

Demographic Bias: A Challenge for Fingervein Recognition Systems?

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Abstract—Recently, concerns regarding potential biases in the underlying algorithms of many automated systems (including biometrics) have been raised. In this context, a biased algorithm produces statistically different outcomes for different groups of individuals based on certain (often protected by anti-discrimination legislation) attributes such as sex and age. While several preliminary studies investigating this matter for facial recognition algorithms do exist, said topic has not yet been addressed for vascular biometric characteristics. Accordingly, in this paper, several popular types of recognition algorithms are benchmarked to ascertain the matter for fingervein recognition. The experimental evaluation suggests lack of bias for the tested algorithms, although future works with larger datasets are needed to validate and confirm those preliminary results.

Index Terms—Biometrics, Fingervein Recognition, Bias

I. INTRODUCTION

Automated systems (including biometrics) are increasingly used in decision making processes within various domains, some of which have traditionally enjoyed strong anti-discrimination legislation protection (see *e.g.* [1]).

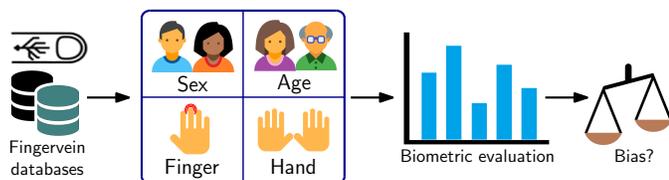


Fig. 1: Overview of the conducted experiments

In recent years, substantial media coverage of systemic biases inherent to several such systems have been reported and hotly debated. In this context, a biased algorithm produces statistically different outcomes (decisions) for different groups of individuals, *e.g.* based on sex, age, and ethnicity [2]. For biometric recognition specifically, it means that the score distributions and therefore the chances of false positives and/or false negatives may vary across the groups. This, in consequence, may impact the outcomes on the system/application level – for example, one recent study claimed disproportionately high arrest and search rates for certain groups based on decisions made by automatic facial recognition software [3].

Although some studies have approached bias measurements and ensuring fairness in various machine learning contexts (see *e.g.* [4] and [5]), for computer vision and biometrics in particular, this remains a nascent field of research. In [6], it was reported that facial recognition algorithms tend to exhibit higher biometric performance with individuals from ethnic groups corresponding to the area of development of the algorithm; presumably due to training data availability. In [7] and [8], some facial biometrics algorithms were shown to exhibit lower recognition and classification performances for certain groups of individuals (in particular women and non-white people), whereas [9] conducted a large-scale benchmark of commercial and academic algorithms controlling for various demographic (and other) attributes. Proof-of-concept studies into bias mitigation for facial soft biometric classification using neural networks were presented in *e.g.* [10] and [11].

While facial recognition is certainly the most widely covered and discussed biometric characteristic recently, also with some existing preliminary studies in the context of bias and fairness, this topic remains even less explored for other biometric characteristics. In general, algorithmic bias is considered (by some influential researchers) to be one of the, as of yet unresolved, challenges in biometric systems [12]. For fingervein specifically, a small study evaluating the biometric performance w.r.t. sex and age of the subjects (as a part of a paper presenting a new dataset) has been conducted in [13]. Intuitively, the demographic covariates could be proxies for certain anatomical features which might influence the performance of fingervein recognition systems (*e.g.* the thickness of the finger). Otherwise, currently no studies benchmarking the potential biases in fingervein algorithms have been reported in the scientific literature. In this paper, a benchmark is conducted to address the following two questions, see figure 1:

- Do score distributions computed by fingervein recognition algorithms on disjoint groups of data instances (*i.e.* based on metadata attributes, such as subject sex, age, and others) exhibit statistically significant differences?
- Do these results persist across fundamentally different types of fingervein recognition algorithms?

The remainder of this paper is organised as follows: the experimental setup is described in section II. The results of the evaluation are presented in section III, while concluding remarks and a summary are given in section IV.

