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EXPERIMENTS ON IRIS CLASSIFICATION AND RETRIEVAL WITH FIXED NUMBER OF SURF KEYPOINTS AND TEXTURE FEATURES

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The paper discusses the results obtained in some experiments made on iris images classification using texture features and SURF (Speeded Up Robust Features) keypoints. We used a method proposed by us, which we named DENOL, that generates a fixed number of SURF keypoints for each image in the dataset, by adapting for each image, in SURF keypoints generation process, the Hessian threshold parameter. To obtain texture features we have used four MATHLAB different programs. The experiments used two well-known datasets, UBIRIS and UPOL. The matching procedure for two images is based on the nearest neighbour ratio equation. The results obtained are comparable with those provided by Masek implementation of Daugman's method.

Keywords: SURF keypoints, iris classification, iris recognition, Daugman method, Masek implementation

1. INTRODUCTION

Nowadays, increasingly accurate biometric identification and security systems that rely on biometrics are more and more numerous. Many times, verification and confirmation of identity is done automatically, based on the biometric characteristics of the current person. A person's identity is authenticated by comparing some biometric features acquired at a given time with other previously acquired features of the same person (associated with the respective person). In biometrics, an extremely well-known measure is represented by the iris. For example, a person's iris who intends to access a certain location is compared to that of all persons whose access is authorized.

The state-of-the-art of the methods and current direction research regarding the problem of iris recognition are presented in [1]. The problems that may occur in the process of image acquisition (non-uniform illumination, missing information) can be resolved with techniques using keypoint detectors for iris characterization. They have the advantage of not requiring a segmentation procedure of the iris. Techniques like SIFT or SURF (that use keypoints) are successfully employed in [2–4], yielding a significant gain in recognition accuracy. Most significant iris information can be obtained analyzing the iris texture. In [5] it is proposed a method based on three feature extraction techniques: DSIFT, HOG and DCT. The obtained results show that the performance of the Iris Recognition System has increased significantly, due to the matching score combination rules.

In this paper, we present the results of some experiments on the classification and retrieval of images containing irises using SURF descriptors, as well as texture features. One or more sets of texture features were used to select one or more subsets of images. The final subset is then processed using SURF keypoints. These experiments are part of a broader goal that aims at developing a method in several steps, one that also uses SURF keypoints and texture features, obviously with results superior to those obtained when using only SURF keypoints or texture features.

Section 2 presents three collections containing the iris images used in our experiments. The methods of obtaining texture features and SURF keypoints are describe in Section 3. Texture features were generated using four different methods for the image collections used in the experiments. A developed method, DENOL, is also presented, allowing the generation of a fixed number of keypoints, or of a number of descriptors in a set interval. In this way, a similar number of SURF features was generated for each image in the collection. The image classification and retrieval method using texture features and SURF descriptors are presented. Section 4 outlines the results of the experiments. The conclusions and the directions we will follow in future research are discussed in Section 5.

2. COLLECTIONS OF DATA USED IN EXPERIMENTS

Three collections containing iris images were used in the experiments, the first two corresponding to the UPOL collection, a variant established by automatic segmentation and a normalized variant. The third collection is a subset of 1205 normalized images of the UBIRIS collection.

The UPOL dataset was created at the Palacky University of Olomouc [6,7]. The collection contains 384 iris images for 64 persons: 6 iris images for each person, three for each eye. The iris images have the same size, 576 × 768 pixels in .PNG format (Fig. 1 (a)) and black homogeneous background. UBIRIS dataset is in fact a part of the UBIRISv1 database [8,9], segmented and normalized [10]. The resulted images have 36,.000 pixels (360 × 100) in .jpg format. There are 5 iris images for each of the 241 persons.

Our experiments were conducted on three versions for UPOL dataset, the first one being the original unsegmented version [Fig. 1(a)]. The second is manually segmented [Fig. 1(b)]. The third version is a standardized segmented version [Fig. 1(c)].

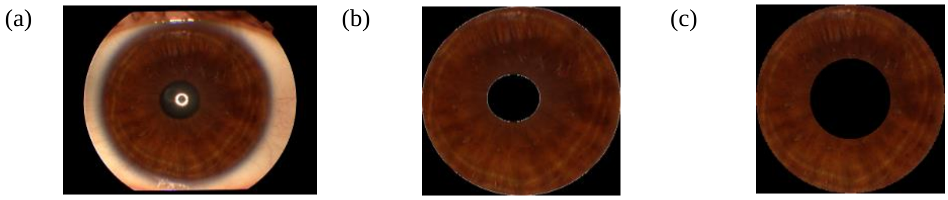

Fig. 1. UPOL iris images – (a) original; (b) – manually segmented; (c) – standardized.

