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Agglomerative Multi-Clustering Process for Fingerprint Matching Using Level 3 Features

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ABSTRACT

Fingerprint minutiae are usually distinct in three levels i.e. Pattern (Level 1), Minutiae points (Level 2) and pores and contour ridges (Level 3). Studies on level 3 features which have accounted significant development in the fingerprint detection accuracy were stranded either on live-scan fingerprints or full (rolled or slap) fingerprints. Consequently, these studies contribute less to do fingerprints, which are exemplified by small size, poor image quality and severe distortion in contrast to full fingerprints. In this paper, the level 3 features, including pores, dots, incipient ridges, and ridge edge protrusions, are used with agglomerative multi-clustering process. With the local pore model, an agglomerative multi clustering is used to organize the clustered features and the template is matched with those clustered parts of the images. Experiments on a good quality fingerprint dataset are performed and the results demonstrate that the proposed Level 3 feature matching model using agglomerative clustering technique performs more accurately and robustly.

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INTRODUCTION

Reliable recognition of an individual is an important problem in diverse applications. Biometrics, a recognition based on different characteristics of a person, has higher potential compared to other identification systems. Fingerprint biometrics is one among the important biometric technique for personal identification. It is hard to devise precise algorithms capable of mining relevant features and matching them; especially in poor quality fingerprint images and small area images. Minutiae-based systems usually rely on deciding communications among the minutia points obtained in “query” and “reference” fingerprint images. These systems usually achieve well with high quality, adequate surface area fingerprint images. This outcome is even further obvious on basically poor quality fingers, where only a division of the minutiae can be mined and used with adequate consistency.

Statistical examination has revealed that Level 1 features, while not distinctive, are practical for fingerprint organization (e.g., into left loop, whorl, right loop, arch etc.), while Level 2 features have adequate discerning power to launch the uniqueness of fingerprints. Likewise, Level 3 features are also maintained to be eternal, absolute, and unique. The forensic experts can present discriminatory information for human identification using Level 3 features.

The literature study on fingerprint biometrics (Anil K. Jain *et al.*, 2007; Anil K. Jain, 2010; Anil K. Jain, 1997; Anil K. Jain, 200; Fierrez-Aguilar, J., 2006; Heeseung Choi, 2011; Prince, 2010 ; Simon-Zorita, D., 2003) reveled that the performance of a fingerprint recognition system is heavily affected by the quality of fingerprint images. Rejecting low quality samples improves false rejection rate at a given false acceptance rate (Fernando Alonso-Fernandez, 2007).

Cluster analysis is an unsupervised tool for discovering the causal composition of a specified data set. Clustering algorithms can be used to detect similar minutiae groups from multiple template images (Ren Qun,) generated from the same finger to create the cluster core set. The agglomerative clustering technique (Mukherjee, D.P., *et al.*, 2002) is performed within a feature matrix where intensity and boundary relations are defined between neighboring segments.

The proposed work uses agglomerative multi-clustering technique for the process of clustering the level 3 features of the given image. Results are then compared with high resolution fingerprint matching using ridges, incipient ridges, scars and pores (Latha Jothi, V., 2012).

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MATERIALS AND METHODS

Agglomerative Multi-Clustering Process for Fingerprint Matching Using Level 3 Features:

The proposed work used agglomerative multi-clustering process for matching the fingerprint efficiently using level 3 features. At first, it deals with acquiring of fingerprint either using sensor device or from a group of fingerprints stored in the form of templates. After that, the feature extraction is done, which combines the process of extracting incipient ridges, scars, ridges and contours using Gabor Filter process. Initially the image performs the enhancement process using Gabor filter. Subsequently the wavelet transform is applied to the image in order to extract the four features. The Gabor filter is of the form:

$$F(a,b,\lambda,\Omega,\mu,\sigma,\rho) = \frac{\exp(a'^2 + \rho^2 b'^2)}{2\sigma^2} \otimes \frac{\exp(i(2\prod(a' + \mu)))}{\lambda} \quad (1)$$

Where a, b represents pixel values, λ denotes the wavelength factor, Ω represents orientation format, μ denotes phase offset value, σ represents sigma value and, ρ denotes spatial aspect. After the selection of feature is done, the multi-clustering process is done for clustering the given image using agglomerative clustering.

