Feature Selection for Hand-Shape Based Identification

Muhammad Hussain, Awabed Jibreen, Hatim Aboalsmah, Hassan Madkour, George Bebis and Gholamreza Amayeh

Abstract The shape of a hand contains important information regarding the identity for a person. Hand based identification using high-order Zernike moments is a robust and powerful method. But the computation of high-order Zernike moments is very time-consuming. On the other hand, the number of high-order Zernike moments increases quadratically with order causing storage problem; all of them are not relevant and involve redundancy. To overcome this issue, the solution is to select the most discriminative features that are relevant and not redundant. There exists a lot of feature selection algorithms, different algorithms give good performance for different applications, and to choose the one that is effective for this problem is a matter of investigation. We examined a large number of state-of-the-art feature selection methods and found Fast Correlation-Based Filter (FCBF) and Sparse Bayesian Multinomial Logistic Regression (SBMLR) to be the best methods that are efficient and effective in reducing the dimension of the feature space significantly (by 62 %), i.e. the storage requirements and also slightly enhanced recognition rate (from 99.16 ± 0.44 to 99.42 ± 0.36).

Keywords Hand-based identification · Zernike moments · Feature selection · Pattern matching · Biometric technology

1 Introduction

Currently, there is an increased interest in biometric technology, which led to intensive research on fingerprint, face, iris, and hand recognition. A hand contains important information and can be used for identification (who the unknown subject is?)

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and verification (is the claimed identify of a subject correct?). Hand based identification has a large range of applications in both government and industry. Many researchers attempted to propose solutions for biometric-technology based on the hand-shape [1]. Guo et al. [2] proposed a contact free hand geometry-based identification system; its average identification rate is 96.23 %; it needs an infrared illumination device. Recently Sharma et al. [3], proposed a multimodal biometric system, which is based on hand-shape and hand geometry. In this method all processing has to be performed with respect to a reference point. Amayeh et al. [4] proposed a hand-based person identification and verification method in 2009, which is a simple and robust method and does not employ any constraint. After the acquisition of hand image and segmenting it into components (fingers and palms), this method extracts features using high-order Zernike moments from each component and then fuses this information to take the final decision. This is a peg-free hand-based identification approach; it is not affected by the motion of fingers or hand, and does not require landmark points' extraction [1]. The geometric information from each part of a hand is represented by high-order Zernike moments, which are invariant to rotation, translation and scaling, and lead to excellent recognition rate [4]. But these moments involve high computational cost. In addition, the number of these moments increases quadratically with their order and this number becomes very large causing the storage problem. To store the templates of a single subject, a huge amount of space is needed. Moreover, this number has an impact on the template matching efficiency and affects the recognition efficiency.

The solution of these problems is to select the most discriminatory features, which are relevant and not redundant. As such, to enhance the efficiency of the person identification system and to reduce the storage requirements, it is imperative to select and use the high-order Zernike moments with the highest discriminative power. There exist a large number of feature selection algorithms with their strengths and weaknesses. Which algorithm results in the best performance for the problem under consideration is a matter of investigation. In this study, we examined a large number of state-of-the-art algorithms for the selection of the most discriminative high-order Zernike moments [5]. We found only three of them suitable for selecting Zernike moments: Fast Correlation-Based Filter (FCBF) [6, 7], Sparse Bayesian Multinomial Logistic Regression (SBMLR) [7] and Spectrum Feature Selection Algorithm (Spectrum) [9]. We thoroughly explored them to find the most efficient and effective algorithms. Finally, we found that FCBF and SBMLR give the best performance. These algorithms help reduce the dimension of the feature space by 62 % and a slight enhancement in the recognition rate. In this paper, we focus only person identification problem. Our main contribution is to reduce the space required to store templates for hand based identification by selecting the most discriminative Zernike moments.

The rest of the paper is organised as follows. In Sect. 2, we give an overview of hand shape based recognition system. Section 3 discusses the feature selection methods. The results have been presented in Sect. 4 and finally Sect. 5 concludes the paper.

2 Hand Shape Based Identification

In this section, we present the hand shape based recognition system. Its flowchart is shown in Fig. 1.

