A Fingerprint Retrieval System Using Bag of Features of SIFT and SURF

Somashekhar B M[1], Sharath Kumar Y H[1], Ranjith K C[1] and Puneeth P[1]
[1] Maharaja Institute of Technology Mysore
somumtech@gmail.com, sharathyhk@gmail.com, ranjithkc01@gmail.com, puneeth0789@gmail.com

Article Info
Page Number: 1772-1786
Publication Issue:
Vol. 71 No. 4 (2022)

Article History
Article Received: 25 March 2022
Revised: 30 April 2022
Accepted: 15 June 2022
Publication: 19 August 2022

Abstract

In this work, we proposed finger print classification using fusion features of robust SURF and scale and rotation invariant SIFT features. The visual vocabulary feature is created with extracted features. Here we are using Bag of Features (BoF) for generating the vocabulary. Clusters of vocabulary words are generated using k-means clustering. Using kNN, the rank of each training dataset image with query image is found and they are arranged in the order of rank. We finally display top *n* similar images from the order of rank as retrieved images.

Experiments are carried out on the FVC fingerprint dataset and captured image dataset to analyze the effectiveness of the proposed method. It is observed from the experiments that the retrieval results contains more than 50% of recall value in almost all cases when concatenated features are used with BoF classifier for calculating similarity between the query and dataset images in both the kind of datasets.

1. Introduction

Extraction of discriminative and reliable features is crucial for fingerprint retrieval. The texture found in images shows an intense segregating feature for image classification and also for image retrieval. In spite of the fact that there does not exist a formal meaning of surface, it can be comprehended as the essential natives in images whose spatial conveyance makes some visual examples [1]. Accordingly, the objective of a surface element extraction strategy is to make a feature vector that catches the image surface data while saving its substance. By considering that the ridges and valleys of finger prints form a textural pattern, it is then possible to capture discriminatory information through their textural representations. Further, the captured representations in the feature vectors can be indexed and stored for image retrieval purposes. Feature extraction is the component of dimensionality minimization. Principal component analysis (PCA) is the most famous feature extraction method, which wants to find a linear mapping to preserve the total variance. Linear discriminant analysis (LDA) is another frequently used feature extraction method; it seeks an optimal projection space [2].

For nonlinear cases, kernel and manifold learning frameworks have pulled in much consideration and some attractive outcomes have been acquired. Kernel PCA (KPCA) and kernel LDA (KLDA) are the nonlinear expansion versions of PCA and LDA respectively; they first guide the input data into the high-dimensional space through the kernel function, and after that perform the feature extraction method. Locality preserving projections (LPP), locally linear embedding (LLE) and isometric feature mapping are three popular manifold learning algorithms [3]. These algorithms and their extensions have been

effectively utilized as a part of many image processing works. Retrieval is defined as given an input finger print filter out a subset of candidate finger prints for the finer matching by coarsely searching the data base. If one of the retrieved candidates originates from the same finger as the input, the retrieval is successful for this input finger print; otherwise, it is a failure. The percentage of success will be calculated [4].
The continuous classification retrieves fingerprints in the database whose features fall in a neighborhood centered at the input. It usually provides better performance and can balance the efficiency and accuracy more easily than the exclusive classification [5]. Here we are using Bag of Features (BoF) for generating the vocabulary. Clusters of vocabulary words are generated using k-means clustering. Using kNN, the rank of each training dataset image with query image is found and they are arranged in the order of rank. We finally display top *n* similar images from the order of rank as retrieved images.
The dominant local feature extractors are the Scale Invariant Feature Transform (SIFT), and the Speeded-Up Robust Feature (SURF) [6]. The proposed work uses SURFand SIFT features of the fingerprint images for retrieval.

2. Literature Survey

Meraoumia et al., [7] incorporated fingerprint as well as Finger- Knuckle Prints (FKP) for constructing effective multi-modal biometrics systems on the basis of matching score levels as well as image-level fusions. In the current work, the investigators utilized Minimum Average Correlation Energy (MACE) as well as Unconstrained MACE (UMACE) filters along with two correlation plane performance metrics, max peak value as well as peak-to-side lobe ratios, for determining efficacy of the technique. Biggio et al., [8] experimented on various datasets with actual spoof assaults linked to multi-modal authentication systems on the basis of facial features as well as fingerprints. Helder Matos et al., [9] have proposed an approach to identify finger valley and tips by determining the skeleton of the hand, from hand images acquired using a scanner without pegs from 46 individuals. The performance result of 8.7% FAR is reported. The database size is too small for evaluation purpose. Rong-Xiang Hua et al. [10] have designed an image acquisition set up for capturing hand images from 200 users using a digital camera. The image acquisition setup consists of a peg free platform on which the users have to position their hand facing the camera. A recognition method based on shape representation, namely shape contexts and inner-distance shape contexts which is proposed by the authors can handle different hand poses.
Park et al., [11] suggested a novel multi-modal biometrics recognition system using finger prints as well as finger veins. The suggested gadget captures both features concurrently and the device is also minute in size and may be adopted onto mobile devices as well. Fingerprints are recognized through minutia points of ridge areas while finger veins were identified through Local Binary Patterns (LBP) with appearance data of finger region. Gnanasivam & Muttan et al., [12] utilized ear as well as fingerprints for identifying people. A new method of Edge Interaction Point‘s Detection (EIPD) was utilized for determining ear attributes. Bu et al., [13] suggested a new multi-modal biometrics on the basis of several hand attributes, that is palm print, palm veins, palm dorsal veins, finger veins as well as hand geometries. Luo et al., [14] suggested a personal identification model that fused palm print as well as palm vein pattern.