II. EXPERIMENTAL SETUP

In this section, the used datasets (subsection II-A) and data processing pipelines (subsection II-C) are presented.

A. Datasets

Four publicly available fingervein databases with metadata labels were used. They are listed in table I, while example images are shown in figure 2. The datasets were chosen based on the presence of the metadata information (sex and age), as well as the presence of samples from both hands and different fingers.

TABLE I: Summary of the chosen datasets

Database	Subjects	Instances	Samples
MMCBNU [14]	100	600	6000
PLUS [13], [15]	78	468	2340
UTFVP [16]	60	360	1440
VERA [17]	110	220	440

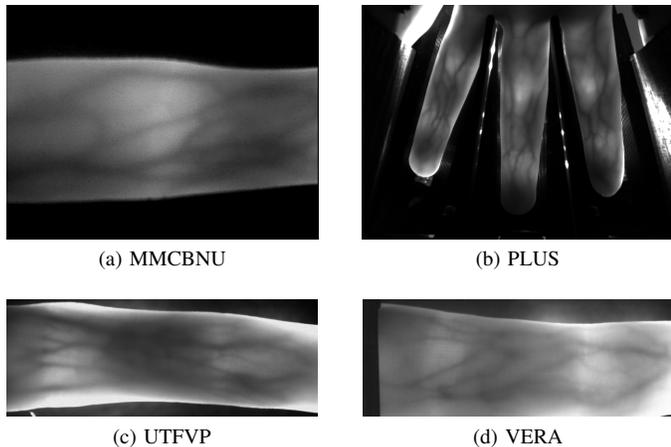


Fig. 2: Example images from the chosen datasets

B. Feature Types

All experiments are executed using four fundamentally different types of vein recognition schemes:

- 1) **Vein pattern:** The first two of the used techniques, Maximum Curvature (MC [18]) and Principal Curvature (PC [19]), aim to separate the vein pattern from the background resulting in a binary image.
- 2) **Keypoints:** In contrast to the vein pattern techniques, key-point based techniques try to use information from the most discriminative points as well as considering the neighborhood and context information of these points by extracting key-points and assigning a descriptor to each key-point. We used a Scale-Invariant Feature Transform (SIFT [20]) based technique with additional key-point filtering. All details of this method are described in [21].

- 3) **Texture:** The used approach is an adapted version of [22]. It combines Log Gabor convolution magnitude and local binary patterns (LBP [23]).
- 4) **Deep learning:** LightCNN with triplet loss (LCNN [24]) is a small neural network which is trained using the triplet loss, a special loss function that enables the identification of subjects that were not included in the training set. By using a more advanced selection of the triplets (input images) for training (hard triplet online selection) and by omitting the supervised discrete hashing of the CNN outputs, the results could be improved w.r.t. [24]. It should be noted that the LCNN was trained according to its actual purpose, the recognition of individuals based on the captured vein images. If the net would be trained according to the chosen groups, such as sex or age, the results might look different.

TABLE II: Biometric performance of the used methods

Dataset	LCNN	EER (in %)			
		LBP	MC	PC	SIFT
MMCBNU	2.2	1.3	1.8	1.7	2.0
PLUS	4.5	3.6	0.5	0.2	0.8
UTFVP	7.0	1.5	0.2	0.4	1.5
VERA	—	3.2	1.8	2.3	2.6

C. Data Processing Pipelines

The finger vein recognition tool-chain consists of the following components: (1) For *finger region detection*, *finger alignment* and *ROI extraction* an implementation that is based on [25] is used. (2) To improve the visibility of the vein pattern, *High Frequency Emphasis Filtering* (HFE) [26], *Circular Gabor Filter* (CGF) [27], and simple *CLAHE* (local histogram equalisation) [28] are used during *pre-processing*. (3a) For the simple vein pattern based feature methods, MC and PC, the binary feature images are compared using a correlation measure, calculated between the input images and in x- and y-direction shifted and rotated versions of the reference image as described in [29]. (3b) The SIFT based method applies feature extraction and comparison as proposed in [21], and (3c) the LBP based approach as described in [22] where the LDP features are replaced with LBP features from [23], respectively. (3d) For LCNN, the ROIs extracted in (1) have been resized to the required input size of 256×256 . For separating training from input data, a 2-fold cross validation has been applied. Due to a limited number of samples, a training on the VERA data set was not possible. The biometric performance of the used methods is summarised in table II.¹

