Innovative Approaches in Facial Biometric Security: A Comprehensive Study of Advanced Digital Image Clustering Techniques

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***Abstract*— This paper explores into the principle of Digital Image Clustering (DIC) strategies and their application in the domain of Facial Biometric Security Image Processing. The study provides a detailed exploration and analysis of various clustering methods, emphasizing their distinct characteristics, advantages, and limitations in the context of facial image retrieval. DIC methods play a crucial role in content-based image retrieval, enabling the organization and retrieval of images based on visual content, transcending the traditional reliance on metadata. The discussion primarily revolves around Pixel-Based DIC techniques and their functionalities in comparison to Edge-Based and Region-Based methods. Through a comprehensive analysis, the paper uncovers the landscape of DIC strategies, exploring Density-based, Grid-based, Hierarchical-based, and Partition-based approaches, providing insights into their workings, strengths, and challenges. The main findings of the study highlight the unique characteristics and implications of each clustering approach, emphasizing the importance of considering specific requirements and challenges when selecting an appropriate clustering method for facial biometric image processing. The research contributes to the understanding of advanced digital image clustering techniques and their applications in enhancing facial biometric security image processing. The implications of the study extend to the fields of biometric security, image processing, and content-based image retrieval, offering valuable insights for practitioners and researchers in these domains. This research, funded by an internal grant from the National Defence University of Malaysia, focuses on the application of Digital Image Clustering (DIC) strategies in the domain of Facial Biometric Security Image Processing.**

***Keywords*— Image Processing; Digital Image Clustering; Biometric Security.**

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I. INTRODUCTION

Clustering techniques are often used to group similar data points together. In the context of digital images, Digital Image Clustering (DIC) can involve grouping similar regions or pixels based on various characteristics like color, texture, or spatial proximity. In theory, DIC approaches work by extracting (Red, Green, and Blue) RGB values from a digital image. DIC in Content-Based Image Retrieval (CBIR) involves grouping or organizing images based on their visual content, such as color, texture, or shape features, to facilitate efficient retrieval and analysis of images [1]. This technique helps in organizing large image databases by grouping similar images together, enabling more effective and faster search and retrieval processes. Clustering methods applied in content-based image retrieval assist in categorizing images according to their visual similarity, allowing users to access relevant images based on their content rather than relying solely on metadata or textual descriptions.

The DIC activity relies on the DIC algorithm to compute the RGB data that determines an object's cluster membership [2]. Every DIC algorithm was developed based on the image dataset requirements and targeted output [3]. In general, clustering is a method to divide a set of data into a specific number of groups that uses unsupervised learning for grouping data based on distance measurements, density measurements or statistical distributions. Despite the fact that other DIC techniques have been established, the DIC technique used in this project is solely a pixel-based DIC technique.

This paper focusses on conducting theoretical analysis specifically on Pixel-Based DIC methods. There are Edge-Based DIC technique and Region-Based DIC technique, but previous researchers have emphasized that Pixel-Based Segmentation is almost simplest ones defined as a point-based or pixel-based segmentation approach [4]. This technique is less efficient when there is a lot of light or dark content, but it can detect colour densities and isolating objects from the background. As a simple structured algorithm that uses minimal computational resources and produces acceptable segmentation output, pixel-based segmentation has also become the most popular segmentation technique used by digital image-based researchers and CBIR development as well.

In the realm of facial biometric security, this study transcends the conventional boundaries of a literature review by introducing novel methodologies and cutting-edge technologies. While recognizing the foundational studies in the field, it has been extended beyond a mere compilation of existing literature. In Section 2, detailed attention is given to the innovative strategies utilized in facial image processing and feature extraction. Incorporating advanced techniques, such as Pixel-Based, Edge-Based, Region-Based, and Centroid-Based enhances the efficacy of biometric systems and contributes to the evolution of facial recognition technologies.