Particular devices were designed to possess Near-Infra-Red (NIR) cameras as well as NIR illumination sources, such that palm prints as well as palm vein data may be obtained in one image concurrently. Osslan Osiris et al., [15] have proposed a verification system based on hand geometry features extracted from hand images acquired using a scanner from 120 individuals. The preprocessed hand image is transformed to wavelet domain and 31 geometrical features are computed to identify users. The nearest neighbor algorithm is applied for classification of the hand image as a genuine or an impostor. Ashok Rao et al. [16] proposed a hand vein biometric for both condition of unimodal as well as multimodal with palmprint. Chetty & Lipton., [17] suggested new local features analyses as well as features level fusion method for detection of tampering as well as forgery for face biometrics based online access control settings. Kanade et al., [18] suggested multi-modal biometric systems based cryptographic key regeneration strategy that joined data from irises as well as faces for obtaining long cryptographic keys possessing great entropies

Chetty et al., [19] suggested a new fusion protocol on the basis of fuzzy fusions of face as well as voice attributes for ascertaining liveness in protected identities authentication systems on the basis of facial as well as vocal biometric features. Goh Kah et al., [20] have identified valley points between adjacent fingers and fingertip points to extract the largest rectangle area lying inside the contour of the finger which is considered as IKP ROI. Finite radon transform which is defined as the summation of image pixel values along a set of lines is applied on IKP to find the ridge let coefficients. Computed coefficients are used to find energy measures, which are considered as IKP features.

Bahareh Aghili et al., [21] Recognition system based on geometrical features of fingers is proposed. Twenty four geometrical features extracted from four fingers are used as features. Anil Jain et al., [22] explored multimodal biometric recognition using fusion of face, fingerprint and hand geometry at score level fusion. Xuebin et al., [23] suggested multi-modal biometrics verification methods on the basis of pixel-level fusions for improving recognition rate of unimodal biometrics as well as for resolving minute sample recognition issue. The investigators utilized two types of biometric methods, palm print as well as face identification. Raghavendra et al., [24] suggested an effective features level fusion strategy which was employed on face as well as palm print scans. The suggested technique was contrasted with Ada Boost and it was proved that the suggested technique outperformed on all accounts. Alsulaiman et al., [25] performed studies for exploring usage of GEP in discovering analytic functions which can act as classifiers in high dimensional haptic features spaces.

Wu et al., [26] suggested a new biometric cryptographic model on the basis of city block distances. Real valued biometric features vectors are initially quantized and later coded into binary strings so that city block distances between two features vector are translated into Hamming distances between two binary strings. Jian-Gang Wang et al., [27] have presented an acquisition setup that acquires the palm print and palm vein images of an individual using two cameras. Nageshkumar et al., [28] have proposed a multimodal biometric system based on face and palm print. U. Jayaraman et al. [29] have proposed an indexing approach using a Kd-tree. Their work is based on feature level fusion which uses the multidimensional feature vector of Iris, Face, Ear, and Signature modalities. Chen & Chandran et al., [30] described a novel technique that utilized entropy-based features extraction procedure along with Reed-Solomon

error correcting codes which can formulate deterministic bit-sequences from outputs of iterative one-way transforms. The method was valuated through three-dimensional face information and is revealed to dependably yield keys of adequate length for 128-bit AES. Wang & Plataniotis., [31] suggested a technique for dynamic generation of cryptographic keys through face biometric signals. The suggested method has its basis in two-dimensional quantization of distance vectors between biometric features as well as pairs of arbitrary vectors. Miguel A et al. [32] proposed a multimodal system based on the hand geometry, palm print and finger print modalities. Different set of rules for feature, score and decision level fusion are proposed. Zheng et al., [33] suggested a lattice mapping based fuzzy commitment technique for generating cryptographic keys from biometric information.
C. Poon et al,. [34] have captured hand images from 170 individuals using a CCD camera without any pegs for hand placement. Valley points between fingers are used as reference points to align the hand image such that the palm region will have minimal rotation and translation errors. Li et al., [35] Gabor transform is used to extract line features from all fingers except the thumb. A hierarchical classification approach is proposed using location and line features of second knuckle print. Location feature is used for coarse level classification, and line features to find the identity of the test image. Experiments conducted on 720 hand images acquired from 72 users report a Rank (1) identification accuracy of 68.8%. Wu et al., [36] have proposed an approach for classifying palm prints extracted from hand image captured from camera into six categories based on the number of the principal lines present, and their intersections.