III. EVALUATION

The conceptual overview of the conducted experiments is shown in figure 1. The descriptive statistics (mean $-\mu$ and standard deviation $-\sigma$) of the score distributions w.r.t. the metadata-based groupings are computed in subsections III-A to III-C. Additionally, for comparison, table III shows

¹Supplementary files (e.g. comparison scores) are available for download at <http://wavelab.at/sources/Drozdzowski20a/>.

the same statistics for all template comparisons without any metadata-based grouping. The algorithms have different ranges of scores. In the context of the conducted bias benchmark, only intra-algorithm comparisons are meaningful – therefore, score normalisation is not required. The results are only listed where available (*e.g.* the VERA dataset only contains two samples per finger and therefore it is not possible to train a CNN using the triplet loss function).

TABLE III: Score distribution statistics without metadata-based grouping

Dataset	Algorithm	Score μ		Score σ	
		Genuine	Impostor	Genuine	Impostor
MMCBNU	LCNN	0.72477	0.26189	0.12129	0.07989
	LBP	0.84812	0.78781	0.02009	0.00805
	MC	0.27205	0.12055	0.04891	0.01730
	PC	0.41059	0.30588	0.02806	0.01654
	SIFT	0.39081	0.01510	0.16538	0.02434
PLUS	LCNN	0.70367	0.25433	0.13798	0.08999
	LBP	0.80302	0.37204	0.16154	0.05899
	MC	0.25004	0.12464	0.03946	0.00874
	PC	0.41261	0.30209	0.03030	0.01361
	SIFT	0.35114	0.01119	0.14678	0.01196
UTFVP	LCNN	0.69713	0.32198	0.11472	0.10833
	LBP	0.84664	0.81038	0.01344	0.00471
	MC	0.23834	0.11789	0.03854	0.00733
	PC	0.40156	0.28823	0.02816	0.01058
	SIFT	0.31269	0.00937	0.15406	0.01071
VERA	LBP	0.81296	0.78861	0.01101	0.00417
	MC	0.24056	0.11351	0.04569	0.00947
	PC	0.38741	0.29499	0.03025	0.01156
	SIFT	0.23220	0.00562	0.14523	0.00822

A. Sex

In this experiment, the data instances are grouped by the subject sex (male and female) with the genuine and impostor score distributions computed within the groups. Table IV shows the descriptive statistics of those score distributions.

B. Age

In this experiment, the data instances are grouped by the subject age (into buckets) with the genuine and impostor score distributions computed within the groups. Table VI shows the descriptive statistics of those score distributions.

C. Finger/Hand

In this experiment, the data instances are grouped by the finger (index, middle, ring) or hand (left, right) with the genuine and impostor score distributions computed within the groups. Tables VII and VIII show the descriptive statistics of those score distributions.

D. Summary

In order to check whether the small differences reported in previous tables are statistically significant, the standard score (Z -score) is computed as shown in equation 1 (absolute value of the means is used, since only the magnitude of the difference is interesting in this case). Using Z -score is possible, since all-against-all comparisons were conducted and as such, the whole population of the comparison scores for each database/algorithm is known.

