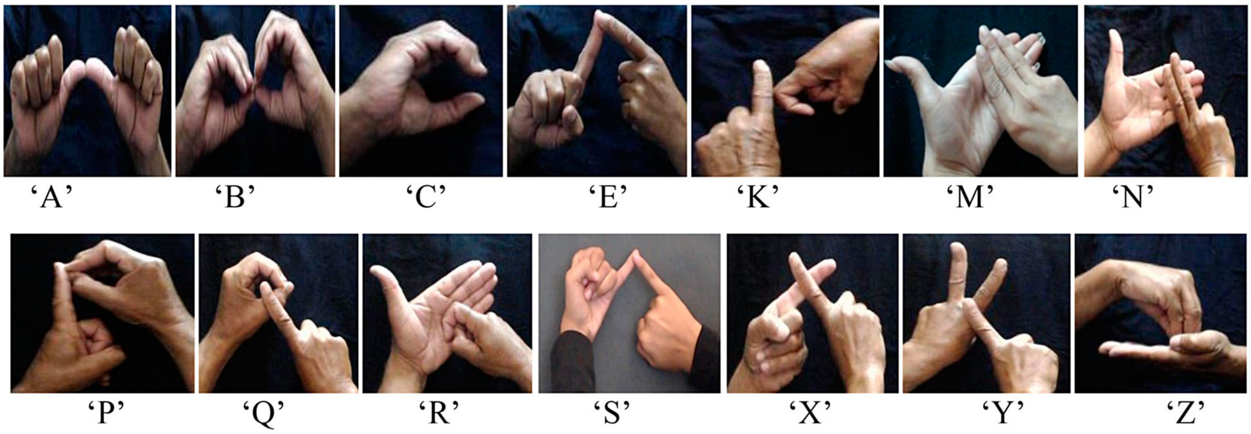


Figure 4. Samples of ISL alphabets. Images reproduced by kind permission of the authors.

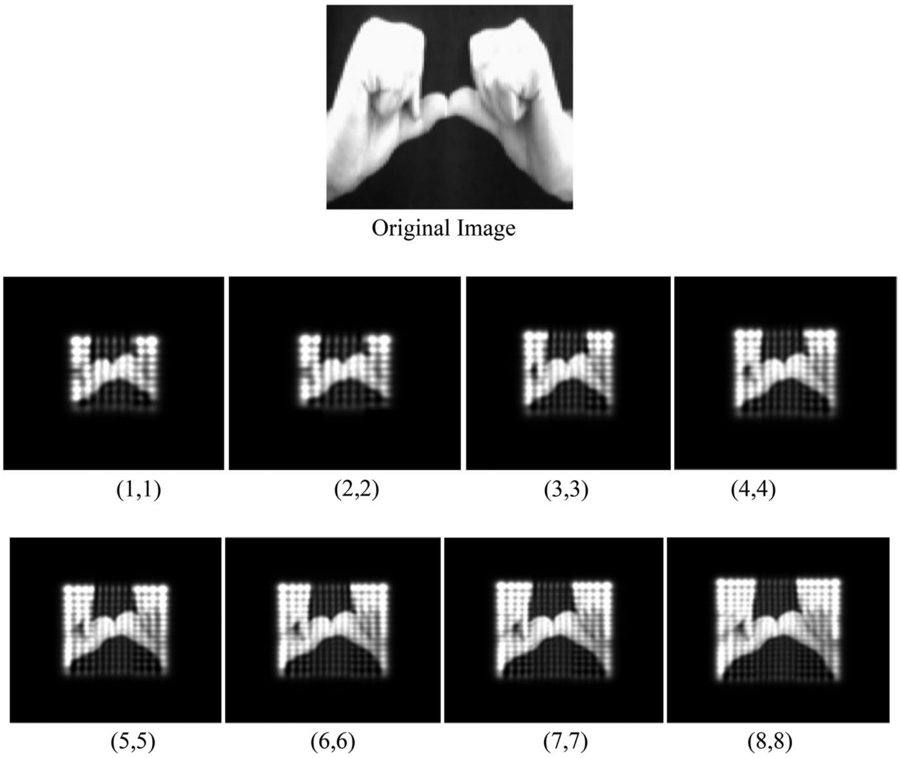


Figure 5. Reconstruction using Krawtchouk moments. Images reproduced by kind permission of the authors.

