Blind Source Camera Clustering of Criminal Case Data

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***Abstract*—This work focuses on the examination of a real word criminal case data set, consisting of still images found on a suspect's computer during a sexual abuse case investigation. Various source camera clustering algorithms, all based on the photo-response non-uniformity (PRNU), are employed to organise the images according to their source camera. The investigated data set poses many challenges to the algorithms due to the unknown origin of its images. The clustering result's quality is examined using different external and internal cluster validity indices (CVIs). Before attempting to cluster the criminal case data, the clustering algorithms and CVIs have been examined on a different data set with known ground truth, which revealed that some algorithms and CVIs are not appropriate for this scenario.**

Finally, we give some recommendations on which clustering algorithms and CVIs can be used in this scenario and discuss the problems and challenges we faced while investigating the data set.

***Index Terms*—Digital Image Forensics, Source Sensor Clustering, PRNU, Criminal Case Investigation.**

I. Introduction

In forensic case work, source camera identification using PRNU can yield important evidence for the criminal investigation. The properties of the examination makes it well suited to be used in a Bayesian evaluation scheme as a Likelihood Ratio (LR) calculation [1]. Typical criminal cases, where such examinations can be of use, include fraud, sexual child abuse, rape and assault. Often, the perpetrators have an urge of documenting their criminal actions, and the imagery is often captured by mobile phones readily at hand. In the ideal case, the suspect's camera is available for collection of all necessary reference data to conduct the examination. A detailed EXIF data analysis is always complementing the PRNU examination and is included in the evaluation. When signs of alteration are found in the EXIF data, the weight of the PRNU examination will be lower and the LR value approaches unity.

However, in cases where reliable reference data can not be obtained, it can be useful to organise the images confiscated on the suspect's computer by their source camera instead. These images should have general properties fitting that of the questioned imagery, and preferably also a connection to the suspect (e.g. family album). For this scenario, a prior screening of the data based on the image origin or source camera could be very useful. Source camera clustering based on the camera's PRNU offers an intuitive solution to this problem by associating images that have been captured with the same device. Such information could be important to identify the number of victims in grooming cases and to find more images taken with the same webcam (victim), or to evaluate the number of perpetrators in sexual child abuse cases.

In the source camera clustering scenario, however, the investigator is usually confronted with a large set of images from unknown source(s). The goal is to group all images according to the source camera, where the number of cameras as well as the distribution of the images among them is unknown. In this case it is usually not possible for the investigator to acquire additional data because the source cameras might not be available. Several classical clustering techniques have been proposed in literature to solve this problem [2–9].

As already mentioned, the source camera clustering problem is solved by partitioning the data set under investigation using a clustering algorithm. According to Wang *et al.* [10] the term *cluster validity assessment* describes the process of evaluating the clustering result. This evaluation is based on two criteria, which are used to determine the "optimal" clustering solution:

- *Compactness*: The members of each cluster should be as close to each other as possible.
- *Separation*: The clusters themselves should be widely separated.

The partition that best fits the underlying data can be considered as the "optimal" clustering solution. Several clustering validity indices (CVIs) have been proposed in literature, which can be divided into external and internal indices (or criteria) [11]: An external index is a measure of agreement between two clusterings where the reference clustering is known a priori, and the second results from a clustering procedure. Internal indices are used to measure the quality of a clustering structure without external information. For external indices the results of a clustering algorithm based on a known cluster structure of a data set (or cluster labels) are evaluated, while for internal indices the results are evaluated using quantities and features

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TABLE I: Properties of images in criminal case data set: number of examinable images for different image sizes, number of those images containing EXIF metadata and number of different camera models in EXIF data.

Image Size	Exam. Imgs.	Imgs. EXIF (%)	# Cameras
$\geq 256 \times 256$	3078	2097 (~68%)	60
$\geq 512 \times 512$	1961	1006 (~51%)	47
$\geq 1024 \times 1024$	851	765 (~90%)	35

inherent in the data set. The optimal number of clusters is usually determined based on an internal validity index.