TABLE IV: Score distribution statistics by subject sex

Dataset	Algorithm	Sex	Score μ		Score σ		
			Genuine	Impostor	Genuine	Impostor	
MMCBNU	LCNN	Male	0.72368	0.25896	0.12250	0.07901	
		Female	0.73008	0.33211	0.11503	0.08697	
	LBP	Male	0.84866	0.78734	0.02047	0.00826	
		Female	0.84547	0.79151	0.01791	0.00685	
	MC	Male	0.27539	0.12060	0.04875	0.01733	
		Female	0.25575	0.12102	0.04635	0.01710	
	PC	Male	0.41292	0.30600	0.02758	0.01652	
		Female	0.39922	0.30596	0.02764	0.01685	
	SIFT	Male	0.39940	0.01577	0.16554	0.02541	
		Female	0.34890	0.01269	0.15805	0.01926	
	PLUS	LCNN	Male	0.69420	0.25298	0.13924	0.08804
			Female	0.71743	0.27548	0.13494	0.09270
LBP		Male	0.79966	0.36896	0.16497	0.05888	
		Female	0.80798	0.37765	0.15622	0.05819	
MC		Male	0.24732	0.12233	0.04122	0.00846	
		Female	0.25398	0.12849	0.03640	0.00836	
PC		Male	0.41017	0.30100	0.03129	0.01399	
		Female	0.41617	0.30414	0.02844	0.01290	
SIFT		Male	0.35073	0.01192	0.15233	0.01227	
		Female	0.35173	0.01076	0.13833	0.01181	
UTFVP		LCNN	Male	0.71090	0.34391	0.11343	0.10297
			Female	0.65934	0.34688	0.10964	0.11891
	LBP	Male	0.84929	0.81163	0.01259	0.00415	
		Female	0.83938	0.81127	0.01301	0.00477	
	MC	Male	0.24182	0.11602	0.03774	0.00674	
		Female	0.22877	0.12381	0.03911	0.00769	
	PC	Male	0.40795	0.28808	0.02460	0.01054	
		Female	0.38403	0.28944	0.02983	0.01064	
	SIFT	Male	0.34616	0.00927	0.14795	0.01062	
		Female	0.22082	0.01078	0.13145	0.01148	
	VERA	LBP	Male	0.81534	0.78890	0.01149	0.00416
			Female	0.80881	0.78950	0.00869	0.00398
MC		Male	0.24689	0.11319	0.04681	0.00946	
		Female	0.22948	0.11463	0.04140	0.00929	
PC		Male	0.39161	0.29269	0.02930	0.01118	
		Female	0.38007	0.30051	0.03050	0.01085	
SIFT		Male	0.26795	0.00549	0.15266	0.00823	
		Female	0.16964	0.00621	0.10518	0.00855	

TABLE V: Z -scores summary for all the experiments

Attribute	Z-score median		Z-score maximum	
	Genuine	Impostor	Genuine	Impostor
Sex	0.23043	0.10282	0.63334	0.76144
Age	0.09125	0.08500	0.29284	0.31685
Finger	0.07717	0.09166	0.26186	0.44955
Hand	0.06384	0.09973	0.22999	0.29002

$$Z = \frac{|\mu_1 - \mu_2|}{\sqrt{\sigma_1^2 + \sigma_2^2}} \quad (1)$$

This computation is done for all the relevant pairs of score distributions for all the experiments. In other words, for each database and recognition algorithm, all permutations of the genuine and impostor distribution pairs are considered within the respective metadata attribute. Table V shows the medians and maximums of the computed Z -scores. Overall, the Z -scores (medians) are very low and those of the outliers (maxima) are relatively low. In other words, statistically significant differences are not present for any of the score distribution pairs within their respective experiments (database, algorithm, and metadata attribute). The biometric performance evaluations (in verification and closed-set identification modes) have also not revealed any statistically significant differences.