The results obtained using the dataset containing the original unsegmented images are inferior to those obtained for manual and standardized segmented datasets. The results obtained for the last two datasets are quite similar, the difference being less than 1%.

In this paper we present the standardized segmented dataset with texture features. For all irises from the 404 × 404 size database, the dataset provides images containing an annular region of the iris with the same size. SURF features are generated on the normalized version of the standardized segmented dataset.

3. FEATURE GENERATION, CLASSIFICATION AND IMAGE RETRIEVAL

3.1. TEXTURE FEATURES

3.1.1. GENERATING TEXTURE FEATURES

The generation of texture features was done using Matlab routines for four different methods, DTCWT, dddtree2 [11,12], GLCM, dddtree2 and LBP [13,14].

Using each of the above methods, two sets of features were calculated; the first obtained using the RGB color images, concatenating the texture features extracted from each color component. The second set is obtained from the grayscale image of the iris. Since the experiments showed that the results for RGB are, on the average, superior to those for gray, we choose to present only the results obtained for RGB. For each image, a vector with "n" components is generated (n depending on the chosen method, as well as on the corresponding parameters).

3.1.2. IMAGE CLASSIFICATION AND RETRIEVAL USE TEXTURE FEATURES

For a test image, the distances from the vector corresponding to this image to the vectors corresponding to the images in the training set are calculated, and subsequently sorted in ascending order. In classification experiments, the image located at the smallest distance is considered the similar image. In the case of retrieval, the first "n" images from the sorted ones are considered. Three distances, Manhattan, Euclidian and Canberra, were used in the experiments.

3.1.3. GENERATION OF DESCRIPTORS SURF, DENOL ALGORITHM

The SURF descriptors are generated using a very known algorithm [15]. The computations, performed using the OpenCV library [16], were done in four stages, generating, depending on the image, a different number of keypoints. For each keypoints, a feature vector with 128 elements is calculated.

Using the same set of parameters for all images in a dataset generates very few descriptors for some images and a very large number for others. This is inconvenient for two reasons:

– the images for which extremely few descriptors (keypoints) are generated either cannot be classified (they may have 0 descriptors), or are most often incorrectly classified.

– the time to search for matches keypoints between two images being directly proportional to the number of keypoints of the two images, it is therefore much higher for images for which extremely many descriptors have been generated.

We have been looking for a solution to this problem. There exists a manual solution, permitting generation of new descriptors for images for which an excessively large number of SURF descriptors are obtained, by choosing an appropriate set of parameters during the generation process, through trials. This approach is expensive from a practical point of view, as it does require much time allocated by the user. Therefore, we approached the problem from another perspective, looking for an automated solution.

By using different values for the contrast Threshold parameter, we get a different number of SURF descriptors, but we cannot know *a priori* how many descriptors we will get. We solved this problem by developing the DENOL method, presented in detail in [17].

In DENOL, to generate a fixed number of keypoints for an image, an iterative algorithm that computes a predetermined number of SURF keypoints by adjusting the threshold parameters hT is used. The algorithm stops either when it finds a value for parameter cT, for which the number of keypoints generated is in the [N-ΔN, N+ΔN] range, or when the maximum number of iterations is obtained.

3.1.4. CLASSIFICATION AND RETRIEVAL OF IMAGES USING SURF DESCRIPTORS

In a first step, all images from the dataset are processed to compute SURF descriptors. Using a matching procedure and the associated descriptors, two images are compared, as described in detail in [18] and conciselyd below.

Considered I as a test image with m feature vectors, (the m keypoints being given by SURF for each keypoint), a 128-dimensional feature vector denoted t_i is computed. Find all matching points between test image I and each image J in the training data set D. Each iris image from the training set contains n feature vectors $d_1, d_2, \ldots, d_n$ (n depending on each image J). The keypoints match between image I and each image J is determined calculating the distances between each test feature vector t_i and all feature vectors d_k of image J. The distances used to compare the two feature vectors $t = (t_1, t_2, \ldots, t_m)$ and $d = (d_1, d_2, \ldots, d_n)$ are Euclidean and Manhattan distances. A test feature vector t_i is considered to match a feature vector d_k of image J if the distance from t_i to d_k is less than the distance between t_i to the next nearest feature vector of image J multiplied by a parameter denoted by T_A:

$$\mathrm{dist}(t_i, d_k) \le T_A \mathrm{dist}(t_i, d_i) \ \textit{where} \ \mathrm{dist}(t_i, d_j) \le_A \mathrm{dist}(t_i, d_p) \forall \ p = 1, \ldots n, p \ne j \quad (1)$$

For image classification, keypoints of a test image are calculated, corresponding to those of the images in the training set. Label the image from the training set with the maximal number keypoints corresponding to those of the test image. If there is more than one image with this property, then the image at the smallest distance from the test image is assigned and calculated as the average of the distances between the matched keypoint locations.