The architecture diagram of the proposed agglomerative multi-clustering process for matching the fingerprint efficiently using level 3 features is shown in Fig 1. The testing and training image is taken out from database. After that, the image has been tested to check whether noise is present or not. Then the feature selection has been done to extract the features of the testing and the training image. Then agglomerative clustering is applied to cluster the level 3 features of the given images.

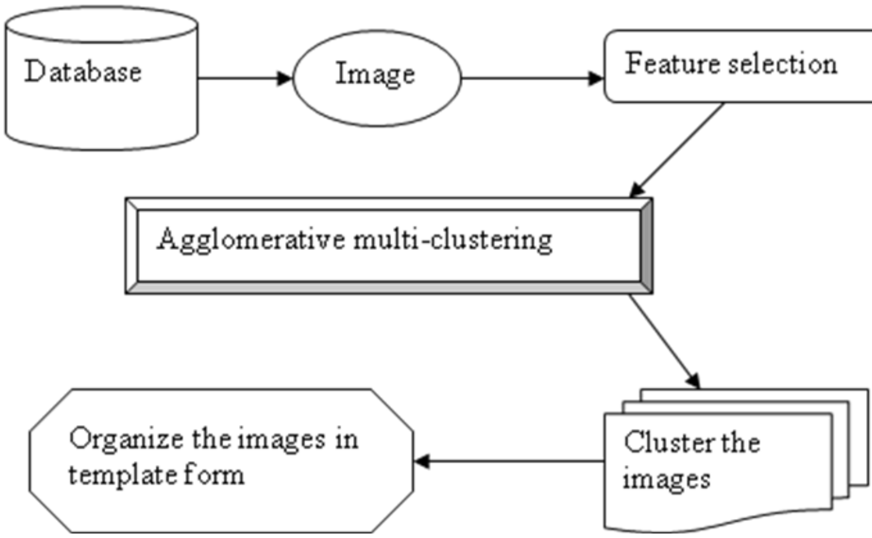

Fig. 1: Architecture diagram of the proposed agglomerative multi-clustering process.

Agglomerative multi-clustering algorithm:

Segmentation of a given image is an important step for automated image analysis applications. The ACA (Agglomerative Clustering Algorithm) forms clusters in a bottom-up manner.
The algorithmic steps can be described as follows:
(1) Primarily, set every article in its individual cluster.
(2) Between all existing clusters, select the two clusters with the minimum distance.
(3) Substitute these two clusters with a novel cluster which is created by integrating the two clusters.
(4) Repeat the above two steps until there is only one remaining cluster in the pool.

Thus, the agglomerative clustering algorithm will produce the outcome in a binary cluster tree with distinct object clusters as its leaf nodes and a root node comprising all the articles. In the clustering algorithm, we use a distance measure based on record probability. For articles *A* and *B*, the distance is termed as

$$d(A,B) = LL(A) + LL(B) - LL(A \cup B) \quad (2)$$

The chronicle possibility LL(X) of an article or cluster *X* is given by a unigram model:

$$LL(X) = \log \prod_{w \in x} px(w^{ex(w)}) \quad (3)$$

Where, *ex(w)* and *px(w)* are the count and probability, respectively, of image *w* in cluster *X*.

Agglomerative clustering is a bottom-up clustering process. At the creation, every input object creates its individual cluster. In every consequent step, the two ’contiguous’ clusters will be combined until only one cluster is leftover. This clustering process formed a chain of command of clusters, such that for any two divergent clusters A and B from probably divergent levels of the hierarchy we have $A \cap B = \phi$. Such a chain of command is practical in many applications, for instance, when one is involved in traditional properties of the clusters or if the precise number of clusters is a priori indefinite.