IV. CONCLUSION

As shown in the evaluation in section III, statistically significant biases in score distributions w.r.t. the sex and age of

TABLE VI: Score distribution statistics by subject age

Dataset	Algorithm	Age	Score μ		Score σ		
			Genuine	Impostor	Genuine	Impostor	
MMCBNU	LCNN	(0, 30)	0.72681	0.26173	0.12008	0.08046	
		(30, 45)	0.71208	0.26273	0.12100	0.07735	
		(45, 60)	0.72994	0.25940	0.15319	0.07661	
	LBP	(0, 30)	0.74951	0.26902	0.09673	0.08338	
		(30, 45)	0.84773	0.78782	0.01985	0.00805	
		(45, 60)	0.84817	0.78764	0.02005	0.00821	
	MC	(45, 60)	0.85522	0.78854	0.02391	0.00740	
		(60, 80)	0.85705	0.78637	0.02181	0.00714	
		(0, 30)	0.27095	0.12056	0.04878	0.01734	
	PC	(30, 45)	0.27476	0.12142	0.04635	0.01731	
		(45, 60)	0.28507	0.11776	0.06421	0.01648	
		(60, 80)	0.27749	0.11873	0.03664	0.01414	
	SIFT	(0, 30)	0.40971	0.30607	0.02818	0.01651	
		(30, 45)	0.41318	0.30462	0.02556	0.01729	
		(45, 60)	0.41856	0.30536	0.03648	0.01512	
	SIFT	(60, 80)	0.41563	0.30253	0.02026	0.01372	
		(0, 30)	0.38601	0.01520	0.16498	0.02444	
		(30, 45)	0.40078	0.01503	0.15826	0.02442	
	SIFT	(45, 60)	0.46074	0.01360	0.19468	0.02238	
		(60, 80)	0.40609	0.00890	0.15790	0.01725	
		PLUS	LCNN	(0, 30)	0.70530	0.24723	0.14055
	(30, 45)			0.70493	0.25356	0.13379	0.09098
	(45, 60)			0.70513	0.27104	0.13314	0.09057
	LBP		(60, 80)	0.69106	0.25425	0.14891	0.08597
(0, 30)			0.82179	0.37210	0.15764	0.05956	
(30, 45)			0.81593	0.37284	0.14697	0.05873	
MC	(45, 60)		0.75727	0.36913	0.17569	0.05507	
	(60, 80)		0.76103	0.37095	0.17469	0.06076	
	(0, 30)		0.28311	0.12303	0.03717	0.00735	
SIFT	(30, 45)		0.28255	0.12219	0.03647	0.00769	
	(45, 60)		0.28268	0.12447	0.04212	0.00770	
	(60, 80)		0.27906	0.12503	0.03901	0.00722	
PC	(0, 30)		0.43334	0.31615	0.02398	0.01348	
	(30, 45)		0.43270	0.31266	0.02275	0.01298	
	(45, 60)		0.42748	0.31316	0.02832	0.01336	
SIFT	(60, 80)		0.42937	0.31625	0.02424	0.01206	
	(0, 30)		0.46978	0.01702	0.14696	0.01886	
	(30, 45)		0.47233	0.01611	0.13525	0.01678	
SIFT	(45, 60)		0.44450	0.01227	0.15632	0.01360	
	(60, 80)		0.43647	0.01328	0.15149	0.01535	
	UTFVP		LCNN	(0, 30)	0.69782	0.32213	0.10992
(30, 45)				0.70565	0.33416	0.12312	0.11310
(45, 60)				0.68730	0.31387	0.13964	0.10498
LBP			(0, 30)	0.84673	0.81045	0.01307	0.00475
		(30, 45)	0.84676	0.80946	0.01522	0.00473	
		(45, 60)	0.84596	0.81029	0.01485	0.00435	
MC		(0, 30)	0.23783	0.11792	0.03854	0.00740	
		(30, 45)	0.24806	0.11696	0.03683	0.00667	
		(45, 60)	0.23632	0.11808	0.03878	0.00707	
PC		(0, 30)	0.40093	0.28823	0.02804	0.01072	
		(30, 45)	0.40530	0.29107	0.02974	0.00960	
		(45, 60)	0.40391	0.28678	0.02781	0.00953	
SIFT		(0, 30)	0.30731	0.00945	0.15074	0.01077	
		(30, 45)	0.35794	0.00984	0.17626	0.01092	
		(45, 60)	0.32461	0.00848	0.15849	0.00999	
VERA		LBP	(0, 30)	0.81264	0.78892	0.01086	0.00414
			(30, 45)	0.81499	0.78846	0.00995	0.00413
			(45, 60)	0.81130	0.78790	0.01243	0.00417
		MC	(0, 30)	0.23409	0.11333	0.04560	0.00945
			(30, 45)	0.24782	0.11324	0.04133	0.00929
			(45, 60)	0.25276	0.11431	0.04766	0.00964
		PC	(0, 30)	0.38283	0.29608	0.03144	0.01165
			(30, 45)	0.39401	0.29441	0.02688	0.01053
			(45, 60)	0.39404	0.29263	0.02745	0.01199
	SIFT	(0, 30)	0.21685	0.00603	0.14440	0.00856	
		(30, 45)	0.25496	0.00511	0.13332	0.00777	
		(45, 60)	0.25356	0.00506	0.15645	0.00768	