3. Methodology

Image Retrieval provides a way for search-engines to retrieve query-similar images from abundantly available/accessible digital images based on visual image contents rather than metadata (manual image labelling / manual image annotation) [37].
For image retrieval, there are two steps which include feature extraction and fingerprint retrieval. For feature extraction, we are using the following techniques.

i. Speeded Up Robust Features (SURF)
ii. Scale Invariant Feature Transform (SIFT) and
iii. Concatenation of SURF and SIFT

The experiments are carried out for key point description by using SIFT and SURF separately as well as the concatenation of both the features. In this work the feature extraction using SURF and SIFT retrieval using BoF is discussed.

3.2.1 Feature Extraction

In this proposed method the given manuscript is pre-processed. The features like SIFT and SURF are extracted then clustered by using clustering methods, which described following subsection.

3.2.1.1 Scale Invariant Feature Transform

Scale-Invariant Feature Transform (SIFT) [38][39] is normally used to depict neighborhood locales from a picture in a scale and rotational invariant way. More often than not, SIFT alludes to a two-advance procedure including key points identification (utilizing for instance the Difference of Gaussian (DoG) strategy) and calculation of SIFT descriptors around these key points. The initial step can any way be supplanted by some other technique, for example, Harris indicator or a straight forward standard framework of key points. Given a key point (arranges), its scale (characterizing the zone canvassed by the descriptor in the picture) and the principle over whelming direction of the angle inside that zone, neighborhood slope histograms were inspected in eight ways on a 4 × 4 frame work. A 128-dimensional SIFT descriptor was then framed by amassing the 16 histograms of angles in the frame work. At long last, standardization is frequently applied on the subsequent vector.

The subsequent highlights are known to be scale and turn invariant, which implies that a pivoted and scaled picture ought to give fundamentally the same as SIFT highlights than those figured on the first picture. For characterization errands, it enables more robustness to these changes. Strikingly, on account of standard key point location just, tests yield fundamentally less keypoints than symptomatic documents, which bodes well since key points chiefly respond to venation and edges while manifestations likewise trigger numerous different key points at various scales. The scale space for the j^{th} and $(j+1)^{th}$ octave is shown in figure 4.1. The orientation histograms are relative to the key point orientation as shown in figure 4.2.

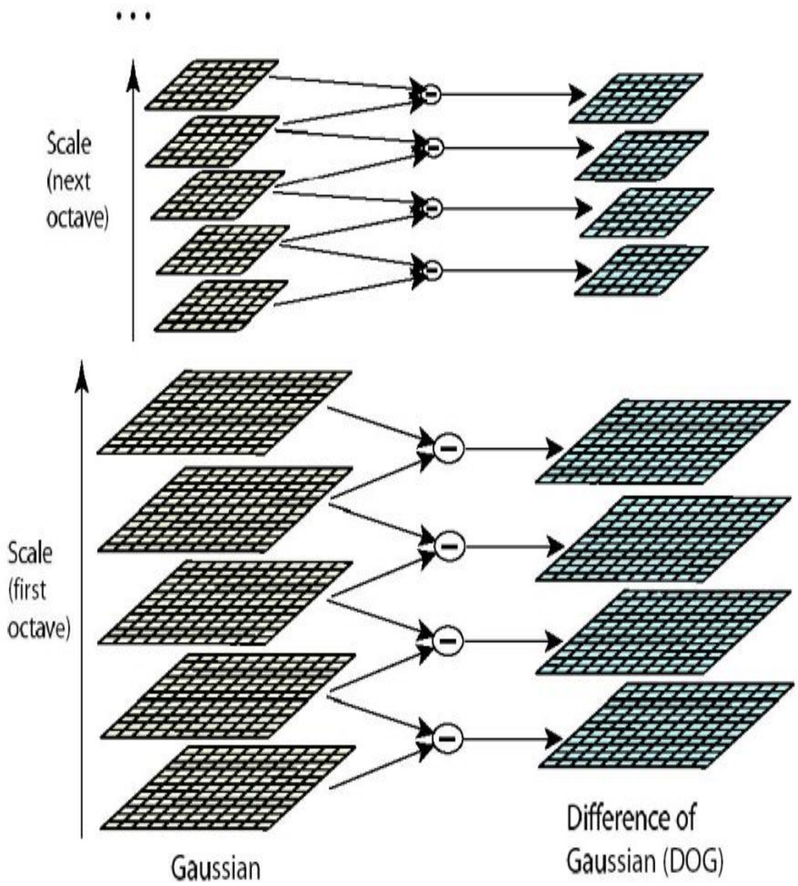

Figure 3.1. The Gaussian convolved images at different scales, and the computation of the Difference-of-Gaussian images