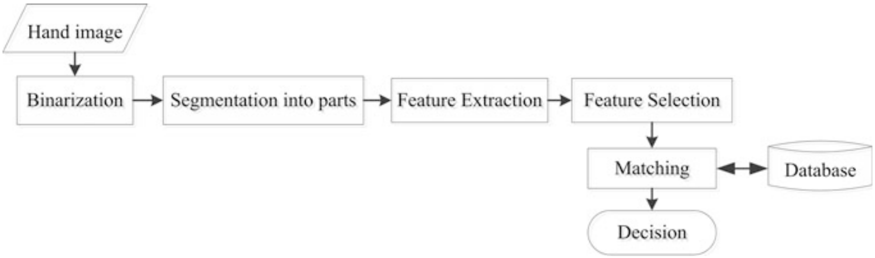

Fig. 1 Flowchart of the hand based Identification

2.1 Pre-processing

The image of a hand is acquired using a VGA resolution CCD camera and a flat lighting table. After image acquisition, it is converted into a binary form, and hand is separated from arm using segmentation. Finally, hand is segmented into palm and fingers; the detail can be found in [4]. After segmentation, the six hand parts that are used for recognition are little finger (F1), ring finger (F2), middle finger (F3), Index finger (F4), thumb finger (F5), and the Palm (P).

2.2 Feature Extraction

After extracting hand components, each component is described using high-order Zernike moments. These moments have high discriminative potential and effectively describe each component. Figure 2 shows the detail of feature extraction and feature selection.

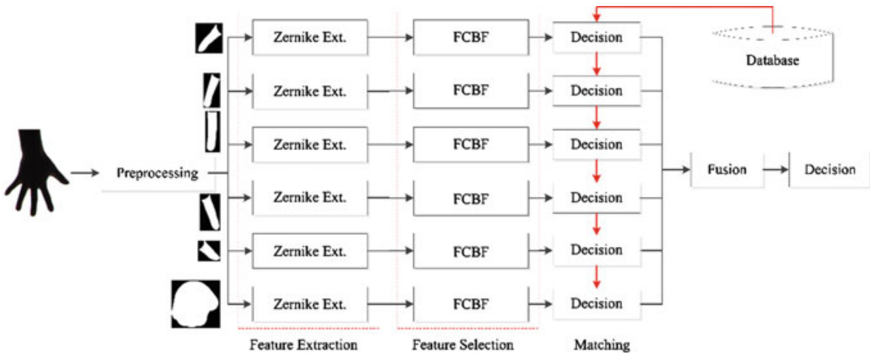

Fig. 2 Detail of feature extraction and feature selection

Zernike moment $Z_{n,m}$ depends on two parameters (n, the order and m, the repetition), its calculation involves a high computational cost [10]. The time complexity of computing a Zernike moment of order n of an image of size $M \times M$ is $O(n^2M^2)$. The number of Zernike moments up to order n with repetition n is $(n/2 + 1)^2$ i.e. the number of high order Zernike moments increases quadratically with their order, for detail consult [4]. Though high-order Zernike moments result in excellent recognition performance, their time and space complexity increases with order.

2.3 Selection of Discriminative Zernike Moments

The number and computational complexity of high-order Zernike moments increase quadratically with their order. The solution of this problem is to select the discriminative Zernike moments. It is a well-known feature selection problem, and many powerful feature selection algorithms have been proposed during the last decade [5], which are mainly based on either filter model or wrapper model. Wrapper algorithms select features involving a certain classifier, which are optimized for that classifier; moreover, their time complexity is high. Filter algorithms discover the discriminant features optimizing some criterion based on their intrinsic properties and are usually fast [5]. Filter algorithms are mainly categorized as supervised (use labels of the instances) and unsupervised algorithms. In our case, labels are known, so for the selection of Zernike moments, we considered three state-of-the-art power filter based supervised algorithms: Fast Correlation-Based Filter (FCBF) [6, 7], Sparse Bayesian Multinomial Logistic Regression (SBMLR) [8] and Spectrum Feature Selection Algorithm (SPEC) [9]. In the following paragraphs, we give an overview of these algorithms.

Fast Correlation-Based Filter (FCBF)
It is a fast correlation-based filter algorithm, which is effective in selecting relevant features and removing redundant features for the classification of high dimensional data. It efficiently and significantly reduces the dimension of a feature space and improves classification accuracy. It operates in two phases: relevance analysis and redundancy analysis. The relevance analysis phase selects the features which are relevant to a target class. After selecting the relevant features, the redundancy analysis phase uses the concept of predominant correlation to discover redundancy among the selected relevant features and selects the predominant features. It gives better performance than both feature weighting (e.g. ReliefF) and subset search (e.g. CFS) algorithms for feature selection in terms of speed, dimensionality reduction and classification accuracy [6, 7].

