Multivariate Analytic Technique for Forensic Human Identification based on Dual Cross Patterns of Hand Radiographs

Sagar V. Joshi, Rajendra D. Kanphade

Abstract*: *In recent times, the necessity for personal identification systems has increased due to several accidents. Under circumstances of human-made and natural disasters, it is not possible to employ a traditional biometric system. Hence, biometric radiographs of the skull, hands, and teeth are good replacement methods to identify victims. The fundamental intent of the research is to acquire a novel approach for identifying missing and anonymous individuals based on Dual Cross Pattern (DCP) features of hand radiographs. The suggested technique has contains two major steps: feature extraction and classification of the feature vectors. In this paper, an effort is made to find the most adequate classifier between the Classification Tree (CT), Feed forward Neural Network (FNN), Multiclass Support Vector Machine (m-SVM), and k-Nearest Neighbor (k-NN) based on the accuracy of retrieval of 10 adult subjects from the dataset of 300 right-hand radiographs. The classification results attained from simulation and discriminant analysis on a small primary database are encouraging.

Keywords: Discriminant analysis, dual* cross grouping, *hand radiographs, pattern encoding.

I. INTRODUCTION

Crime and disaster incidents in recent times have emphasized the importance of biometric radiographs to procure the attention of the public. In recent times, authentication and identification of a person have become essential parts of security systems. In the recent past, biometric identification was used mainly for a variety of applications, including smart cards, law enforcement, access control, information security, and forensics, due to their level of accuracy, reliability, and performance [1, 2].There are two types of biometric features, behavioral and physical. The first type covers only behavioral traits, which include the signature, gait, and voice. The second type covers human anatomical parts such as the retina, face, fingerprints, hand veins, hand geometry, and ear shape [3]. Traditional biometric techniques are not applicable to victims of natural disasters such as tsunami, earthquake, and others. In such cases, forensic radiography is useful to identify an unknown person. It is one of the forensic fields that involve recognizing people through post-mortem radiological images of different parts of the body including teeth, hand, skeleton, and skull. These radiological images of the dead body are compared with a missing person's ante-mortem reports to find out similarities. Radiographs acquired before and after death are termed as Antemortem (AM) and Post Mortem (PM) radiographs respectively [4]. Generating a biometric feature for victims using a computer has become a challenging research topic. Additionally, there are many traditional biometric features, fingerprints, face, and iris; however, there is no specific research to focus on hand radiographs. Therefore, in this paper, a computer-facilitated human identification technique based on hand radiographs of victims or deceased people through Dual Cross Patterns (DCP) texture features of is presented.

Identification of a person using hand biometric is not a new concept. Traces of such methods date back to the early 1970s and are comparatively older than palm print - a part of dactyloscopy. Human hand consists of sufficient anatomical characteristics through which a person can be identified; however, it does not include any particular mechanism to find a person. Numerous studies have investigated hand-based biometry in general perspective. Certain schemes directly depend on geometrical features whereas others are using the silhouette shape of hands [5, 6]. Some systems are developed using characteristics like finger width, palm and finger length, deviations of fingers, and angles with horizontal lines [7–10]. In general, these systems can be used to either measure or analyze the overall shape, structure, and thickness, length, and width. In some specific methods, the user must keep his hand in a decided predefined position [7, 11]. This gives additional information about problems regarding the users' health and hygiene [12]. Kumar et al. [13] have suggested a unified system using hand geometry features with hand-based verification. Some studies [6, 14-16] explained hand radiograph applications in different fields to examine the hand of an unknown or known person. Pietka [14] developed a computer- aided classification algorithm to help radiologists to examine the bones of pediatric patients. Pietka et al. [15] provided an examination of skeletal maturity through computer-assisted analysis conducted on a hand radiograph. Pietka et al. [16] clinically examined skeletal maturity. Garcia et al. [17] proposed active contours based algorithm for identification of hand bone contours. An automated system has been developed using the Tanner-Whitehouse (TW2) method by Neimeijer et al. [18]. Zelinski and Wojciechowski [19] discovered erosions and osteophytes and employed computer-based hand

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radiograph analysis. Pathak et al. [20] examined the structural progress of metaphysis and epiphysis in a child's growth. Simu et al. [21] suggested an automated extraction approach for radius and ulna bones. Simu and Lal [22] compared evolutionary and non-evolutionary segmentation algorithms for hand radiographs, which identify the shapes and borders of bones. Yuh et al. [23] proposed an algorithm that is used for both analyzing and extracting texture features of phalanges ROI of hand radiographs and it can be used to give firm and effective stage bone age assessment.