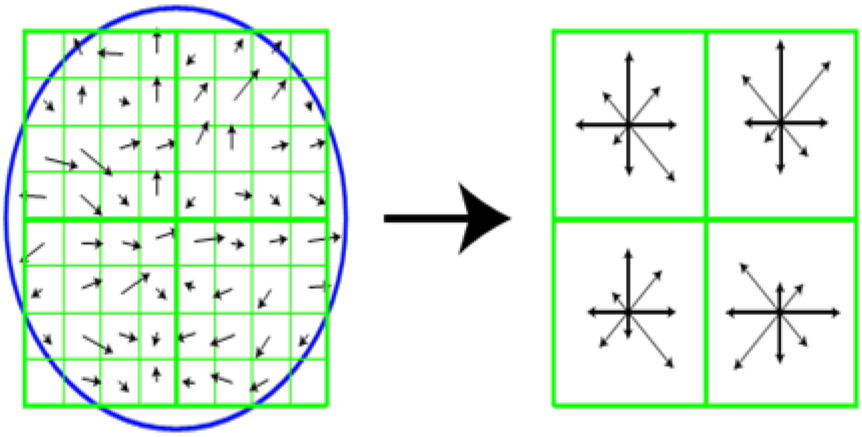

Figure 3.2. Image gradients and Key point descriptor

3.2.1.2 Speeded Up Robust Features

Speeded Up Robust Features (SURF)[40][41] is a scale invariant and rotation invariant interest point detector and descriptor. This algorithm has been used in face and ear [67] based personal identification systems. This method used for recognizing hand written Nandinagari character [50] and is used in the proposed work because it provides good distinct features and is robust to scale, rotation, illumination and view point changes. This algorithm uses a key point detector and descriptor method which is explained as below.

1. **Detecting Keypoints with Fast-Hessian**
2. **Extracting SURF Descriptor**
3. **Orientation Assignment**
4. **Descriptor Components**

3.2.2 Retrieval using Bag of Features

The bag of features provides a concise encoding scheme to represent a large collection of images using a sparse set of visual word histograms. The following steps outline the procedure:

- Select the Image Features for Retrieval
- Create a Bag Of Features
- Index the Images
- Search for Similar Images

In recent past, Bag-of-Features (BoF) model is getting popularity in the area of image retrieval, also known as object retrieval, based on local feature, due to the scalability of retrieval system. In this model, local features are trained to build visual vocabulary in advance. This vocabulary is then used to quantify the local features of image, the similar local features are presented in approximation as tier cluster Centre, as visual word. The quantization of visual word affects the retrieval result strongly in the image retrieval based on local features. Moreover, there is a crucial effect of pre-trained bag-of-features on the quantization of visual word.

In BoF based image retrieval system, to improve the visual word training, a k-means clustering algorithm is used. The distribution of features data on each dimension is analyzed and the distance method, which is used to partition the data space in high-dimensional indexing according to the data distribution adaptively, is combined to obtain the initial clustering centers. Finally the visual vocabulary is obtained by using k-means algorithm to cluster the feature data and train the visual words.

3.2.3 Image Retrieval System

The primary strategies of image recovery in light of sack of words model incorporate two stages, building index table and retrieval. During building index table, images in data set are changed to sets of visual words, and are introduced by visual words in comparing data set. In retrieval process, the question picture is changed to a bunch of visual words from the start, and each visual word is utilized to figure out relative listed pictures in inverted index table.

A generalized diagram of image retrieval using bag of features is shown in Fig. 1.

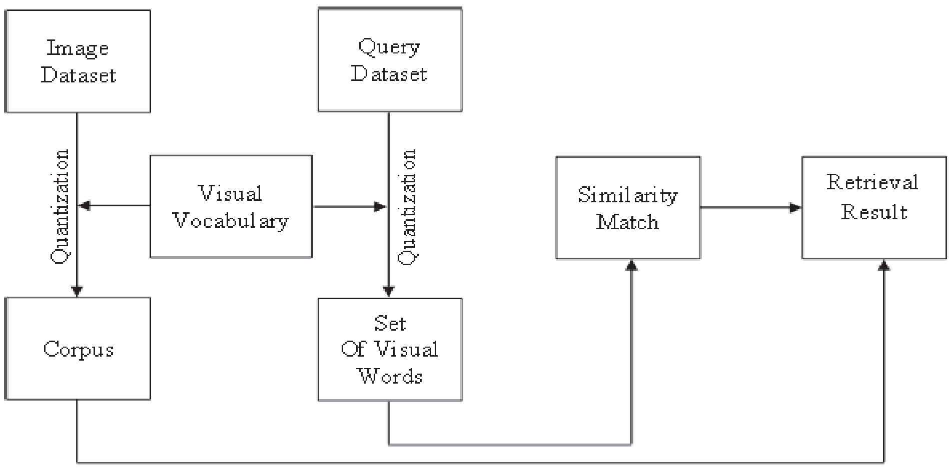

Figure 3.3: Image Retrieval on the basis of Bag of Words

The major process of transform from image to visual words includes the following steps.

Detection features and description of features

SIFT and SURF features are extracted from each image in image database to describe local features.

Training the Visual Vocabulary

In BoF model, the training of visual vocabulary is an important step. This step aims to obtain a space division of features description vector. In the phase of feature quantization phase, feature description vectors which are falling into the same space division should be treated as the same visual word.

Quantization of features

Quantization of features is the process of assigning one feature to one or multiple visual words. To assign an image features to visual word(s), the common way is to search for nearest neighbors among the vocabulary obtained in the vocabulary generation step. Finally the visual word ID is used to index file is generated.

3.2.4 K-Means Clustering

K-means algorithm is popular because of its linear complexity and adaptability to sparse data.