In order to term the agglomerative approach correctly, we have to identify a distance appraisal among clusters. Given a distance function among data objects, the subsequent distance among clusters are regularly used. In the single linkage strategy, the distance among two clusters is termed as the distance among their contiguous pair of data objects. It is not rigid to observe that this approach is equal to evaluating the smallest spanning tree of the graph persuaded by the distance function using Kruskal’s algorithm.

Fingerprint matching with level 3 features using agglomerative multi-clustering process:

Acquisition of fingerprint is the first step. The image is then preprocessed to get the good quality of the image. Enhancement of the image is the next step which increases the clarity of the image. Level 3 features are then extracted from the image. Agglomerative multi-clustering process is than done for clustering the level 3 features of the given fingerprint image. The process of Fingerprint matching with level 3 features using agglomerative multi-clustering is described in Fig 2.

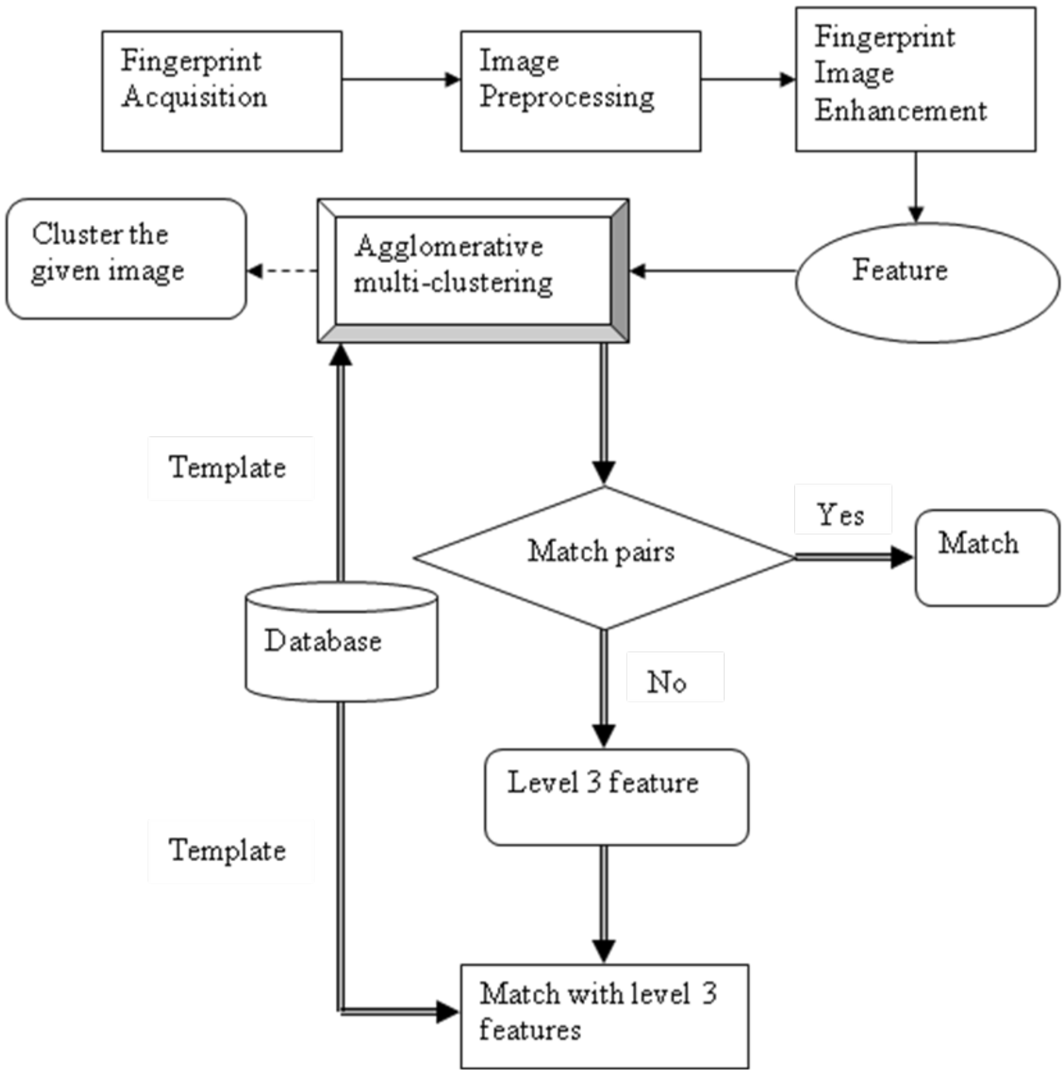

Fig. 2: Process of agglomerative multi-clustering with level 3 features.