II. PROPOSED SYSTEM OVERVIEW

The suggested technique displays human classification based on the descriptor of the DCP function. The detailed evaluation of texture characteristics plays a crucial role in the content-based data recovery scheme. The key feature for any image is its texture feature as it provides color & intensity to the spatial arrangement of a picture. Other renowned techniques for extracting texture characteristics are Local Binary Pattern (LBP) [24] and Discrete Wavelet Transform (DWT) [25], but DCP is essential because it performs the extraction of the second order discriminative data from an input image in all possible directions [26, 27].As DCP uses highest Shannon Entropy Grouping of sampled pixels, it provides pixel details twice as much as LBP [26, 27]. Fig. 1 presents sample right hand radiographs from the dataset collected.

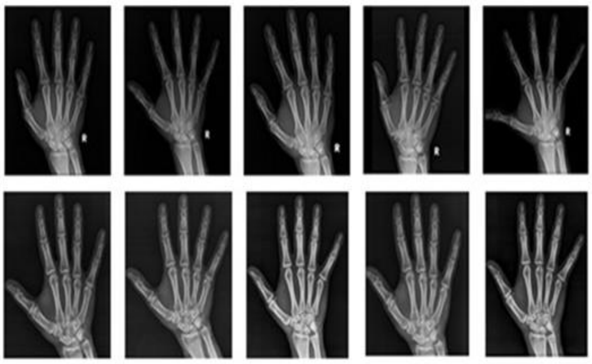


Fig.2. Sample hand radiographs from the dataset.

There are several steps involved in advancing human identification from hand x-rays. The proposed method (see Fig. 2) can execute two operations when entering an image: - 1) Generating a training database or 2) Searching for a similar record in a dataset. In both stages, feature extraction is mandatory [27]. At the end phase, the difference between the two tasks happens when the system determines what function to perform. When the system is created, the final stage is to reserve the extracted data in the database. Comparison of the extracted information function values with the data records from the database is the final stage. In this study, it is assumed that even after the death of the subject radiographs of the hand remain unchanged.

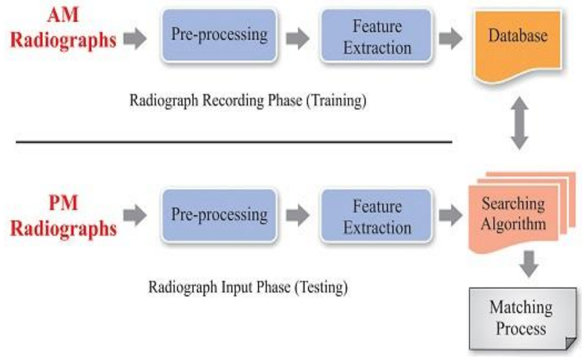


Fig.1. Block diagram of hand radiograph based human identification system using DCP

There are three components of the human hand X-ray, Phalanges, Metacarpals and Carpals. The proposed research is only focused on phalanges and metacarpals extraction using DCP since a carpal study can be regarded as separate research. Extraction of the DCP feature consists of filtering of the input images, local sampling and encoding patterns [26, 27]. DCP encrypts statistical second-order information owing to distinct patterns of encoding and local sampling methods.

A. Local Sampling

The DCP is successful, as it carries local sampling (see Fig. 3) and the encoding of patterns in all the required directions confined to hand radiographs [26, 27]. The local sampling is directed symmetrically in all eight directions for each pixel I_0, (0, π/4, π/2, 3π/4, π, π/4, 5π/4, 3π/2, and 7π/4). Sampling in the entire neighborhood direction provides the necessary information on the texture. In each direction, two pixels are sampled as $\{I_{A1},I_{B1};I_{A2},I_{B2};I_{A3},I_{B3};I_{A4},I_{B4};I_{A5},I_{B5};I_{A6},I_{B6};I_{A7},I_{B7};I_{A8},I_{B8}\}$