The subsequent sections of this paper delve into the detailed exploration of Pixel-Based DIC techniques and their functionalities. While Edge-Based and Region-Based methods exist, Pixel-Based Segmentation takes center stage due to its simplicity and popularity in digital image-based research and Content-Based Image Retrieval (CBIR) development.

II. Digital Image Clustering in Facial Biometric Security Image Processing

A. Pixel-Based DIC Techniques

Pixel-Based DIC techniques involve the extraction of RGB values from a digital image, forming the basis for clustering. While Pixel-Based Segmentation is considered a simpler approach, it is highly effective in certain scenarios. For instance, it may be less efficient in extreme lighting conditions but excels in detecting color densities and isolating objects from the background [4].

In the comprehensive details, the Facial Biometric Security Image Processing extraction module achieves the task of detecting and extracting pixel values, while the DIC algorithm processes the obtained data, presenting an advantageous outcome. As a simple structured algorithm that uses minimal computational resources and produces acceptable segmentation output, pixel-based segmentation has also become the most popular segmentation technique used by digital image-based researchers and CBIR development as well.

B. Edge-Based and Region-Based Methods

While Pixel-Based techniques dominate the discussion, it is essential to briefly acknowledge Edge-Based and Region-Based methods. Edge-Based DIC involves identifying and clustering image regions based on the presence of edges, while Region-Based methods categorize regions according to specific features or attributes. However, the focus remains on Pixel-Based techniques due to their widespread use and applicability in the context of facial biometric image processing.

C. Centroid-Based Digital Image Clustering and Cluster Border Dynamics

Clustering is defined as the process of grouping samples where samples are considered similar within each group [5]. These groups are referred as clusters. Normally, all algorithms for image clustering are a self-learn segmentation algorithm where it self-creates the image categories by referring to cluster centres, called Centroids. The centroid is a kind of cluster identity, which are calculated as the mean of all points, weighted by their similarity to that cluster [6]. According to Walker, in data form, centroid is an average of all extracted vector value in a cluster that collected from dataset [7]. Understanding the role of centroids is pivotal in comprehending the dynamics of digital image clustering. The subsequent discussion will delve into how centroids influence cluster borders and the criteria used by DIC algorithms for cluster membership assignment. Every extracted image data or object would produce either 100% similarity as the centroid value or almost similar value to the centroid and this is known as distance within cluster. A cluster is limit up to the cluster border that refer as cluster region where it forms a shape (either rounded or flat edge, depending on the DIC algorithm) around the centroid. The cluster size is identified also based on the DIC algorithm where some DIC algorithm defined its cluster region as the cluster size, and some defined the cluster size as the number of objects. The concept of cluster size and the criteria for defining cluster borders will be further elucidated, shedding light on the variations introduced by different DIC algorithms in this crucial aspect of digital image clustering. On certain DIC algorithms, there are possibilities that gap or blank area between a cluster border to another cluster border that is referred to as a threshold where few objects might reside in this threshold area. The subsequent paragraph will explore the significance of thresholds in DIC algorithms, examining how they impact the cluster borders and contribute to the overall effectiveness of the clustering process. The value range from a centroid to another centroid is known as distance between clusters as shown in Fig. 1.