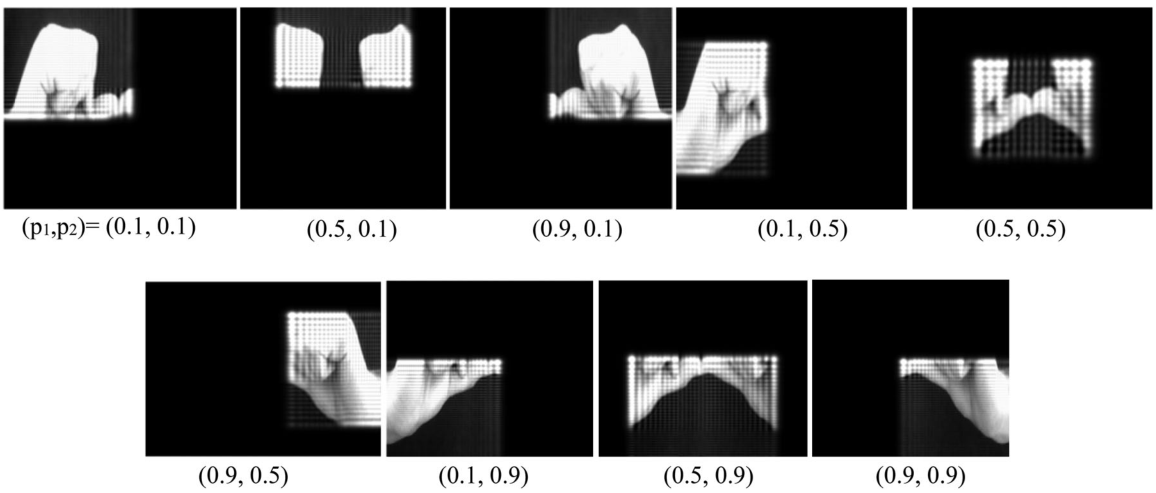


Figure 6. Different ROIs for feature extraction. Images reproduced by kind permission of the authors.

Table 1. Comparison of moments for centre-aligned ISL database.

			SVM				ELM		
Feature-set	*k*-NN ED (%)	*k*-NN MD (%)	Polynomial (%)	RBF (%)	PUK (%)	MLP (%)	Poly (%)	RBF (%)	Linear (%)
Raw feature-set									
Hu (7 features)	57.1	55.3	50	60.5	70.2	58.5	**70.9**	69.5	68.9
Zernike (36 features)	75.3	75.1	82	77.9	**82.4**	75.6	76	76.5	75.9
Krawtchouk (36 features)	85.4	85	85.1	84.8	**85.8**	84.4	85.6	85.4	85.3
Normalised feature-set									
Hu	58	56.3	55.7	**70.9**	62.4	60.1	**70.9**	70.2	70.2
Zernike	77.2	78.7	82.4	78.4	**82.6**	78	79.7	79.4	78.4
Krawtchouk	86	85.7	86.2	85.3	**86.6**	85.1	86.5	86.2	86.5

Note: Bold values indicate maximum recognition accuracies.

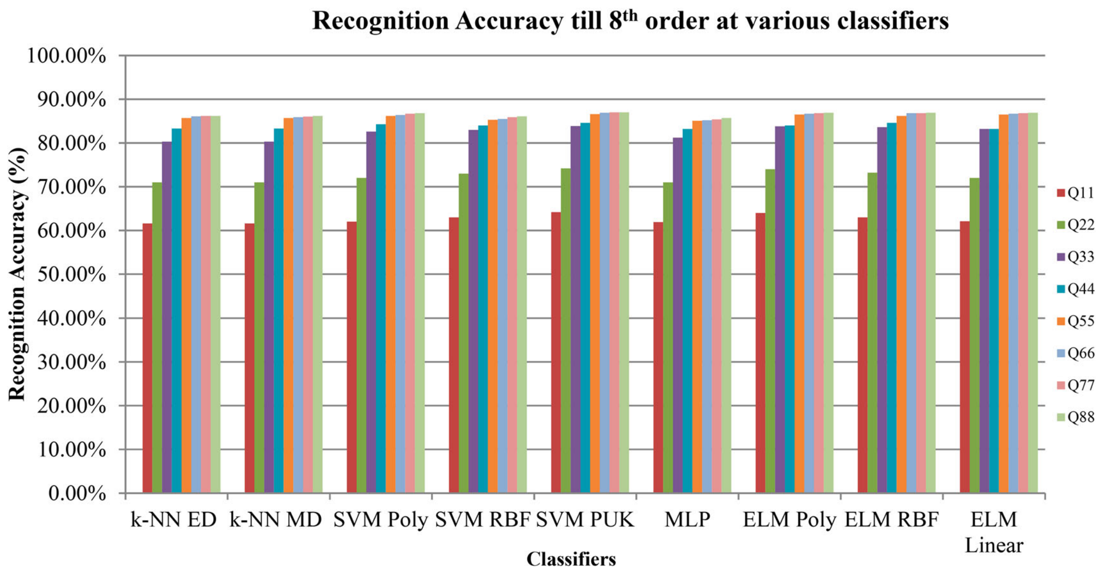


Figure 7. Recognition accuracy till 8th order.

Table 2. Results for Jochen Triesch's database.