the data subjects, as well as the chosen finger/hand **have not been detected** for the five fingervein recognition algorithms tested on the four datasets. Accordingly, no impact on the biometric performance in neither the biometric verification nor biometric identification mode has been discovered. The results thus indicate that various fundamentally different classes of fingervein recognition algorithms might be suitable for application irrespective of the tested meta-parameters. This also points to a potential advantage in certain application scenarios

TABLE VII: Score distribution statistics by subject finger

Dataset	Algorithm	Finger	Score μ		Score σ		
			Genuine	Impostor	Genuine	Impostor	
MMCBNU	LCNN	Index	0.73789	0.29660	0.11795	0.08182	
		Middle	0.73756	0.26873	0.11508	0.07969	
		Ring	0.69886	0.29819	0.12638	0.08600	
	LBP	Index	0.85083	0.79090	0.01973	0.00675	
		Middle	0.85045	0.79195	0.01959	0.00632	
		Ring	0.84307	0.79134	0.02000	0.00708	
	MC	Index	0.27596	0.12006	0.04771	0.01683	
		Middle	0.27706	0.12477	0.04816	0.01881	
		Ring	0.26312	0.12124	0.04960	0.01695	
	PC	Index	0.41200	0.30462	0.02856	0.01614	
		Middle	0.41366	0.31002	0.02642	0.01815	
		Ring	0.40611	0.30702	0.02859	0.01608	
	SIFT	Index	0.40806	0.01389	0.16277	0.02202	
		Middle	0.40803	0.01753	0.16304	0.02634	
		Ring	0.35635	0.01822	0.16490	0.02812	
	PLUS	LCNN	Index	0.69603	0.31173	0.13513	0.09410
			Middle	0.72436	0.32433	0.12724	0.09138
			Ring	0.69037	0.31674	0.14844	0.09366
		LBP	Index	0.77026	0.39889	0.17601	0.06769
			Middle	0.82733	0.42928	0.13097	0.06253
			Ring	0.81040	0.40845	0.16954	0.06858
		MC	Index	0.27348	0.12309	0.04082	0.00786
			Middle	0.28568	0.12384	0.03394	0.00713
			Ring	0.28800	0.12297	0.03753	0.00763
PC		Index	0.42761	0.31202	0.02737	0.01388	
		Middle	0.43428	0.31422	0.02249	0.01201	
		Ring	0.43326	0.32050	0.02292	0.01275	
SIFT	Index	0.43889	0.01861	0.15240	0.01762		
	Middle	0.47702	0.01313	0.13071	0.01350		
	Ring	0.47255	0.02040	0.15133	0.02180		
UTFVP	LCNN	Index	0.69280	0.35131	0.11088	0.11909	
		Middle	0.69936	0.36379	0.11254	0.10415	
		Ring	0.69923	0.36727	0.12042	0.11219	
	LBP	Index	0.84579	0.81212	0.01321	0.00518	
		Middle	0.84737	0.81179	0.01281	0.00446	
		Ring	0.84677	0.81165	0.01421	0.00474	
	MC	Index	0.23730	0.11875	0.03743	0.00743	
		Middle	0.23542	0.11804	0.03727	0.00737	
		Ring	0.24230	0.11776	0.04052	0.00730	
	PC	Index	0.40019	0.28935	0.02829	0.01115	
		Middle	0.40176	0.28892	0.02687	0.01004	
		Ring	0.40274	0.28858	0.02922	0.01116	
SIFT	Index	0.30573	0.01048	0.15129	0.01137		
	Middle	0.31932	0.00907	0.14986	0.01025		
	Ring	0.31302	0.01048	0.16053	0.01153		
VERA	LBP	Index	0.81296	0.78861	0.01101	0.00417	
	MC	Index	0.24056	0.11351	0.04569	0.00947	
	PC	Index	0.38741	0.29499	0.03025	0.01156	
	SIFT	Index	0.23220	0.00562	0.14523	0.00822	