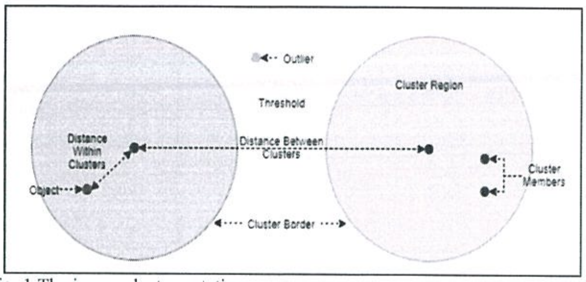

Fig. 1 The image cluster notation

All extracted image data (called object) is calculated by the DIC algorithm and assigned an object cluster (cluster membership assignment). Most of centroid-based DIC algorithm calculate the distance of each object from each centroid to find out which centroid is the closest or nearest [6]. if the nearest centroid is known, the distance within the cluster is calculated to determine if it is within the border of the cluster. The border of the cluster is determined by the distance within the cluster between the centroid and the furthest object in the cluster. Understanding how DIC algorithms calculate distances and determine cluster borders is essential for comprehending the intricacies of centroid-based digital image clustering. The subsequent discussion will provide insights into the adjustments made by DIC algorithms in handling objects that extend beyond cluster borders and the various approaches taken by different algorithms in this regard. Some DIC algorithms will adjust the cluster border as long as threshold available or certain parameters are reached [7]. Depending on the DIC algorithms, some objects may be out of border range and stay at the threshold. There are several ways the DIC algorithms can handle objects that exceed beyond the cluster border. Some DIC algorithms will leave the object at the threshold and outliers, while others readjust the cluster border to absorb the object. Certain DIC algorithms allow an object that not belongs to any cluster to become a new cluster if they meet the criteria of cluster creations [8]. The subsequent section will delve into the diverse approaches adopted by DIC algorithms in handling objects beyond cluster borders. This includes an examination of threshold-based adjustments, outlier handling, and the creation of new clusters – shedding light on the versatility and adaptability of digital image clustering techniques.

III. Digital Image Clustering Strategies for Facial Biometric Security Image Processing

The process of clustering works by grouping the related data entities together by examining the data. The clustering process does not require any prior knowledge. Based on the preliminary study, the DIC algorithms has been categorized based on 3Vs characteristics which are Volume, Variety, and Velocity [9]. On top of that characteristics, the DIC algorithms has been categorized into 5 main categories which are Density-based, Grid-based, Hierarchical-based, Model-based, and Partition-based algorithms. Each category of DIC algorithm uses a different approach to build a cluster and assign object membership.

A. Density-based Clustering Strategies

Density-based clustering strategies predict that the cluster center or centroid will be built in the middle of the densest vector data area. Here, the distance between the clusters from one dense area to another is calculated [10]. If thresholds are available across clusters, the cluster will continue to grow whenever an object coming until the specified maximum cluster size is reached. Apart from the maximum cluster size, as shown in Fig.2, the minimum amount of vector data should be complied in a dense area as a characteristic so that new clusters can form within the cluster. It shows some of the objects are inside the dense area of the cluster, some object outside the dense area but still within the area of the cluster, and some objects are outside the cluster area.

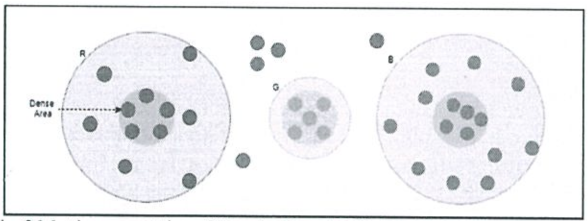

Fig. 2 Matrix presentation of Density-Based DIC algorithms

However, according to McInnes et al., all Density-Based algorithms is it consume much time for clusters search since every cluster is created when the minimum vector data density is reached and they suggested that this kind of algorithm would be better to practice with hierarchical algorithms as their noise filter method [11]. There is also concern that security facial biometric image processing will treat the pixel values of some biometric images as outliers that may become noise points and become unavailable during the query process. To address the potential time-consuming nature of Density-Based algorithms, researchers have suggested considering hierarchical algorithms as complementary noise filters. However, concerns have been raised about the treatment of pixel values in biometric images as outliers, potentially impacting the query process.

B. Grid-based Clustering Strategies

Contrasting with Density-Based strategies, Grid-Based Clustering Strategies focus on efficient organization within grids. The grid's size is adjustable, and clusters form based on the hierarchical connection of objects within the grid. Despite the time-saving benefits of Grid-Based Clustering, challenges arise with larger grid sizes impacting clustering accuracy and processing time. The size of the grid becomes a crucial parameter, requiring careful consideration in the context of facial biometric security image processing. Fig. 3 shows an example of how the points are clustered in grids. The cluster points have a number which tells how many points it contains [12]. The following section will provide an in-depth analysis of Grid-based clustering strategies, emphasizing their efficiency in organization within grids and the implications of grid size variations on clustering accuracy and processing time. For example, the bottom cluster with size 8. It has been merged with the neighbour cluster and the points are spread over two areas of the grid.