Consider T and Q is the template and query images which have to be matched with each other. At first, the agglomerative multi-clustering process is done with the given quality of images for the clustering process of level 3 features (scars, width, pores, shape, incipient ridges, and edge contour) to measure the similarity among the two representations. These level 3 features are clustered and processed. The fingerprint matching is done with the template for the extraction of level 3 features and the enhancement of image matching process is efficiently done with the feature extraction process.

Results:

A widespread experimental study has been conducted to scrutinize the proposed agglomerative multi-clustering process with level 3 features for fingerprint matching concepts. The algorithm is implemented using Java. The experiments were run on an Intel P-IV machine with 4 GB memory and 3 GHz dual processor CPU. The data sets were stored on the local disk. The algorithm has been efficiently designed for matching the fingerprint framework with the clustered images derived from database. The performance of the algorithm is measured in terms of

i) Clustering efficiency
ii) Peak Signal to Noise Ratio (PSNR)
iii) Matching rate

The efficiency of clustering process is evaluated based on the image that has been clustered after extraction of features in a particular interval of time by using the Eq. (4)

$$C = \frac{1}{n}\sum_{a=1}^{n} \max_{a=b}\left(\frac{\mu_a + \mu_b}{d(D_a, D_b)}\right) timet \tag{4}$$

Where n is the number of clusters,
D_a is the centroid of cluster ‘a’,
t is the time taken to cluster the level 3 features,
μ_a is the average distance of clustered features of ‘a’ to centroid D_a to form a template T,
d (D_a, D_b) is the distance between centroids D_a and D_b.
Eq. 4 described the efficiency of AMP clustering process. Lower the value C, higher the efficiency would be.
The Peak Signal to Noise Ratio (PSNR) and Mean Square Error (MSE) lies among the given image and template image for matching the fingerprint concepts. The PSNR value is the measure of peak error.

$$MSE = \sum\sum[I(a,b) - I'(a,b)] \tag{5}$$

Where a = 1, 2,…n and b = 1,2,… n, where n is the size of the image in pixels. In Eq. (5), I(a,b) represents the given image whereas I’(a,b) represents the template. The dimensional values are denoted by using m and n.

$$PSNR = 10\log 10\frac{R^2}{MSE} \tag{6}$$

PSNR value is calculated in terms of decibels. PSNR ratio is used to measure the quality of image. Higher the PSNR rate better will be the quality of matched image.

Discussion:

The results of the proposed agglomerative multi-clustering process with level 3 features for fingerprint matching concepts is compared with the results of the existing High-Resolution Fingerprint Matching Using Level 3 Incipient Ridges and Scars (HRFM) written in mainstream languages such as Java. Different sets of images for comparing the results.

The Table 1 and Fig, 3 described the performance evaluation of the two techniques. Clustering efficiency is calculated for number of user using both the techniques. The graph is plotted for number of user versus clustering effectiveness (%). It is observed from the graph that effectiveness of the clustering (%) obtained for the proposed agglomerative multi-clustering process with level 3 features for fingerprint matching concepts is higher when compared to existing HRFM technique.

Australian Journal of Basic and Applied Sciences, 7(14) December 2013, Pages: 204-210

Table 1: No. of user vs. Clustering efficiency.