				SVM			ELM			
Order	Feature-set	*k*-NN ED (%)	*k*-NN MD (%)	Polynomial (%)	RBF (%)	PUK (%)	Polynomial (%)	RBF (%)	Linear (%)	MLP (%)
Raw feature-set										
Q_{11}	36	55	55.6	60	60.2	**61**	60.3	60.4	60.1	60.1
Q_{22}	81	60.2	60.6	66.8	65.4	**70.5**	70.2	**70.5**	69.4	69.3
Q_{33}	144	72.2	72.4	75	77	**78.4**	75.7	77.4	76.2	75.7
Q_{44}	225	80.2	80.9	82.4	83.5	**84.9**	83.7	**84.9**	83.9	83.2
Q_{55}	324	89	89.5	90	90.7	**91.5**	90.5	90.9	90.1	89.8
Normalised feature-set										
Q_{11}	36	56.2	56.4	61.2	61.1	**61.3**	61	61.2	61	61
Q_{22}	81	61.5	61.9	67	66.8	**73.2**	71	71.4	70.7	70.5
Q_{33}	144	72.9	72.9	76.5	79	**79.5**	76.4	78.9	77.6	76
Q_{44}	225	80.9	80.9	83.4	84	**85.3**	83.9	**85.3**	84.3	83.9
Q_{55}	324	90.1	90.2	90.3	90.9	**92.4**	90.7	91.8	90.8	90

Note: Bold values indicate maximum recognition accuracies.

Table 3 shows that the proposed method performs better as compared to recently proposed methods for Jochen Triesch's database. Table 4 shows the comparative analysis of recognition accuracies for ISL database. For raw feature-set, SVM PUK and ELM RBF give 97.5%. However, on normalising the feature-set, the accuracy improves to 97.8% for SVM PUK and 97.7% for ELM RBF. Table 5 shows that CFS algorithm selects 220 from original 324 features. Feature selection results in slight improvement with best results given by SVM PUK and ELM with 97.9% accuracy.

Table 3. Performance of Jochen Triesch's dataset with recent methods.

Reference	Feature extraction	Recognition accuracy (%)
[13]	Elastic graph matching	92.9
[19]	Modified census transform	89.9
[20]	Weighted Eigen-space size functions	85.1
[21]	Tchebichef (till 9th order), Hu and geometric features	84.63 (dark background) 95.55 (light background)
[22]	Krawtchouk features till 3rd order	84.9
Proposed method	**Krawtchouk features till 5th order**	**92.4**

Note: Bold value indicate maximum recognition accuracies.

Table 4. Results for ISL images.

				SVM			ELM			
Order	Feature-set	*k*-NN ED (%)	*k*-NN MD (%)	Polynomial (%)	RBF (%)	PUK (%)	Polynomial (%)	RBF (%)	Linear (%)	MLP (%)
Raw feature-set										
Q_{11}	36	74.9	74.8	75.9	75.5	**75.9**	**75.9**	75.4	74.9	74.7
Q_{22}	81	85.6	85.7	85.8	85	**85.9**	85.1	85.8	85	85
Q_{33}	144	87.1	87.1	88.3	88.7	**89.4**	88.5	88.7	88.2	87.9
Q_{44}	225	90.9	90.3	92.1	92.6	93.8	92.3	**94**	93	92.9
Q_{55}	324	95.9	95.9	96.1	97.4	**97.5**	97.1	**97.5**	96.9	95.3
Normalised feature-set										
Q_{11}	36	75.5	75.9	75.9	75.8	76.5	**76.7**	76.2	75.1	75.2
Q_{22}	81	86	86.5	86.7	**87**	**87**	85.8	85.9	85.4	85.3
Q_{33}	144	87.6	87.6	88.5	88.9	**89.7**	88.7	**89.7**	88.9	87.4
Q_{44}	225	91.2	91.1	93	93.2	**94.9**	93.5	**94.9**	94	93
Q_{55}	324	96	96.1	96.9	97.6	**97.8**	97.4	97.7	97.2	96.6

Note: Bold values indicate maximum recognition accuracies.

Table 5. CFS selected feature-set.

			SVM			ELM			
CFS (220 features)	*k*-NN ED (%)	*k*-NN MD (%)	Polynomial (%)	RBF (%)	PUK (%)	Polynomial (%)	RBF (%)	Linear (%)	MLP (%)
Raw features	96.2	96.2	96.7	97.5	97.5	**97.6**	97.4	97	96.3
Normalised features	96.4	96.4	97.4	97.3	**97.9**	97.8	**97.9**	97.4	96.9

Note: Bold values indicate maximum recognition accuracies.

In the previous work of the authors, Krawtchouk-based moment invariants were extracted only till 3rd order by varying the ROI for a dataset of 10 ISL centre-resized alphabets for which an accuracy of 90% was achieved by SVM PUK [22]. However, in this paper for 26 ISL alphabets with variations in position, rotation and scale the best accuracy results are given by SVM PUK with 97.9%.

Conclusion and future scope

In this paper, the shape recognition capability of Krawtchouk moment-based local features at lower orders is studied on 26 ISL alphabets. The proposed method shows competent results when compared to recently proposed methods for Jochen Triesch's database. Even for a small feature vector size, the recognition accuracy obtained for Krawtchouk moments is better than Zernike and Hu. An accuracy of 97.9% is achieved for ISL database, thus proving that Krawtchouk moment-based local features are rotation, scale, translation and user invariant. They also have shape identification capability to distinguish between similar shapes. In future, the static gestures can be extended to dynamic gestures, involving movement of hands.

Disclosure statement

No potential conflict of interest was reported by the authors.

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