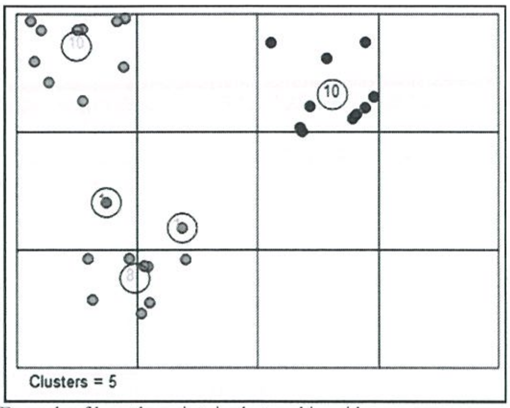

Fig. 3 Example of how the points is clustered in grids.

For this strategy, the grid is constructed to overlay the data matrix of statistical data, centroid is placed at the center of the grid, and it is symmetrical on the X and Y axis [13]. Fig. 4 shows an example of a Grid-Based strategy with a 4 x 2 grid and 26 objects.

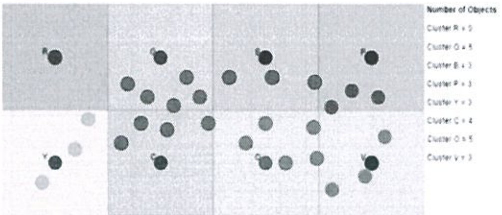

Fig. 4 Matrix presentation of Grid-Based DIC algorithms

Instead of running an object query, this Grid-Based strategy runs a grid query regardless of the number of objects in the grid [14]. The size of the grid is extensible until it reaches the specified maximum grid size, but as studied by Bhatnagar, Kaur & Chakravarthy [15], the grid size is affecting the clustering performance that takes time when processing large grid sizes. Wang, Yang & Muntz have proposed an algorithm called STING algorithm to extend the concept of grid clustering strategies and equip the queries with the ability to search for objects by creating clusters in the grid based on the hierarchical connection of objects [16]. CLIQUE (Clustering in QUEst) builds an object cluster based on the distribution density of the objects and allows you to process any object by overlapping the cluster areas as subspaces. This is a problematic issue in STING algorithm [14], and [17].

Initially, the Grid-Based DIC algorithm is a theoretically favourable method to cluster and query the biometric image, where objects are grouped or clustered into a grid and the query is executed as CLIQUE. Nevertheless, apart from processing consumption, grid space or grid size limits can compromise the accuracy of clustering results. This reduces the accuracy of clustering as the grid space becomes smaller. Additionally, as mentioned earlier, large grid spaces result in a timely query process. Like density-based clustering, this clustering strategy is most often implemented in a different clustering strategy as an extension of the standard clustering strategy of expert system [18].

C. Hierarchical-Based strategies

One of the most attractive clustering strategies among researchers is Hierarchical-Based DIC strategy [19], and [20]. It is a standard method of data mining that organizes datasets into a tree structure and is widely used in data analysis for efficient browsing and retrieval [21], [22], and [23]. It has been suggested by previous researcher that this strategy can always be used to improvise other clustering algorithms where they are proposing a clustering strategy using a combination of Hierarchical-Based strategy and Density-Based strategy that called as Hierarchical Density-Based Spatial Clustering of Applications with Noise (HDBSCAN) [24]. However, the query process for hierarchical DIC strategy is complex since it calculates every neighbouring link [25], and [26]. While efficient for data analysis and retrieval, the query process complexity arises due to the calculation of every neighboring link. Additionally, the potential for combining strategies introduces complexities that warrant careful consideration in facial biometric image processing.