K-means Clustering Algorithm

Step1: Partition objects into k non void subsets

Step2: Compute seed focuses as the centroids of the groups of the current segment (the centroid is the middle, i.e., mean point, of the bunch)

Step3: Assign each object to the group with the closest seed point

Step4: Go back to Step 2, stop when not any more new task

Finally, this algorithm aims at minimizing an objective function knows as squared error function given by:

$$J(V) = \sum_{i=1}^{c} \sum_{j=1}^{c_i} (\| x_i - v_j \|)^2$$

where, '$\|x_i - v_j\|$' represents the Euclidean distance between the x_i and v_j.

'c_i' denotes the number of vocabularies in i^{th} cluster.

'c' shows the number of cluster centers.

3.2.5 Image ranking using k-NN

In this Phase, divided into the training and classification stages. First stage consists only of storing the feature vectors and class labels of the training samples. In second stage k is a user-defined constant, and an unlabeled vector (a query or test point) is classified by assigning the label which is most frequent among the k training samples nearest to that query point. Fig. 3.4 shows the retrieval system diagram used for the experiments.

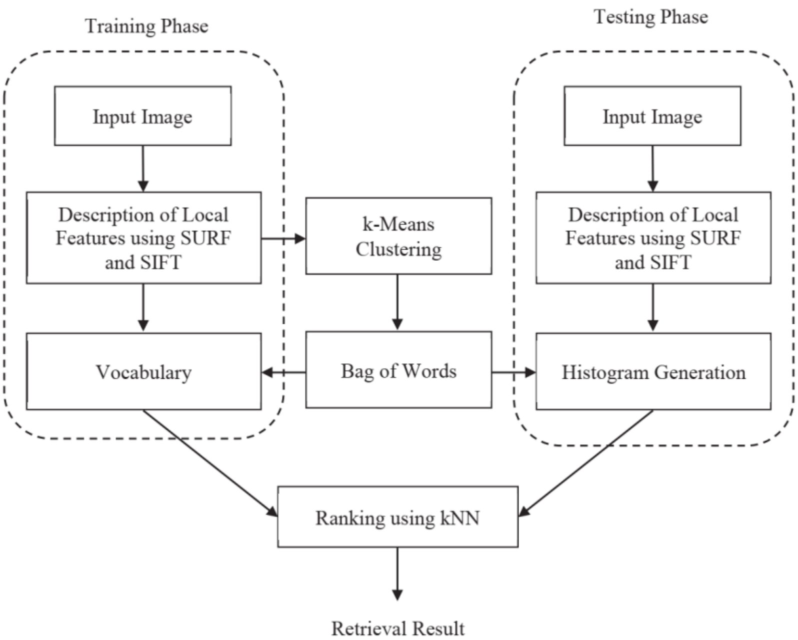

Figure 3.4: Retrieval Flow

3.2.6 Fingerprint Classification using kNN

The training data is mapped into multi-dimensional element space. The feature space is divided into locales in light of the nearest highlight space in the training set. The training data is mapped into multidimensional feature space. The element space is apportioned into locales in view of the classification of the preparation set. A point in the element space is allotted to a specific class in the event that it is the most continuous classification among the K closest preparing information.

In the classification stage, this classification method finds the K nearest named training tests for an unlabeled info test and allocates the information test to the classification that seems most frequently inside the K subset. This classification approach is exceptional with its straight forwardness. It performs well even in dealing with the arrangement tasks with multi-ordered document. It finds the gathering of the k nearest instances in the training set to the test examples. From these k neighbor occurrences a choice is made in light of the power of a specific class. As a result, both the distance metric used to process the closeness of the cases and the number of neighbors considered are the key components in this strategy. With a specific end goal to locate the best value for these parameters a cross-approval strategy can be taken after utilizing the accessible training data [115].

4. Experimental Results

The proposed method is simulated on Intel Core i5, 2.60 GHz processor, 64-bit Operating System in MATLAB 2016a environment. The effectiveness of the method is measured by applying it on standard dataset, i.e. FVC which contains 1483 images of each fingerprint classes.

The experiments have been carried out using various images for testing purpose arbitrarily from the datasets of FVC and captured images. The testing images are selected by randomly. Testing images are excluded from training phase. The results of various test images are shown further. Fig. 4.1 shows the sample dataset images used. Fig. 4.2 is showing the sample query and retrieved images. Following performance measurement equations are used to analyze the results:

Precision (P) = True Positives / (True Positives + False Positives) (2.10)

Recall (R) = True Positives / (True Positives + Missed) (2.11)

The result analysis of FVC dataset images and captured image dataset is shown in Table 4.1 to 4.4. Table 4.1 shows the precision and recall values on FVC dataset, when SIFT, SURF and fusion features are used without applying classification phase. Euclidean distance is used to rank the similar images. Table 4.2 shows the precision and recall values on FVC dataset, when SIFT, SURF and fusion features are used after applying KNN classifier. Retrieval results are obtainedusing BoF classifier to rank the similar images. Table 4.3 shows the precision and recall values on captured image dataset, when SIFT, SURF and fusion features are used without applying classification phase. Euclidean distance is used to rank the similar images. Table shows the precision and recall values on captured image dataset, when SIFT, SURF and fusion features are used after applying

KNN classifier. Retrieval results are obtained using BoF classifier to rank the similar images.