of the vascular characteristics in comparison to others (*e.g.* face, see section I), for which potential biases have been reported in the literature. An obvious limitation of this work is the size of the used fingervein datasets – unfortunately, no larger ones (with metadata present) are currently publicly available. Hence, an important avenue of future research in this area would be the acquisition of a more sizeable dataset and a validation of the scalability of those preliminary results.

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TABLE VIII: Score distribution statistics by subject hand

Dataset	Algorithm	Hand	Score μ		Score σ		
			Genuine	Impostor	Genuine	Impostor	
MMCBNU	LCNN	Left	0.73241	0.27535	0.11214	0.08060	
		Right	0.72972	0.28659	0.10971	0.08007	
	LBP	Left	0.84654	0.78811	0.02014	0.00803	
		Right	0.84969	0.78784	0.01993	0.00819	
	MC	Left	0.26829	0.12023	0.04914	0.01738	
		Right	0.27581	0.12124	0.04838	0.01735	
	PC	Left	0.40823	0.30551	0.02880	0.01697	
		Right	0.41295	0.30658	0.02710	0.01618	
	SIFT	Left	0.37725	0.01505	0.16594	0.02398	
		Right	0.40438	0.01532	0.16370	0.02490	
	PLUS	LCNN	Left	0.71348	0.25962	0.13772	0.09873
			Right	0.69663	0.29911	0.13051	0.09379
LBP		Left	0.79772	0.38143	0.16295	0.06064	
		Right	0.80837	0.37036	0.15992	0.06330	
MC		Left	0.28116	0.12307	0.03837	0.00744	
		Right	0.28375	0.12302	0.03763	0.00768	
PC		Left	0.43033	0.31581	0.02397	0.01204	
		Right	0.43320	0.31342	0.02495	0.01422	
SIFT		Left	0.45395	0.01591	0.14634	0.01645	
		Right	0.47223	0.01610	0.14504	0.01828	
UTFVP		LCNN	Left	0.69651	0.33332	0.11244	0.11739
			Right	0.69369	0.35340	0.11329	0.10294
	LBP	Left	0.84549	0.81043	0.01359	0.00483	
		Right	0.84780	0.81076	0.01319	0.00476	
	MC	Left	0.23586	0.11704	0.03855	0.00711	
		Right	0.24082	0.11883	0.03838	0.00752	
	PC	Left	0.39946	0.28827	0.02852	0.01059	
		Right	0.40367	0.28838	0.02764	0.01052	
	SIFT	Left	0.30254	0.00917	0.15592	0.01036	
		Right	0.32287	0.00966	0.15148	0.01107	
	VERA	LBP	Left	0.81147	0.78964	0.01143	0.00402
			Right	0.81446	0.78940	0.01036	0.00432
MC		Left	0.23471	0.11385	0.04772	0.00959	
		Right	0.24641	0.11477	0.04277	0.00939	
PC		Left	0.38461	0.29604	0.03262	0.01128	
		Right	0.39022	0.29487	0.02740	0.01167	
SIFT		Left	0.21957	0.00583	0.14676	0.00826	
		Right	0.24482	0.00612	0.14257	0.00868	

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