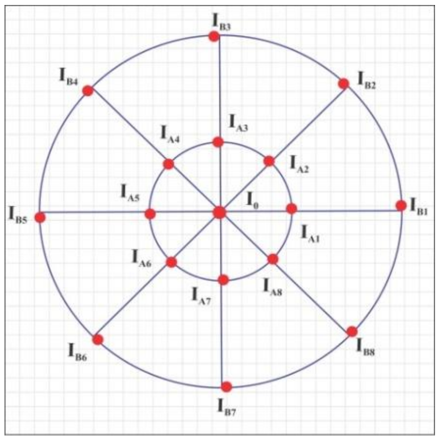


Fig.3. Process of sixteen point local sampling around the central pixel I_0 in DCP.

B. Pattern Encoding

The sampled point encoding is performed in two steps: 1) Encoding of textual information in all eight directions independently and 2) Evolution of DCP code by integrating them in order to appraise the statistics of texture in each direction of sampling [27], for each pixel, we designate a decimal quantity as:

$$DCP_i = D(I_{Ai} - I_0) \times 2 + D(I_{Bi} - I_{Ai}), 0 \le i \le 7 \quad (1)$$

$$\text{Where, } D(x) = \begin{cases} 1, & x \ge 0 \\ 0, & x < 0 \end{cases} \quad (2)$$

And I_0, I_{Ai}, and I_{Bi} signify the center pixel and neighborhood pixel gray values Ai and Bi respectively.

C. Dual Cross Grouping

DCP considers all eight neighborhoods; the overall range of DCP codes is 4^8= 65536. This code descriptor is just too big for a realistic hand recognition system, so we take the next step, in which, an encoder is formulated by grouping two subsets of all 8 directions, the total quantity of the local pattern is reduced to $4^4 \times 2$= 512, which is adroit. Applying grouping technique on eight directions a total of 35 combinations are produced. A joint Shannon entropy criterion is used [26, 27] for an optimum grouping of eight directions to preserve information required for image recovery.

$$H(DCP_0, DCP_1, DCP_2, DCP_3) = -\sum_{dcp0} \dots \sum_{dcp3} P(dcp_0 \dots dcp_3) \log_2 P(dcp_0 \dots dcp_3) \quad (3)$$

Where, $(dcp_0 dcp_1, dcp_2, dcp_3)$ are particular values of $(DCP_0, DCP_1, DCP_2, DCP_3)$ respectively and $P(dcp_0 \dots . dcp_3)$ is the Probability of $(dcp_0 \dots . dcp_3)$values. The image is more independent of each other as the pixel are more scattered. Sample point separation with maximum distance result into maximum joint Shannon entropy in each subgroup [26,27].

$$DCP - 1 = \sum_{k=0}^{3} DCP_{2k} + 4^k \quad (4)$$

$$DCP - 2 = \sum_{k=0}^{3} DCP_{2k+1} + 4^k \quad (5)$$

The Final DCP descriptor of the image is formed by combination of DCP-1 and DCP-2 for every pixel

$$DCP = \left\{ \sum_{k=0}^{3} DCP_{2k} + 4^k, \sum_{k=0}^{3} DCP_{2k+1} + 4^k \right\} \quad (6)$$

D. Image Database and The Influence Of Block Number

In this paper, hand radiographs are assumed to remain unvaried after the death of the subject. An expert in forensic science has supported the proposed hypothesis [28, 29]. This proposed method of radiographs has completely taken into consideration adults, not children. All right-hand radiographs are acquired from Siemens and Vision-C X-ray machine from Needan Diagnostics, and Om X-ray Clinic, Chinchwad, Pune, India. The database consists of total 300 right-hand radiographs recorded at different positions for ten different subjects belong to age groups in between 18 to 42 years. Keeping the hand position fixed ensures a higher level of accuracy for experimentation purposes but not on a real-time basis. Hence, by doing this, an attempt has been made to improve the accuracy level when matching is done on a real-time basis rather than to serve the experiment purpose solely. The database is divided into 200 training and 100 testing image. PM images are not used in the introduced dataset.