(c) (b)

Figure 4.1: Sample images from the dataset used; a) FVC2002, b) FVC2004 and c) Captured

(a)

Figure 4.2: a) Query fingerprint image and b) retrieved similar images

Table 4.1 and 4.2 gives the experiment results on FVC dataset images. Table 4.3 and 4.4 gives the experiment results on captured image dataset. First column shows the fingerprint image used as a query image for retrieval. Next four columns represents the results when SURF and SIFT descriptors are used independently. Next two columns represent the retrieval results when SURF and SIFT features are concatenated. The last two columns represent the results of BoF classifier used with concatenated features. Table 4.1 shows the results without using classification before retrieval phase. Table 4.2 shows the results of retrieval after applying classification results as discussed in chapter 4. Table 4.3 and 4.4 gives the experiment results on captured image dataset similar to Table 4.1 and 4.2.

Table 4.1: Retrieval Result analysis of FVC dataset images without performing classification phase

Dataset	SURF with BoF		SIFT with BoF		Concatenation		Bag of Features	
	Precision	Recall	Precision	Recall	Precision	Recall	Precision	Recall
101_1	0.40	0.57	0.40	0.57	0.60	0.86	0.50	0.71
102_2	0.50	0.71	0.50	0.71	0.50	0.71	0.50	0.71
103_3	0.40	0.57	0.40	0.57	0.50	0.71	0.40	0.57
104_4	0.30	0.43	0.40	0.57	0.20	0.29	0.40	0.57
105_5	0.40	0.57	0.30	0.43	0.50	0.71	0.60	0.86

106_6	0.50	0.71	0.60	0.86	0.40	0.57	0.30	0.43
107_7	0.30	0.43	0.30	0.43	0.30	0.43	0.40	0.57
108_8	0.40	0.57	0.40	0.57	0.50	0.71	0.60	0.86

Table 4.2: Retrieval Result analysis of FVC dataset images after performing classification phase

Dataset	SURF with BoF		SIFT with BoF		Concatenation		Bag of Features	
	Precision	Recall	Precision	Recall	Precision	Recall	Precision	Recall
101_1	0.50	0.71	0.60	0.86	0.60	0.86	0.70	1.00
102_2	0.50	0.71	0.60	0.86	0.60	0.86	0.50	0.71
103_3	0.50	0.71	0.70	1.00	0.50	0.71	0.60	0.86
104_4	0.60	0.86	0.30	0.43	0.40	0.57	0.40	0.57
105_5	0.30	0.43	0.40	0.57	0.50	0.71	0.70	1.00
106_6	0.50	0.71	0.50	0.71	0.60	0.86	0.60	0.86
107_7	0.60	0.86	0.60	0.86	0.50	0.71	0.70	1.00
108_8	0.60	0.86	0.50	0.71	0.60	0.86	0.60	0.86

Table 4.3: Retrieval Result analysis of Captured Image dataset images without performing classificationphase

Dataset	SURF with BoF		SIFT with BoF		Concatenation		Bag of Features	
	Precision	Recall	Precision	Recall	Precision	Recall	Precision	Recall
finger163_2	0.20	0.67	0.20	0.67	0.20	0.67	0.20	0.67
finger18_3	0.10	0.33	0.20	0.67	0.20	0.67	0.20	0.67
finger1_1	0.20	0.67	0.10	0.33	0.20	0.67	0.20	0.67
finger27_1	0.10	0.33	0.10	0.33	0.10	0.33	0.20	0.67

Table 4.4: Retrieval Result analysis of Captured Image dataset images after performing classification phase

Dataset	SURF with BoF		SIFT with BoF		Concatenation		Bag of Features	
	Precision	Recall	Precision	Recall	Precision	Recall	Precision	Recall
finger163_2	0.20	0.67	0.20	0.67	0.20	0.67	0.20	0.67
finger18_3	0.20	0.67	0.20	0.67	0.20	0.67	0.20	0.67
finger1_1	0.20	0.67	0.10	0.33	0.30	1.00	0.30	1.00
finger27_1	0.10	0.33	0.10	0.33	0.10	0.33	0.20	0.67

3. Concluding Remarks

The retrieval system proposed in this chapter demonstrates the use of fusion features using robust SURF and scale and rotation invariant SIFT features. The feature vector, generated by processing training images is given as an input to the BoF classifier to rank the similarity of dataset images and *n* most similar images are displayed as a result.

Experiments are carried out on the FVC fingerprint dataset and captured image dataset to analyze the effectiveness of the proposed method. FVC dataset if mainly used for the purpose of fingerprint verification. As it contains eight image of each human finger, it is suitable for evaluating fingerprint retrieval. Fingerprint images are arbitrarily considered for testing. The test-set of the images is excluded from training-set. FVC dataset used for the experiments, contains total 1483 fingerprint image. The dataset of captured images contains four images of one human finger. This dataset used for the experiments, contains total 366 fingerprint images. The result analysis is done by displaying minimum n(n=10) most similar images as a retrieval result. As, the number of images per fingerprintis less than minimum similar images to be displayed, recall measurement features the actual efficiency of the system. It is observed from the experiments that the retrieval results contains more than 50% of recall value in almost all cases when concatenated features are used with BoF classifier for calculating similarity between the query and dataset images in both the kind of datasets. This recall value is found better than the few fingerprint retrieval systems presented in the literature.