No. of users	Efficiency of clustering process	
	Proposed AMP technique	Existing HRFM
1	25	15
2	40	30
3	33	22
4	48	20
5	42	25

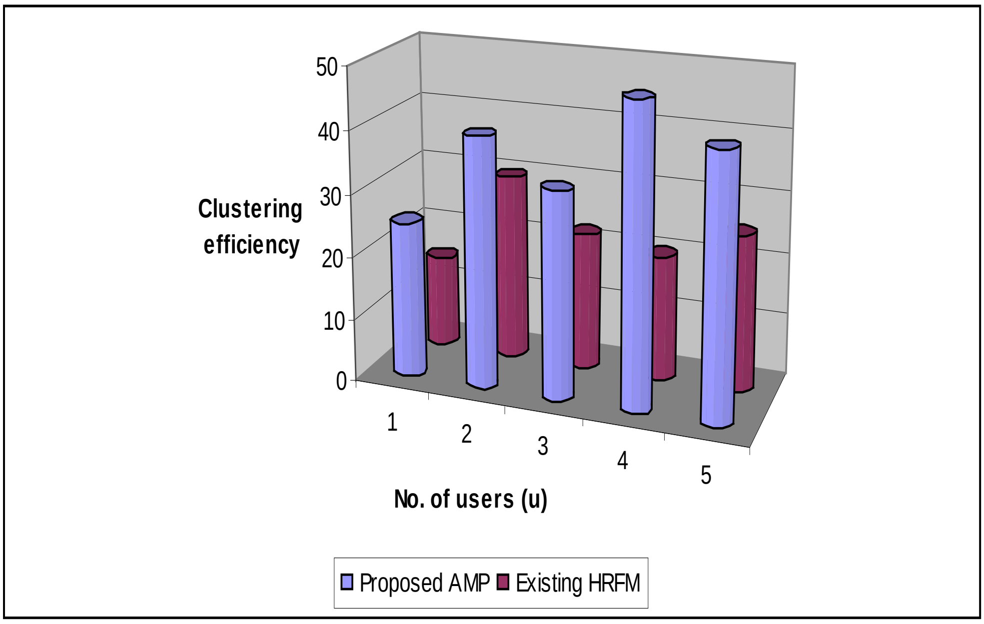

Fig. 3: No. of user vs. clustering efficiency.

The PSNR (Peak Signal to Noise Ratio) rate is then calculated for fingerprint samples retrieved from the database using both the techniques. The calculated values are then plotted for number of users using a graph. The calculated values are tabulated in Table 2 and the plotted graph is shown in Fig 4. It is observed from the graph that PSNR rate (%) obtained for the proposed agglomerative multi-clustering process with level 3 features for fingerprint matching concepts is higher when compared to existing HRFM technique. The quality of the image is also being high in the proposed technique.

Table 2: No. of user vs. PSNR rate.

No. of users	PSNR rate (%)	
	Proposed AMP technique	Existing HRFM
1	28	12
2	45	21
3	50	35
4	67	48
5	80	57