The introduced system is implemented in MATLAB and executed on a PC with 3Gb RAM, Intel (R) Core 2 Duo processor, and WINDOWS 7 professional OS. Here, rather than selecting a single block per radiograph, the radiograph is divided into N blocks. The histogram computed over a complete image describes the intensity distribution weakly. For achieving the best description of the image, local regions are selected by considering multiple blocks of the image. Multiple blocks consider multiple windows. DCP feature vectors are calculated for block sizes 1x1, 2x2, 4x4, and 8x8 respectively to study the influence of block size on retrieval accuracy and recognition time.

III. RESULT AND DISCUSSION

The descriptor of DCP feature is extracted by integrating S-1 and S-2 and then the ten subjects are classified using different classifiers such as Multiclass Support Vector Machine (m-SVM), Feedforward neural network (FNN), k-NN(N=3 and N=5) and Classification Tree (CT) Classifier are performed. From statistical learning, SVM is widely used for pattern regression and recognition. It is also known as supervised learning machine. By applying this, SVM along with the radial basis function, the kernel can be employed as one classifier. γ and C parameters, which employ a five-fold cross-validation process are selected. One versus all SVM is used for multiclass classification. The linear kernel is used for the class separating hyper-plane creation. SVM is trained for one against other class features. k-NN is the simplest classifier as it takes no time for training. Only the testing time is more as it finds the nearest neighbor using squared Euclidean distance. Odd Number of neighbors are selected for testing as recognition depends on the maximum number of neighbors' class and when K is even, it fails to give maximum neighbors. The proposed work performs subject classification using k–NN with K=3 and K=5. Different features can be provided to k-NN that determines classification accuracy. The number of neighbors of every single feature set varies and accurate classification can be made accordingly. In general, the classifier is used to find patterns and classify data mining. The FNN classifier used in this paper consists of 20 hidden layers. The scaled conjugate gradient method is used for training of the proposed neural network. The maximum number of training epoch used is 1000. The classifier except for m-SVM used in this study are reproducible from MATLAB inbuilt functions.

Table- I: Percentage Cross Validation Accuracy of DCP for block size N=1, N=2, N=3 and N=4. Red value represents incorrect retrieval of subject

Feature Extracted	Block Size (Feature Vector Length)	Name of Classifier	Cross Validation Accuracy in Percentage										Avg. Classification Accuracy
			Subject										
			1	2	3	4	5	6	7	8	9	10	
Dual Cross Pattern	N=1 (512)	k-NN (N=3)	50	90	80	90	60	70	70	60	70	50	69
		k-NN (N=5)	90	90	90	90	60	60	50	50	50	40	67
		CT	40	20	20	90	60	40	10	30	70	30	41
		m-SVM	20	40	50	100	40	100	10	40	100	90	59
		FNN	60	50	30	90	40	60	30	50	60	20	49
	N=2 (2048)	k-NN (N=3)	100	100	100	100	90	90	100	80	100	100	96
		k-NN (N=5)	100	80	80	100	90	70	90	80	80	50	82
		CT	40	50	10	90	20	50	50	40	40	20	41
		m-SVM	0	10	0	100	30	100	40	100	100	90	57
		FNN	50	50	40	90	30	90	60	90	80	50	63
	N=4 (8192)	k-NN (N=3)	80	100	100	100	80	100	100	90	100	100	95
		k-NN (N=5)	100	80	90	90	80	90	60	90	60	60	80
		CT	50	50	60	90	70	30	10	60	30	10	46
		m-SVM	0	0	0	90	10	90	60	100	100	100	55
		FNN	40	50	50	60	40	90	50	90	30	70	57
	N=8 (32,768)	k-NN (N=3)	70	100	100	100	90	100	100	70	70	90	89
		k-NN (N=5)	80	100	60	100	70	80	60	90	60	60	76
		CT	20	30	30	60	50	40	10	70	20	10	34
		m-SVM	0	0	0	90	10	20	0	90	100	90	40