In the first stage of the experiments, we tested the Manhattan, Euclidean and Canberra distances. The results obtained by applying the Manhattan distance, which gave the best results for a short computation time, are presented.

4. RESULTS

In all experiments, one image from the collection was used successively as a test image, while the others were considered as a training set.

4.1. RESULTS OBTAINED USING TEXTURE FEATURES

In the experiments performed for the three collections (the UPOL collection in the automatically segmented and normalized versions, and the third collection in a subset of 1205 normalized images of the UBIRIS collection) using texture features, we considered the first element and, respectively, the first 5, 10, 20, 30, 40, 50, 60 and 75 elements found (applying one of the Manhattan, Euclidean, Canberra distances). The following tables list the number of images that do not have a similar image in the first 1,5,10, etc. images found. One observation is that the results for RGB are, on the average, superior to those for gray, therefore only the results obtained for RGB will be presented below. The results obtained for the automatically segmented UPOL collection, RGB, using the three distances, are presented in the following table:

Table 1

Results for automatically segmented UPOL – RGB

	1	**5**	**10**	**20**	**30**	**40**	**50**	**60**	**75**
GLCM-Manhattan	7	5	4	2	1	1	1	1	1
GLCM- Euclidian	8	5	4	4	3	1	1	1	1
GLCM- Canberra	5	3	3	1	1	1	1	1	1
dddtree2-Manhattan	4	1	1	1	1	1	0	0	0
dddtree2- Euclidian	3	2	1	1	1	1	1	1	1
dddtree2- Canberra	8	2	2	1	1	0	0	0	0
DTCWT – Manhattan	2	1	1	1	1	1	0	0	0
DTCWT – Euclidian	2	2	1	1	1	1	1	1	1
DTCWT – Canberra	3	2	0	0	0	0	0	0	0
LBP – Manhattan	11	3	2	2	1	1	0	0	0
LBP – Euclidian	20	10	7	3	1	1	1	0	0
LBP – Canberra	9	3	3	2	1	1	1	0	0

Analysis of the above results leads to following two observations. First, the results for Euclidian are, on the average, inferior to those obtained using the Manhattan distance. For reasons of space, we choose to present only the results obtained using the Canberra and Manhattan distances. Similarly with the results presented in Table 1, on the average, the best results are those obtained for DTCWT, followed closely by those obtained using dddtree2 features. For automatically segmented UPOL, for RGB, the best classification results are obtained using DTCWT and Manhattan distance. However, if we refer to the results obtained in retrieval, the best are those obtained using DTCWT and the Canberra distance.

The results obtained for the normalized UPOL collection, RGB, are shown in the following table:

Table 2

Normalized results UPOL – RGB

	1	**5**	**10**	**20**	**30**	**40**	**50**	**60**	**75**
DTCWT – Manhattan	11	6	4	3	2	2	2	2	1
DTCWT – Canberra	13	3	3	3	2	2	1	1	1
LBP – Manhattan	34	11	5	1	1	1	1	0	0
LBP – Canberra	58	20	8	3	2	1	0	0	0

	1	5	10	20	30	40	50	60	75
GLCM-Manhattan	13	7	6	3	2	1	1	1	1
GLCM- Canberra	15	9	7	2	2	1	1	1	1
Dddtree2-Manhattan	13	5	3	2	1	1	1	1	1
Dddtree2-Canberra	23	11	5	4	2	1	1	1	1

The results obtained for the UPOL collection containing normalized images are inferior to those obtained in the experiments performed on the automatically segmented collection. This can be explained, among others, by the fact that the images were resized. The best results, both in classification and retrieval, are also obtained for DTCWT. The most modest results are obtained for LBP.

We performed the same experiments for the UBIRIS sub-collection, the results being shown in Table 3.