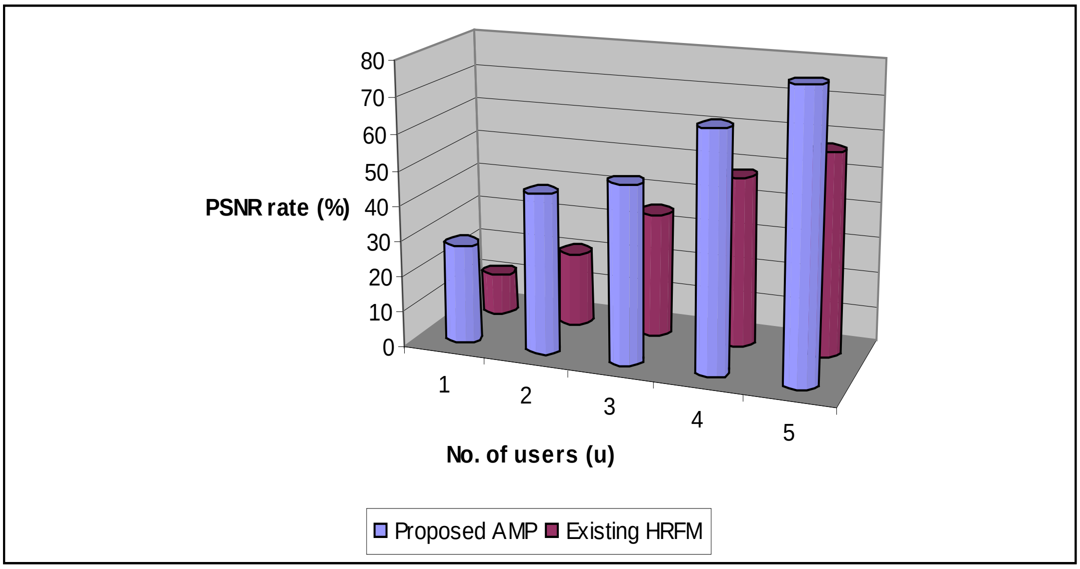

Fig. 4: No. of user vs. PSNR rate.

Matching rate is then calculated for fingerprint samples present in the database and tabulated in Table 3. The results are then plotted for number of user versus matching (%) in the form of a graph as in Fig. 5. It is observed from the graph that matching (%) obtained for the proposed agglomerative multi-clustering process with level 3 features for fingerprint matching concepts is higher when compared to existing HRFM technique.

Table 3: No. of user vs. Matching.

No. of users	Matching (%)	
	Proposed AMP technique	Existing HRFM
1	15	10
2	24	18
3	54	28
4	48	32
5	60	48

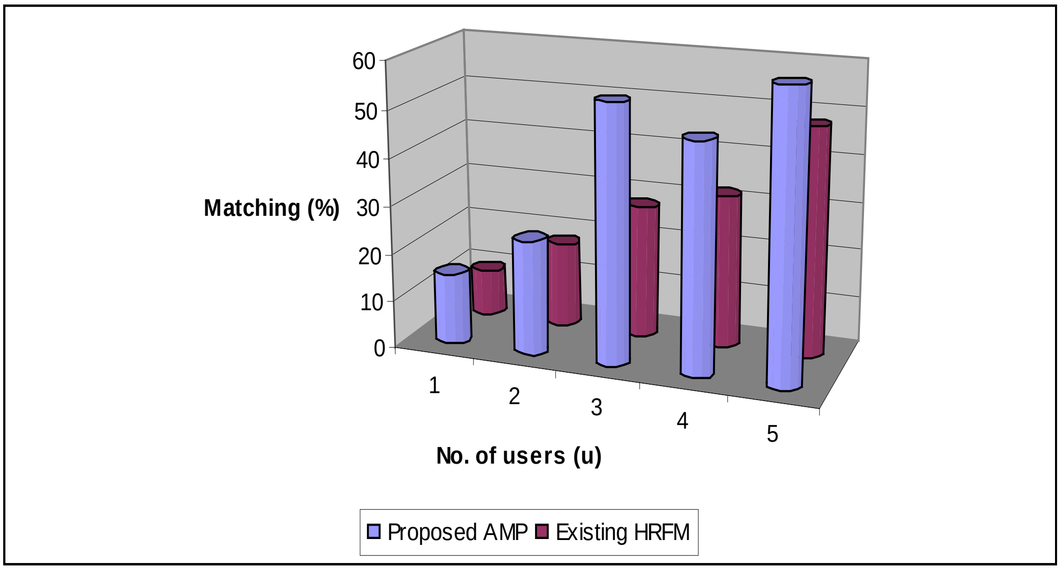

Fig. 5: No. of user vs. Matching.

Conclusion:

The high resolution fingerprint matching for Level 3 features using agglomerative multi-clustering process is efficiently presented in this work. It produces higher PSNR rate with reduce in error rate. The experimental result shows that the proposed fingerprint matching pairs using agglomerative multi-clustering process achieves 93.4% of performance in matching concepts over the existing HRFM model which achieves only 86.23%. In addition the clustering efficiency for our proposed fingerprint matching pairs using agglomerative multi-clustering process gain 4.94% when compared to the existing HRFM work which attains only 2.62%. The use of integrated Level 3 features with agglomerative multi-clustering process minimizes the error rates and increases the matching pairs of fingerprints. Finally matching process is performed using agglomerative multi-clustering process with test and training images to enhance the capability of the work.

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