A. Discriminant Analysis using SPSS Software

This article performs discriminatory analysis to classify information into the corresponding class. Analysis of discrimination creates a predictive model for group membership. The model consists of a discriminating feature based on linear predictor variables combinations that provide the best group discrimination. The features are produced from a sample of instances for which group membership is known and can then be implemented to fresh instances with readings for predictor factors but unknown group membership. Multivariate normal distribution assumptions maintain that each of the dependent variables is normally distributed within groups. A sufficient amount of instances must apply to each group. Depending on whether the variance-covariance matrices are equivalent across groups, different classification techniques may be used. Prior probabilities determine whether classification coefficients are adapted for prior group membership information provided that all groups are identical and have no impact on the coefficients. The sample group sizes noted determined prior probabilities of group membership. For each case, codes are displayed for real group, anticipated group, subsequent probabilities, and discriminating results. The amount of instances allocated properly and wrongly to each group is called the Confusion matrix based on the discriminating assessment. Table 2 and Table 3 show the direct method confusion matrix with a. 57.0 percent of the initial grouped instances properly categorized and the Stepwise technique properly categorized with 100 percent of the initial grouped instances. To classify instances using a matrix of covariance within groups that pooled covariance matrix within groups is used to classify instances or a matrix of covariance between separate groups. This choice is not always equal to quadratic discrimination because classification is based on the discriminating features. Here, the scatter plot of the first two discriminating feature values is created by an all group, mixed groups. In addition, separate-group produces the first two discriminating feature values scatter plots. The table of the Standardized Canonical Discriminant Function Coefficients and the table of the Structure Matrix are mentioned in various premiers. The standardized discriminating coefficients work in an analogous way to standardized coefficients of regression in the regression of OLS. The canonical construct, also referred as canonical loading or discriminating loading, represents correlations between the factors observed and the discriminating features not observed. The discriminating features are a kind of latent variable and the correlations are factor loads similar. Group Centroids are the canonical variables class means. Table 4 compares current comparable methods with the suggested accuracy / error rate recovery technique.

IV. CONCLUSION

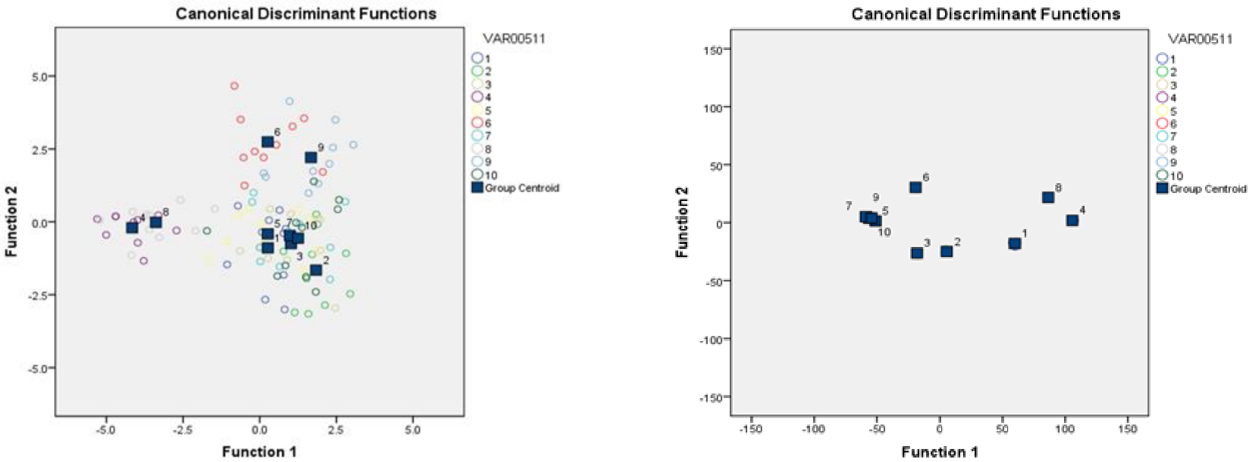
Using DCP as texture categorization methods, human identification has been presented in this paper based on hand radiographs. The proposed method is developed for a dataset of adults (18 years to 42 years). The initial results on a minimum dataset indicated that hand radiographs are an appropriate approach for human identification.