Table 3

UBIRIS results – RGB

	1	5	10	20	30	40	50	60	75
DTCWT – Manhattan	31	20	13	10	7	5	4	4	4
DTCWT – Canberra	20	14	10	8	7	5	5	3	3
LBP – Manhattan	31	18	16	12	9	8	8	8	8
LBP – Canberra	146	37	21	14	11	10	9	8	7
GLCM-Manhattan	32	25	20	15	11	10	9	9	9
GLCM- Canberra	33	25	20	16	10	9	8	8	7
dddtree2-Manhattan	23	14	12	10	10	9	9	9	6
dddtree2-Canberra	13	11	9	7	5	5	5	5	3

This time, on the average, the best results are obtained for dddtree2 and DTCWT, and the most modest for LBP. We also note that, on the average, the best retrieval results are for dddtree2 and for the Canberra distance.

The natural question we ask ourselves is whether or not the incorrectly classified images using the Manhattan distance are the same as those using the Canberra distance. From the general experiments carried out, a first conclusion has emerged, that the images incorrectly classified using the Manhattan distance are broadly identical to those incorrectly classified using the Euclidean distance. The same cannot be said for Manhattan and Canberra distances, which leads to the natural idea of combining the sets of retrieved images. Thus, combining the sets containing the first 1, 5, 10, 15 and 25 retrieved images gives the results for UPOL automatically segmented using RGB, listed in the following table. We have noted by M and C the Manhattan and Canberra distances, respectively.

Table 4

UPOL_automatically segmented – RGB

Nr. crt.		1	5	10	15	25
1	**Dddtree2-C + DTCWT-M**	2	1	1	1	0
2	**Dddtree2-C + GLCM-M**	5	1	1	0	0
3	**Dddtree2-C + LBP-M**	5	0	0	0	0
4	**DTCWT-C + Dddtree2-M**	2	1	0	0	0
5	**DTCWT-C + GLCM-M**	3	1	0	0	0
6	**DTCWT-C + LBP-M**	2	0	0	0	0
7	**GLCM-C + Dddtree2-M**	2	0	0	0	0
8	**GLCM-C + DTCWT-M**	0	0	0	0	0
9	**GLCM-C + LBP-M**	3	0	0	0	0
10	**LBP-C + Dddtree2-M**	2	0	0	0	0
11	**LBP-C + DTCWT-M**	0	0	0	0	0
12	**LBP-C + GLCM-M**	3	1	1	1	1
13	**Dddtree2-C + Dddtree2-M**	4	1	1	1	0
14	**DTCWT-C + DTCWT-M**	1	1	0	0	0
15	**GLCM-C + GLCM-M**	4	3	3	2	1
16	**LBP-C + LBP-M**	7	2	2	2	0

On the average, the best results are obtained using the (LBP-C, DTCWT-M) and (GLCM-C, DTCWT-M) couple pairs. Combining two different methods, we obtain a maximum of 5 misclassified images when reuniting sets containing a single image. Reuniting the sets containing the first 5 images retrieved, we have 7 situations (out of 12) in which the respective reunions (maximum 10 images, because part of them is repeated) do not contain an image similar to the test image. Performing the same experiments for UBIRIS, we obtain the results presented in the following table.

Table 5

Results obtained in the retrieval for UBIRIS (probably) – RGB

Nr. crt.		1	5	10	15	25
1	**Dddtree2-C + DTCWT-M**	11	11	8	7	4
2	**Dddtree2-C + GLCM-M**	12	11	9	8	5
3	**Dddtree2-C + LBP-M**	11	9	7	6	4
4	**DTCWT-C + Dddtree2-M**	12	9	8	8	6
5	**DTCWT-C + GLCM-M**	18	13	10	9	8
6	**DTCWT-C + LBP-M**	18	11	9	9	5
7	**GLCM-C + Dddtree2-M**	13	10	8	8	6
8	**GLCM-C + DTCWT-M**	19	12	8	8	6
9	**GLCM-C + LBP-M**	20	13	11	10	4
10	**LBP-C + Dddtree2-M**	15	9	9	9	5

Nr. crt.		1	5	10	15	25
11	**LBP-C + DTCWT-M**	22	14	8	8	6
12	**LBP-C + GLCM-M**	20	15	12	9	7
13	**Dddtree2-C + Dddtree2-M**	12	10	9	8	5
14	**DTCWT-C + DTCWT-M**	16	11	7	7	6
15	**GLCM-C + GLCM-M**	31	23	16	15	11
16	**LBP-C + LBP-M**	27	16	14	13	9

As observed, when two different textures are combined, better results are obtained. Thus, the results of combining two sets of 5 are, on the average, better than those obtained for the first 10 images retrieved.