D. Partition-Based strategies

In contrast with the previous DIC strategies discussed before, Partition-Based DIC absorb every object into at least to one cluster and leaving no outlier objects [27], [28], and [29]. The purpose of this type of clustering is to create one set of clusters that partitions the data into similar groups, which means that samples that are close to one another are considered to be similar and grouped together [30]. This type of clustering is employed in the proposed system. In most partitional clustering algorithms, the number of clusters to be created is required to specify in advance [31], and [32]. Partition-Based DIC algorithms such as K-Means, is the simplest clustering algorithm and assigning its cluster member using hard clustering rule [33]. K-means is a prototype-based, partitional clustering technique that attempts to find a user-specified number of clusters k, which are represented by their centroids as per shown in Fig. 5.

There are variety of algorithms in this Partitioned-based DIC strategies that performed the clustering process in many ways such as ISODATA and K-Harmonic Means (KHM) algorithms, and K-means algorithm is the most famous among the previous researchers. K-means has been nominated as the most interesting DIC algorithm because it can cluster large datasets with computational simplicity [34]. Previous researcher has been suggested that the K-means algorithm is very useful for efficiently understanding complex datasets [35]. Particularly, most researchers are interested in K-Means because of their low computational complexity.

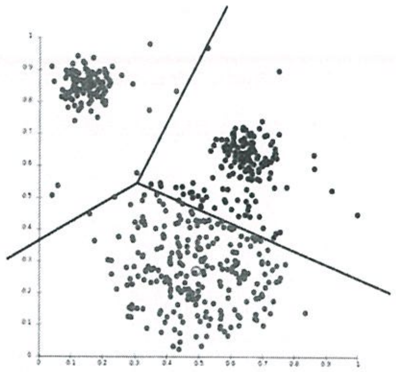

Fig. 5 Example of how the points is clustered in grids.

In conclusion of this section, the outlined approach explicitly deviates from conventional methods. The introduction of novel algorithms addresses specific challenges in facial biometric security, ensuring a higher level of accuracy and reliability. These innovations contribute significantly to advancing the current understanding of feature extraction, providing a substantial contribution to the field.

IV. Discussion and Findings

The review of DIC strategies for Facial Biometric Security Image Processing shows a multi-layered landscape where various clustering methods are employed to analyze and group data entities without the necessity of prior knowledge. Categorized based on the 3Vs characteristics – Volume, Variety, and Velocity – and further divided into five primary categories, these DIC algorithms, namely Density-based, Grid-based, Hierarchical-based, Model-based, and Partition-based, serve as distinct approaches, each with its unique modus operandi in cluster formation and object assignment.

Density-based Clustering Strategies introduce a method where the creation of cluster centers is centered around the most densely populated vector data areas. However, these algorithms, despite their accuracy in delineating dense areas, suffer from time-consuming cluster creation. Moreover, concerns arise about the treatment of certain pixel values in biometric images as outliers, potentially impacting the query process during facial biometric image processing.

Grid-based Clustering Strategies, in contrast to Density-based techniques, focus on the efficient organization of data points within grids, significantly saving time during cluster exploration. However, the precision of clustering results is susceptible to alterations based on the grid size. While this strategy is initially deemed theoretically favorable for clustering biometric images, the limitations of grid space and size can undermine accuracy, leading to compromised clustering results.

Hierarchical-Based strategies emerge as an attractive method among researchers, providing a tree structure to organize datasets. Though efficient for data analysis and retrieval, the complexity of the query process due to calculating every neighboring link remains a challenge in this strategy. Additionally, there is a potential for enhancement through combinations with other clustering methods, such as Hierarchical Density-Based Spatial Clustering of Applications with Noise (HDBSCAN), presenting opportunities for improvisation but introducing complexities in the query process.