Sparse Bayesian Multinomial Logistic Regression (SBMLR)
It is based on sparse multinomial logistic regression with Laplace prior that induces sparsity and makes the regularization parameters to be integrated out analytically. It is fully automatic and its space complexity scale only linearly with the number of

model parameters. To determine the model parameters, it uses a simple but efficient training algorithm [8]. It is a kind of subset search algorithm.

Spectrum Feature Selection Algorithm (Spectrum)

In this algorithm, features are evaluated and ranked using a graph spectrum. A set of pair wise instance similarities S is represented as a graph G. Each feature that is consistent with the structure of the graph is assigned a value similar to those features that are close to it on the graph [9]. It is a feature waiting algorithm and ReliefF and Laplacian Score are special cases of this algorithm.

2.4 Pattern Matching

After extracting Zernike moments from hand component and selecting the most discriminative ones, Euclidean distance $d(Q, T_i)$ is computed between the query Q and all enrolment templates T_i in the database. The unknown person with query Q is identified with rank-one (having the smallest distance d) template. Similarly, a decision is made using each hand component, and the final decision is taken using decision based fusion with a majority vote.

3 Results and Discussion

For validation, we used the same dataset that was used in [4]. This dataset was collected from 99 subjects capturing 10 hand images from each subject. The total number of hand image samples is 990.

For evaluation, we randomly divided the 10 samples of each subject in the ratio n:10–n, denoted by (n, 10-n), where n samples were used as enrolment templates (for training) and the remaining samples (10-n) were used for testing. For experiments, we used $n = 6, 5, 4, 3$ and repeated the experiments 30 times for each n. To measure performance, we used commonly used measures: accuracy (the percentage of query images which are correctly identified) and Cumulative Match Characteristic (CMC) curve that is a plot of true match rate versus rank [11].

Tables 1, 2, 3, 4, 5, and 6 shows the identification rates based on F1, F2, F3, F4, F5 and P without and with feature selection as average percentage accuracies together with standard deviation (Acc ± Std) over 30 runs of the system with random selection of enrolment templates and query samples and the numbers of selected features by the four methods for different divisions. For F1 and the divisions (5, 5), (4, 6) and (3, 7), SBMLR gives the best results with only 38 features and FCBF gives the best accuracy for (6, 4) with 55 features in this case. The best identification accuracy for F2 is obtained with FCBF for all divisions, and the numbers of selected features are 50 and 47.

The best accuracy for F3 is also given by FCBF for all divisions with the numbers of selected features 68 and 51. For F4, SBMLR gives the best accuracy with 50 selected features in case of (4, 6) and (3, 7) divisions, whereas

Table 1 Identification rate based on F1 (little finger) only

Method	(6,4)		(5,5)		(4,6)		(3,7)	
	#F	Acc ± Std	#F	Acc ± Std	#F	Acc ± Std	#F	Acc ± Std
NoFS	121	96.57 ± 094	121	95.92 ± 0.66	121	94.70 ± 0.87	121	93.20 ± 1.15
SBMLR	38	96.73 ± 0.90	38	**95.91 ± 0.62**	38	**95.08 ± 0.93**	38	**93.32 ± 0.87**
FCBF	55	**96.99 ± 0.59**	38	92.87 ± 1.02	38	91.76 ± 0.72	38	90.01 ± 1.14
SPEC	55	94.89 ± 0.98	38	91.00 ± 1.03	38	89.14 ± 0.94	38	87.01 ± 1.29

Table 2 Identification rate based on F2 (ring finger) only

Method	(6,4)		(5,5)		(4,6)		(3,7)	
	#F	Acc ± Std	#F	Acc ± Std	#F	Acc ± Std	#F	Acc ± Std
NoFS	121	97.66 ± 0.67	121	97.14 ± 0.66	121	96.64 ± 0.61	121	95.64 ± 0.70
SBMLR	55	98.07 ± 0.54	47	95.79 ± 0.76	47	95.28 ± 0.70	47	93.80 ± 0.77
FCBF	50	**98.25 ± 0.70**	47	**97.85 ± 0.50**	47	**97.32 ± 0.58**	47	**96.17 ± 0.58**
SPEC	55	96.83 ± 0.86	47	95.53 ± 0.73	47	94.41 ± 0.81	47	92.76 ± 0.93