4.2. RESULTS OBTAINED USING SURF DESCRIPTORS

The first natural question we asked ourselves is whether the use of the DENOL method leads to superior results. Thus, using the values 50, 100, 200, 300 and 400, respectively, for the Hessian Threshold parameter, we obtain in classification, using the Manhattan distance, for the values 0.6 and 0.7 of the thresold parameter, the results listed in the following table for the normalized UPOL collection (number of correctly classified images). From Table 6, we see that, for values 5, 10, 25, 50 and 100 of the Hessian Threshold parameter, we obtain, on the average, 298, 278, 213, 152, 67 and 25 keypoints, respectively. Generating a fixed number of keypoints for each image (of those specified above) gives the results listed in the following table. The first line shows the average number of points generated, lines 2 and 3 contain the results obtained using the previous method for values 0.6 and 0.7 of the threshold parameter, respectively, and the last two lines contain the results obtained using the DENOL method.

Table 6

UPOL normalized results

	25	67	152	213	278	298
0.6	313	362	382	382	382	382
0.7	283	349	382	382	384	384
DENOL – 0.6	377	380	383	383	382	382
DENOL - 0.7	375	382	384	384	384	384

It can be seen that clearly superior results are obtained for a small number of points generated. Thus, for hT = 5 (an average of 25 points generated) and t = 0.6, the method used previously gave a result of 313 correctly classified images (out of 384), a percentage of 81.5%. Using the DENOL method, 377 images are correctly classified, *i.e.* 98.18%. For t = 0.7, in the first case, a percentage of 73.70% is obtained, while the DENOL method gives a result of 97.66%.

Obviously, as the number of points generated increases, the differences become smaller and smaller. However, it should be kept in mind that the interest is to work with as few SURF descriptors as possible, because this ensures a higher computational speed. Analogously, for UBIRIS, we have the following results for the values of the threshold parameter t = 0.6 and t = 0.7, for the values 10, 25, 50 and 100 of the hT parameter. For these values, we have an average of 205, 157, 106 and 43 points generated. The results are given in the following table for the sake of comparison.

Table 7

UBIRIS results

	43	106	157	205
0.6	1019	1149	1163	1159
0.7	1019	1144	1169	1172
DENOL – 0.6	1118	1145	1166	1163
DENOL - 0.7	1141	1167	1171	1173

Large differences in classification for an average of 43 points can be seen. Thus, using the classical method, 1,019 images are correctly classified (out of 1,205, a percentage of 84.56%).

The experiments made for UPOL dataset suggest that the proposed SURF classification method gave better results than those obtained by the classification provided by Masek implementation [19,20] for the Daugman procedure [21,22].

4.3. EXPERIMENTS WITH FIXED NUMBER OF SURF KEYPOINTS AND TEXTURE FEATURES

The experiments carried out evidenced that increasing the number of SURF features leads to better results, up to a threshold where saturation is achieved. Starting from this, in the experiments we conducted we considered a two-step approach:

Step 1. Selection, using one or more methods, of a set of candidate images. If several subsets of candidate images are selected, their reunion is performed.

Step 2. Using SURF features in classification/ retrieval for the subset obtained in Step 1, generating a large number of keypoints for each image, to get the best possible results. Using the DENOL method, an equal number of keypoints can be obtained for all images in the subset.

Remark 1. In Step 1, you can use for example texture features, SURF descriptors, SURF, colour features, ORB features, etc. If you select using different features, several subsets, they will be merged.

Remark 2. Obviously, the proposed method can be adapted by generating SURF descriptors in the first step. Thus, for a test image, the “n” most similar images can be selected for a value of the cT parameter, which allows generation of a small number of SURF descriptors. This makes the process fast.

We have performed several such experiments. For example, in one experiment we selected a subset of 5 images using DTCWT features and Canberra distance, subsequently we selected a subset of 5 images using LBP features and Manhattan distance. The two sets were merged.

Generating 152 keypoints for each image in the subset (there are at most 10 images) gives a classification coefficient of 100%.

5. CONCLUSIONS, FUTURE DIRECTIONS

The experiments carried out on the three sets of images showed that the proposed method gives good results, because the operations performed in Step 1 are not costly in terms of processing time, once the number of SURF descriptors generated is relatively small for each image. Only in Step 2 we have generated a very large number of SURF descriptors for each image, but the number of images involved in processing in this step is very small. Obviously, the manner in which the features are combined is extremely diverse; however, this also depends on the collection of processed data. It should be noted that, in the tests carried out, collections containing a relatively small number of images were used. In the next stage, we will perform experiments on the image collection developed in the institute in previous stages. In a future step, we plan to experiment both the DENOL method and the method developed and tested previously on image collections containing fingerprints.

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