References

1. Han, Junwei, Xiang Ji, Xintao Hu, Dajiang Zhu, Kaiming Li, Xi Jiang, Guangbin Cui, Lei Guo, and Tianming Liu. "Representing and retrieving video shots in human-centric brain imaging space." IEEE Transactions on Image Processing 22, no. 7 (2013): 2723-2736.
2. Gu, Xingjian, Chuancai Liu, Sheng Wang, Cairong Zhao, and Songsong Wu. "Uncorrelated slow feature discriminant analysis using globality preserving projections for feature extraction." Neurocomputing 168 (2015): 488-499.
3. Zheng, Feng, Zhan Song, Ling Shao, Ronald Chung, Kui Jia, and Xinyu Wu. "A semi-supervised approach for dimensionality reduction with distributional similarity." Neurocomputing 103 (2013): 210-221.
4. Iancu, Ion, and Nicolae Constantinescu. "Intuitionistic fuzzy system for fingerprints authentication." Applied Soft Computing 13, no. 4 (2013)
5. Abdullahi, Sani M., and Hongxia Wang. "Robust enhancement and centroid-based concealment of fingerprint biometric data into audio signals." Multimedia Tools and Applications (2017): 1-30.
6. Awad, Ali Ismail. "Fingerprint local invariant feature extraction on GPU with CUDA." Informatica 37, no. 3 (2013): 279.
7. Meraoumia, A, Chitroub, S & Bouridane, A 2012, ‗Multimodal biometric person recognition system based on fingerprint & fingerknuckle- print using correlation filter classifier', In Communications (ICC), 2012 IEEE International Conference on IEEE, pp. 820-824.
8. Biggio, B, Akhtar, Z, Fumera, G, Marcialis, GL & Roli, F 2012, ‗Security evaluation of biometric authentication systems under real spoofing attacks', IET biometrics, vol.1,no. 1, pp.11-24
9. Helder Matos, Helder P. Oliveira, Filipe Magalhaes,"Hand-Geometry Based Recognition System A Non Restricted Acquisition Approach", International conference on image analysis and recognition (ICIAR 2012, vol. 7325, Lecture Notes in Computer Science, pp 38-45,2012.
10. Rong Xiang Hua, Wei Jia, David Zhang, Jie Gui, Liang-Tu,"Hand shape recognition based on coherent distance shape contexts", Pattern Recognition, no. 45, pp 3348–3359, 2012.

11. Park, YH, Tien, DN, Lee, EC, Park, KR, Lee, EC, Kim, SM & Kim, HC 2011, ‗A multimodal biometric recognition of touched fingerprint and finger-vein', In Multimedia and Signal Processing (CMSP), 2011 International Conference on IEEE, vol. 1, pp. 247-250.
12. Gnanasivam, P & Muttan, S 2011, ‗Ear and fingerprint biometrics for personal identification', In Signal Processing, Communication, Computing and Networking Technologies (ICSCCN), 2011 International Conference on IEEE, pp. 347-352.
13. Bu, W, Zhao, Q, Wu, X, Tang, Y & Wang, K 2011, ‗A novel contactless multimodal biometric system based on multiple hand features', InHand-Based Biometrics (ICHB), International Conference on IEEE, pp. 1-6.
14. Luo, N, Guo, Z, Wu, G & Song, C 2011, ‗Joint palmprint and palmvein verification by dual competitive coding', In Advanced Computer Control (ICACC), 2011 3rd International Conference on IEEE, pp. 538-542.
15. Osslan Osiris Vergara Villegas, Humberto de Jesus Ochoa Dominguez, Vianey Guadalupe Cruz Sanchez, Leticia Ortega Maynez and Hiram Madero Orozco, "Biometric Human Identification of Hand Geometry Features Using Discrete Wavelet Transform", Discrete Wavelet Transforms - Biomedical Applications, Prof. Hannu Olkkonen (Ed.), ISBN: 978-953-307-654-6,2011.
16. Ashok Rao, M Imran, R Ragavendra, Hemantha Kumar G,: Multibiometrics: Analysis and Robustness of Hand Vein and Palm Print Combination Used for Person Verification, International Journal for Emerging Trends in Engineering and Technology (IJETET), (2011).
17. Chetty, G & Lipton, M 2010, ‗Multimodal feature fusion for video forgery detection. In Information Fusion (FUSION), 2010 13th Conference on IEEE, pp. 1-7.
18. Kanade, S, Petrovska-Delacrétaz, D & Dorizzi, B 2010, ‗Obtaining cryptographic keys using feature level fusion of iris and face biometrics for secure user authentication', In Computer Vision and Pattern Recognition Workshops (CVPRW), 2010 IEEE Computer Society Conference on IEEE, pp. 138-145.
19. Chetty, G 2010, ‗Biometric liveness checking using multimodal fuzzy fusion', In Fuzzy Systems (FUZZ), 2010 IEEE International Conference on. IEEE, pp. 1-8.
20. Goh Kah Ong Michael, Tee Connie, Andrew Teoh Beng Jin, "An innovative contactless palm print and knuckle print recognition system", Pattern Recognition Letters, 31, pp 1708–1719, 2010.
21. Bahareh. Aghili, Hamed.Sadjedi, "Personal Identification/Verification by Using Four Fingers", 3rd International Congress on Image and Signal Processing (CISP2010), 16th-18th October 2010, Yantai China, IEEE ,pp 2619-2623, 2010.
22. Xuebin, X, Deyun, Z, Xinman, Z, Hongyu, L, Xi, C & Cailing, W 2009, ‗NSCTWavelet: An efficient method for multimodal biometric recognition based on pixel level fusion', In Industrial Electronics, 2009. ISIE 2009. IEEE International Symposium on IEEE, pp. 1893-1898.
23. Raghavendra, R, Dorizzi, B, Rao, A & Hemantha, KG 2009, ‗PSO versus AdaBoost for feature selection in multimodal biometrics', In Biometrics: Theory, Applications, and Systems, 2009. BTAS'09. IEEE 3rd International Conference on IEEE, pp. 1-7.
24. Alsulaiman, F, Sakr, N, Valde, JJ, El Saddik, A & Georganas, ND 2009, ‗Feature selection and classification in genetic programming', Application to haptic-based biometric data. In