Table 3 Identification rate based on F3 (middel finger) only

Method	(6,4)		(5,5)		(4,6)		(3,7)	
	#F	Acc ± Std	#F	Acc ± Std	#F	Acc ± Std	#F	Acc ± Std
NoFS	121	98.04 ± 0.69	121	97.68 ± 0.63	121	97.01 ± 0.67	121	95.78 ± 0.67
SBMLR	50	97.78 ± 0.61	51	96.01 ± 0.68	51	95.29 ± 0.65	51	93.47 ± 0.86
FCBF	68	**98.72 ± 0.49**	51	**97.91 ± 0.56**	51	**97.65 ± 0.57**	51	**96.70 ± 0.87**
SPEC	60	97.04 ± 0.71	51	95.08 ± 0.89	51	94.22 ± 1.01	51	92.47 ± 0.82

Table 4 Identification rate based on F4 (index finger) only

Method	(6,4)		(5,5)		(4,6)		(3,7)	
	#F	Acc ± Std	#F	Acc ± Std	# F	Acc ± Std	#F	Acc ± Std
NoFS	121	98.47 ± 0.62	121	98.18 ± 0.61	121	97.79 ± 0.64	121	96.89 ± 0.61
SBMLR	50	98.87 ± 0.53	50	96.85 ± 0.59	50	**98.23 ± 0.53**	50	**97.57 ± 0.40**
FCBF	48	**99.02 ± 0.34**	50	**98.33 ± 0.41**	50	97.70 ± 0.5	50	97.40 ± 0.73
SPEC	50	97.31 ± 0.72	50	96.75 ± 0.89	50	96.16 ± 0.73	50	94.56 ± 0.93

Table 5 Identification rate based on F5 (thumb) only

Method	(6,4)		(5,5)		(4,6)		(3,7)	
	#F	Acc ± Std	#F	Acc ± Std	#F	Acc ± Std	#F	Acc ± Std
NoFS	121	90.84 ± 1.43	121	89.17 ± 1.69	121	87.52 ± 1.48	121	84.59 ± 1.14
SBMLR	58	91.68 ± 1.56	58	90.52 ± 1.10	58	**88.69 ± 1.06**	58	85.59 ± 1.20
FCBF	48	**91.60 ± 1.05**	75	**90.69 ± 1.13**	58	88.22 ± 0.99	58	**85.50 ± 1.18**
SPEC	50	88.86 ± 1.42	58	88.06 ± 1.10	58	85.66 ± 1.39	58	82.39 ± 1.30

Table 6 Identification rate based on P (palm) only

Method	(6,4)		(5,5)		(4,6)		(3,7)	
	#F	Acc ± Std	# F	Acc ± Std	#F	Acc ± Std	#F	Acc ± Std
NoFS	256	97.44 ± 0.85	256	96.72 ± 0.81	256	95.85 ± 1.08	256	94.05 ± 0.97
SBMLR	46	98.00 ± 0.74	46	97.50 ± 0.60	46	96.33 ± 0.65	46	**95.38 ± 0.77**
FCBF	46	**98.31 ± 0.60**	41	**98.43 ± 0.56**	46	**97.08 ± 059**	46	91.40 ± 1.05
SPEC	50	98.21 ± 0.46	46	98.18 ± 0.52	46	93.49 ± 0.69	46	95.07 ± 0.840

FCBC results in the best accuracy with 48 and 50 features in case of (6, 4) and (5, 5) divisions, respectively. For the thumb, the best accuracy is obtained using FCBF that selects 48, 75 and 58 features, respectively, for (6, 4), (5, 5) and (3, 7) divisions and SBMLR gives the best accuracy for (4, 6) selecting 58 features. For palm, again FCBF is the winner in case of (6, 4), (5, 5) and (4, 6) with selected features 46, 41 and 46, respectively, whereas in case of (3, 7), SBMLR gives the best accuracy with 46 features. The results discussed so far indicate that overall for all hand components, FCBF emerged out to be the winner for selecting the discriminative higher order Zernike moments.