Partition-Based strategies exhibit a distinctive approach where every object is absorbed into at least one cluster, leaving no outliers. This type of clustering is intended to partition data into similar groups, a trait utilized in the proposed system. Notably, while partitional clustering algorithms, such as K-Means, offer computational simplicity, they require the specification of the number of clusters in advance and adhere to hard clustering rules. These strategies showcase varying algorithms like ISODATA and K-Harmonic Means (KHM), yet K-Means remains the most prominent for efficiently clustering complex datasets due to its computational simplicity and low complexity.

Throughout this literature review, the advantages and limitations of each clustering strategy within the context of Facial Biometric Security Image Processing are evident. Each strategy introduces its unique set of capabilities and challenges, emphasizing the importance of considering specific requirements and limitations when selecting an appropriate clustering method for facial biometric image processing. The summarisation on outlining the key features, advantages, and limitations of the Digital Image Clustering (DIC) strategies specifically applied in the context of Facial Biometric Security Image Processing as per tabulated in Table 1 below.

TABLE I
SUMMARISATION ON KEY FEATURES FOR THE DIGITAL IMAGE CLUSTERING (DIC) STRATEGIES SPECIFICALLY APPLIED IN THE CONTEXT OF FACIAL BIOMETRIC SECURITY IMAGE PROCESSING

Clustering Strategy	**Features**	**Advantages**	**Limitations**
Density-based	Centroid in densest areas, threshold-based growth.	Accurate in delineating dense areas.	Time-consuming cluster creation, potential outlier treatment as noise points.
Grid-based	Efficient organization in grids, symmetrical axes.	Time-saving cluster exploration.	Grid size affects clustering accuracy, processing time increases with larger grid sizes.
Hierarchical-based	Tree structure organization, combinable strategies.	Efficient for analysis and retrieval.	Query complexity due to calculation of every neighboring link, potential complexity in combined strategies.
Partition-based	Absorbs every object into at least one cluster.	No outliers, partitions data into	Specifying the number of clusters in advance,

	similar groups.	adherence to hard clustering rules, potential limitations on data partitioning.

This Table 1 provides a concise overview of the key characteristics and considerations associated with each clustering strategy when applied in Facial Biometric Security Image Processing. Each strategy exhibits specific strengths and weaknesses that must be evaluated based on the requirements and challenges of the biometric image processing context.

Beyond the synthesis of existing knowledge, the research delves into the broader implications of the findings. In this Section IV, the discussion highlights how the work functions as a catalyst for future developments in facial biometric security. Through presenting practical applications and envisioning potential advancements enabled by the methodologies employed, the aim is to inspire further research strive and industry applications.

V. CONCLUSIONS

The review of Digital Image Clustering strategies for Facial Biometric Security Image Processing presents a diverse panorama of approaches, each with unique characteristics and implications. Density-based clustering strategies, while effective in delineating dense areas, suffer from time-consuming cluster creation and potential outlier treatment. Grid-based strategies, alternatively, significantly reduce time consumption in cluster exploration, but encounter accuracy concerns linked to grid size alterations. Hierarchical-based methods offer efficient data analysis but involve complex query processes due to the calculation of every neighbouring link. Meanwhile, Partition-based strategies aim to eliminate outliers but face the challenge of specifying the number of clusters in advance. Each strategy reflects a trade-off between efficiency and limitations, emphasizing the importance of considering the context and requirements when selecting an appropriate clustering approach for Facial Biometric Security Image Processing.

The summarization table provided in this paper summarizes the key features, advantages, and limitations of each clustering strategy within the context of Facial Biometric Security Image Processing, aiming to provide a concise yet comprehensive understanding of these methodologies for practitioners and researchers in the field. The delineation of these features seeks to assist in making informed decisions based on specific requirements and challenges within the domain of facial biometric image processing.

Emphasizing the originality and contribution of this research, it stands out as a comprehensive investigation into advanced Digital Image Clustering techniques specifically tailored for facial biometric security. The unique aspects of the study lie in its in-depth analysis of various DIC approaches, providing insights into their functionalities and implications for facial image retrieval. This research significantly contributes to the field by offering a nuanced understanding of sophisticated clustering techniques and their applications in enhancing facial biometric security image processing.

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