Table- II: Confusion matrix using direct method

Group No.	Predicted Group Membership										
	1	2	3	4	5	6	7	8	9	10	Total
1	60	0	10	0	10	0	20	0	0	0	100
2	10	50	10	0	0	0	20	0	0	10	100
3	10	10	30	0	30	0	20	0	0	0	100
4	0	0	0	70	0	0	0	30	0	0	100
5	10	0	30	0	50	0	10	0	0	0	100
6	0	0	0	0	0	80	0	0	20	0	100
7	10	20	0	0	20	0	50	0	0	0	100
8	0	0	0	30	0	0	0	70	0	0	100
9	0	0	0	0	10	20	0	0	70	0	100
10	10	10	0	0	0	0	20	10	10	40	100

Table- III: Confusion matrix using stepwise method

Group No.	Predicted Group Membership										
	1	2	3	4	5	6	7	8	9	10	Total
1	100	0	0	0	0	0	0	0	0	0	100
2	0	100	0	0	0	0	0	0	0	0	100
3	0	0	100	0	0	0	0	0	0	0	100
4	0	0	0	100	0	0	0	0	0	0	100
5	0	0	0	0	100	0	0	0	0	0.	100
6	0	0	0	0	0	100	0	0	0	0	100
7	0	0	0	0	0	0	100	0	0	0	100
8	0	0	0	0	0	0	0	100	0	0	100
9	0	0	0	0	0	0	0	0	100	0	100
10	100	0	0	0	0	0	0	0	0	0	100



(a) **(b)**

Fig.4. SPSS Discriminant Analysis for (a) Direct Method (b) Stepwise Method

Table- IV: Comparison of the proposed method with similar existing techniques for retrieval accuracy/error rate.

Sr. No.	Method	Accuracy /Error rate with dataset used
1	Hand radiograph segmentation for radius and ulna bones [22]	The result of segmentation are above average value, i.e., 3.5 for 19 images (1 for each age group from 0 to 18 year) from Children's Hospital Los Angeles, USA
2	Classification of a PROI and CROI by performing their independent analysis [14]	The accuracy of 90% with the discrepancy of 2-year error rate between PROI & CROI for 120 children's radiographs
3	Bone age assessment based on Epiphyseal/Metaphyseal ROI Extraction[16]	Feature extraction accuracy of 91%, 83 %, and 75% for distal, middle and proximal ROI respectively from 200 left-hand images below the age of 14
4	Skeletal maturity estimation of children using Tanner Whitehouse-Method[18]	Out of 71 cases,73.2% correct and 97.2% incorrect staged ROI, the error rate not more than one stage
5	Later stage bone age assessment using Wavelet transform, SVD and SVM [23]	21 hand radiographs from 7 years old to 12 years old are evaluated with average the accuracy of 92.41%
6	Automatic skeletal maturity identification using hierarchical three stages of syntactic recognition[20]	Presented the structural development of 128x145 dimension radiographs of 10-12 year boy
7	Automated radiographic assessment of hand in Rheumatoid Arthritis (RA)[28,29]	Joint space width segmentation using Active Appearance Model of 100 plain left and right hand radiographs of 40 different patients
8	DCP feature based subject identification from right-hand x-ray images (proposed)	Accurate retrieval of 100 test radiographs of 200x200 dimension acquired from adults(18 year to 42 year)

The proposed method is effortless and effective. Practically, it is indicated that by picking the suitable feature vector of an appropriate block size with acceptable classifiers can offer better texture categorization outcome. Multiclass Support Vector Machine (m-SVM), Classification Tree (CT), and Feedforward Neural Network (FNN), and k-Nearest Neighbor (k-NN) are the classifiers employed in DCP for human identification comparative study. Even though the proposed concept is easy, the experimental outcomes are favorable.

The experimental results based on DCP feature vector of hand radiographs give maximum retrieval accuracy level of 96% for a block size N=2 (feature vector length=2048) with k-NN (N=3), and 95% for a block size N=4 block size (feature vector length=8192) along with k-NN (N=3) . The retrieval accuracy of DCP is minimized to 37% for N=8 block size (feature vector length=4096) with CT classifier. It is evident that the result of this hand identification system is good. However, future work will involve database extension of hand radiographs that servers various age groups and influences the complete accomplishment of the presented method. This new dataset needs challenging and detecting many essential features of hand radiographs and well-suited classifiers for accurately retrieving the details of unidentified and missing people. Several difficulties have been faced during the retrieval of hand radiographs from the dataser such as pose, lighting, and age variations. In future, a unique method can be developed by integrating quality based frame selection and mark based matching method.

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