Computational Intelligence for Security and Defense Applications, 2009. CISDA 2009. IEEE Symposium on IEEE, pp. 1-7.
25. Wu, X, Wang, P, Wang, P & Xu, Y 2009, ‗Biometric cryptographic key generation based on city block distance', In Applications of Computer Vision (WACV), 2009 Workshop on IEEE, pp. 1-5.
26. Garcia-Baleon, HA, Alarcon-Aquino, V, Starostenko, O & Ramirez- Cruz, JF 2009, Bimodal Biometric System for Cryptographic Key Generation Using Wavelet Transforms. In Computer Science (ENC),2009 Mexican International Conference on IEEE, pp. 185-196.
27. Jian-Gang Wang, Wei-Yun Yau, Andy Suwandy, "Feature Level Fusion of Palmprint and palm vein for person recognition based on a "Junction Point" Representation", International conference on image processing, Cario, Egypt, pp 253-256, 2009.
28. Nageshkumar. M, Mahesh.PK and M.N. Shanmukha Swamy,"An Efficient Secure Multimodal Biometric Fusion Using Palmprint and Face Image", IJCSI-International Journal of Computer Science Issues, vol. 2, pp 49-53, 2009.
29. U. Jayaraman, S. Prakash, P. Gupta, "Indexing multimodal biometric databases using kd-tree with feature level fusion", Proceedings of 4th International Conference on Information Systems Security, Springer-Verlag, pp 221– 234, 2008.
30. Chen, B & Chandran, V 2007, ‗Biometric based cryptographic key generation from faces', In Digital Image Computing Techniques and Applications, 9th Biennial Conference of the Australian Pattern Recognition Society on IEEE, pp. 394-401.
31. Miguel A. Ferrer, Aythami Morales, Carlos M. Travieso, Jesws B. Alonso" Low Cost Multimodal Biometric identification System Based on Hand geometry, Palm and Fingerprint Texture", 41st Annual IEEE International Carnahan Conference on Security Technology, 2007
32. Wang, Y & Plataniotis, KN 2007, ‗Fuzzy vault for face based cryptographic key generation', In Biometrics Symposium, IEEE, pp. 1-6.
33. Zheng, G, Li, W & Zhan, C 2006, ‗Cryptographic key generation from biometric data using lattice mapping', In Pattern Recognition, 2006. ICPR 2006. 18th International Conference on IEEE, vol. 4, pp. 513- 516.
34. C. Poon, D.C.M. Wong, H.C. Shen, "A New Method in Locating and Segmenting Palmprint into Region of Interest", Proceedings of the 17th International Conference on Pattern Recognition, ICPR 2004, vol. 4 pp 533 - 536, August 2004.
35. Qiang Li, Zhengding Qiu, Dongmei Sun, Jie Wu,"Personal Identification Using Knuckleprint" Advances in Biometric Person Authentication, 5th Chinese Conference on Biometric recognition, Signobiometrics 2004 Proceedings, pp 680-689, 2004.
36. X. Wu, D. Zhang, K. Wang, B. Huang, "Palmprint classification using principle lines", Pattern Recognition, vol. 37, No 10, pp 1987-1998, Oct 2004.
37. Khan, Shaziya, and Shamaila Khan. "An Efficient Content based Image Retrieval: CBIR." International Journal of Computer Applications 152, no. 6 (2016).
38. Zhou, Wengang, Houqiang Li, Yijuan Lu, and Qi Tian. "SIFT match verification by geometric coding for large-scale partial-duplicate web image search." ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM) 9, no. 1 (2013): 4.

39. Panchal, P. M., S. R. Panchal, and S. K. Shah. "A comparison of SIFT and SURF." International Journal of Innovative Research in Computer and Communication Engineering 1, no. 2 (2013): 323- 327.
40. Dharani, T., and I. Laurence Aroquiaraj. "A survey on content based image retrieval." In Pattern Recognition, Informatics and Mobile Engineering (PRIME), 2013 International Conference on, pp. 485-490. IEEE, 2013.
41. Yu, Jing, Zengchang Qin, Tao Wan, and Xi Zhang. "Feature integration analysis of bag-of-features model for image retrieval." Neurocomputing 120 (2013): 355-364.