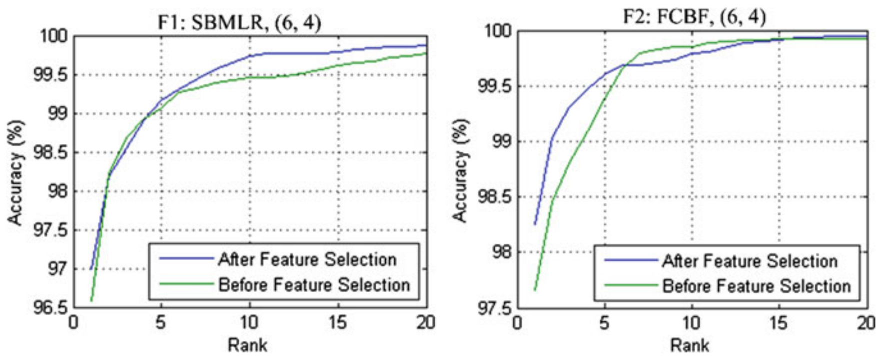

Fig. 3 CMC curves for F1(little finger) and F2(ring finger)

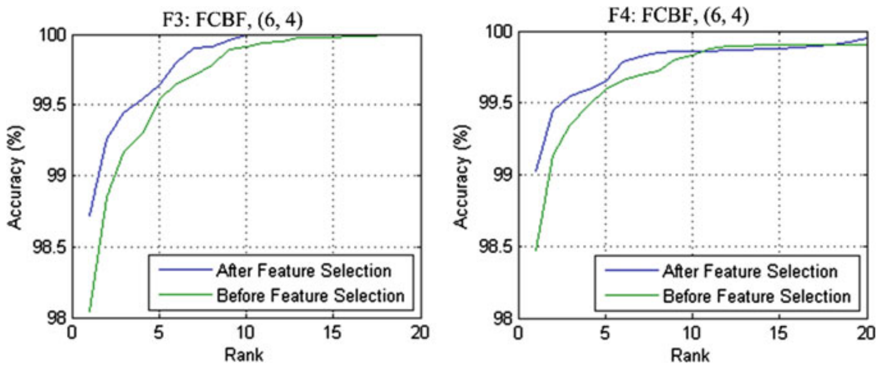

Fig. 4 CMC curves for F3 (middle finger) and F4 (index finger)

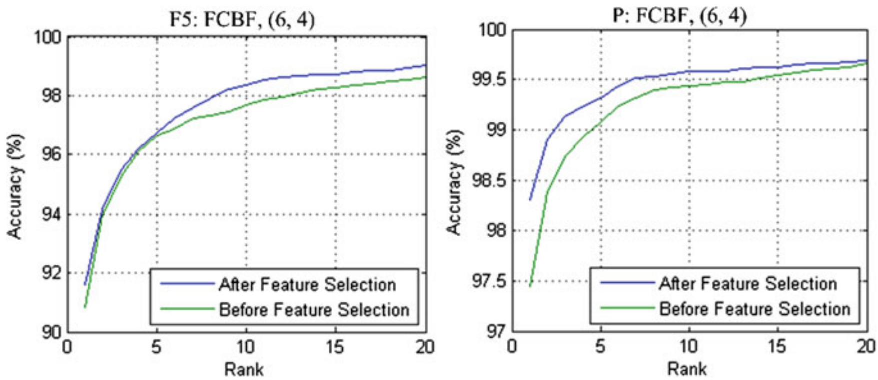

Fig. 5 CMC curves for F5 (thumb finger) and P (palm)

SBMLR occupies the second position in this competition. SPEC gives poor performance in all the cases. The reason why FCBF outperforms other algorithms is that FCBF concentrates not only on discovering the relevance but also in removing the redundancy. It also indicates that all high-order Zernike moments are not relevant, and a large number is redundant from the identification point of view.

Average CMC curves of the best cases for all hand components are shown in Figs. 3, 4, and 5. Overall, the curves corresponding to the systems with feature selection are above those related to the systems without feature selection. These curves indicate that accuracy rates increase with the increase in rank, i.e. the system has stable performance.

The decision level fusion with a majority vote was applied on the matching decisions based on the six hand components, the results are given in Table 7. For each division, fusion was done in two different ways: considering decisions of all components using one method, SBMLR or FCBF, and considering the decisions using SBMLR and FCBF (which result in the best accuracy) for different components. In case of (3, 7) and (4, 6), neither SBMLR nor FCBF gives the best accuracy when either method is used for all components. However, in case for (5, 5) and (6, 4), the best accuracy is obtained when SBMLR and FCBF, respectively, are used for all components. It indicates that as the number of enrolment templates decreases, only one feature selection is not enough for all components. In case of (3, 7), FCBF gives the best accuracy for F1, F4 and P, whereas SBMLR performs best for F2, F3 and F5, the fusion of decisions of F1, F4 and P using FCBF and those of F2, F4 and F5 using SBMLR gives the best results. Almost similar results are for (4, 6).

Table 7 shows that in case of 3 enrolment templates, 861 high order Zernike moments need to be stored for each template without feature selection but with feature selection only 300 of them will be stored. In this way, there will be a reduction of 62 % in the storage space.

Table 7 The results of decision level fusion with majority vote

(*n*, *m*)	F. S. Method	NoFS (861)	With F.S.	
		Acc ± std	#F	Acc ± std
(3, 7)	(1): SBMLR for all components	98.80 ± 0.43	290	98.77 ± 0.46
	(2): FCBF for all components		315	98.40 ± 0.67
	F1(1) + F2(2) + F3(2) + F4(1) + F5(2) + P(1)		300	**98.99 ± 0.58**
(4, 6)	(1): SBMLR for all components	98.75 ± 0.38	290	98.80 ± 0.46
	(2): FCBF for all components		315	98.73 ± 0.57
	F1(1) + F2(2) + F3(2) + F4(1) + F5(2) + P(2)		300	**99.03 ± 0.42**
(5, 5)	(1): SBMLR for all components	98.88 ± 0.39	290	**99.13 ± 0.38**
	(2): FCBF for all components		315	98.89 ± 0.45
	F1(1) + F2(2) + F3(2) + F4(2) + F5(2) + P(2)		298	99.10 ± 0.39
(6, 4)	(1): SBMLR for all components	99.16 ± 0.44	290	99.25 ± 0.33
	(2): FCBF for all components		315	**99.42 ± 0.36**

4 Conclusion

Hand based identification based on high-order Zernike moments is a robust method, but the computation of Zernike moments is time-consuming and their number increases with their order. To select the discriminative Zernike moments, we investigated a number of supervised filter methods. We found that SBMLR, FCBF and SPEC give the acceptable results. Further investigation revealed that only SBMLR and FCBF are the most suitable methods. If the number of enrolment templates is smaller (i.e. 3 or 4), then only one method does not give the best accuracy, in this case both SBMLR and FCBF for different parts result in the best accuracy. Feature selection reduces the number of high-order Zernike moments significantly. Only 300 high-order Zernike moments are discriminative out of 861 when the number of enrolment templates is 3 or 4, which significantly reduce the storage requirements.

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References

1. Duta, N.: A survey of biometric technology based on hand shape. Pattern Recogn. **42**(11), 2797–2806 (2009)
2. Guo, J.M., Hsia, C.H., Liu, Y.F., Yu, J.C., Chu, M.H., Le, T.N.: Contact-free hand geometry-based identification system. Expert Syst. Appl. **39**(14), 11728–11736 (2012)
3. Sharma, S., Dubey, S.R., Singh, S.K., Saxena, R., Singh, R.K.: Identity verification using shape and geometry of human hands. Expert Syst. Appl. **42**(2), 821–832 (2015)
4. Amayeh, G., Bebis, G., Erol, A., Nicolescu, M.: Hand-based verification and identification using palm–finger segmentation and fusion. Comput. Vis. Image Underst. **113**(4), 477–501 (2009)
5. Han, Y., Yang, Y., Zhou, X Co-regularized ensemble for feature selection. In: Proceedings IJCAI-13, (2013)
6. Liu, H., Yu, L.: Feature selection for high-dimensional data: a fast correlation-based filter solution. In: Proceedings of the Twentieth International Conference on Machine Leaning (ICML-03), pp. 856–863, Washington, D.C. (2003)
7. Liu, H., Hussain, F., Tan, C.L., Dash, M.: Discretization: an enabling technique, data mining and knowledge discovery, vol. 6(4), pp. 393–423. Springer, Netherland (2002)
8. Cawley, G.C., Nicola L. C. Talbot, N.L.C., Girolami, M.: Sparse multinomial logistic regression via bayesian L1 regularisation. In: Proceedings of Neural Information Processing Systems (NIPS 2006), pp. 209–216 (2007)
9. Liu, H., Zhao, Z.,: Spectral feature selection for supervised and unsupervised learning. In: Proceedings of the 24th International Conference on Machine Learning (ICML 2007), pp. 1151–1157 (2007)
10. Khotanzad, A., Hong, Y.H.: Invariant image recognition by Zernike moments. IEEE Trans. Pattern Anal. Mach. Intell. **12**(5), 489–498 (1990)
11. Damer, N., Opel, A., Nouak, A.: CMC Curve Properties and Biometric Source Weighting in Multi-Biometric Score-level Fusion. Proc. FUSION **2014**, 1–6 (2014)