The main contribution of this paper is to show the challenges of source camera clustering in a real world application and to give an incentive for future research in this field. The paper is organised as follows: Section II explains the motivation for this work and some further details about the criminal case, Section III describes the examined criminal case data set, Section IV describes the experimental set up, Section V illustrates the results of our experiments and the challenges faced during the investigation, while Section VI concludes the paper.

II. Motivation

The study presented in this paper is based on a criminal case investigated by the Swedish Police Authority. The Swedish National Forensic Centre (NFC) was consulted by the investigators regarding methods of victim identification in large collections of images.

According to the investigators, an offender had been communicating and interacting with young adolescents through an internet based communication application transmitting both video and audio. The investigators also had information that still images had been sent from the various victims to the offender's computer and observed that the confiscated computer of a suspect contained a large amount of still images. Due to the amount of data, the investigators requested a solution for automatically processing this large collection of images, with the aim of finding potential victims within it. The large number of images made manual processing of each image unfeasible.

As part of this, NFC suggested that a clustering approach could perhaps be performed by examining the PRNU of images found on the confiscated computer. If images could be organised by image source, the search for compromising material depicting the victims could be performed more efficiently on a per-source basis. A methodology of clustering images from unknown recording units based on PRNU was not in use at NFC at that time. Due to time constraints, the PRNU approach was abandoned in this specific instance. However, the development of such a method for use in future investigations has led to the study presented here.

III. Criminal Case Data Set

The study presented in this paper is performed on digital still images extracted from the criminal case presented in the previous Section II. Still images, both allocated and unallocated in the file system, have been extracted from the investigated computer. Allocated data files are accessible and readable by means of the file system on the digital storage device, whereas unallocated data files are not. The unallocated still images have been recovered using both commercial and non-commercial forensic tools. These images are filtered based on their uniqueness (calculated hash value) and file size f_z, being in the range of 10 KB $\leq f_z \leq$10 MB. The final data set contains 3078 images.

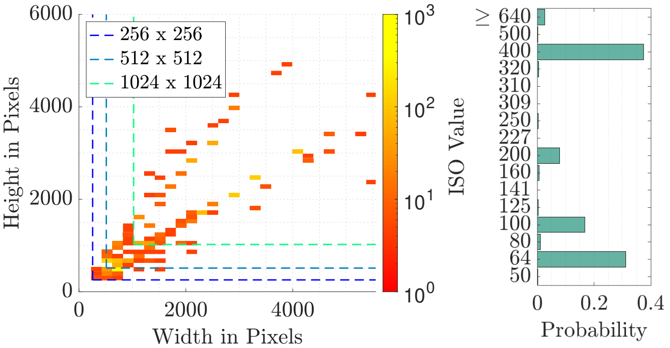


Fig. 1: Distribution of image resolutions and ISO sensitivity of images in the criminal case data set.

Figure 1 depicts the distribution of the images' resolutions and the images usable for different PRNU sizes, i.e. the size of the extracted PRNU patch. From the graphs it is noticeable that the number of the examinable images decreases as the extracted PRNU's size increases, because only images with a size larger than the PRNU size can be examined. Furthermore, it shows a histogram of the different ISO sensitivities used to acquire the images.

Additional metadata information being stored in the EXIF data is extracted and analysed. The EXIF metadata may contain camera model names, suggesting that some of the images might originate from the same camera model/unit. Table I lists the number of examinable images and different camera models retrieved from the EXIF data for each PRNU size.

IV. Experimental Setup

The goal of this work is to cluster images from potentially multiple sensors in the data described in Section III, which was found on a computer during a criminal case. The investigation has been performed by extracting the PRNU with different sizes from the image center: 256×256, 512×512 and 1024×1024 pixels. This enables us to compare the PRNU of images with different image sizes, which are mentioned in Section III. The number of images available for the investigation decreases with increasing PRNU size, which poses a trade-off between the two. The PRNU extraction and calculation of the PRNU fingerprints have been performed as proposed by Fridrich in [12], but the Block-matching and 3D filtering (BM3D) filter proposed by Dabov *et al.* [13] is used instead of the proposed wavelet-based denoising filter. According to [14, 15], BM3D is reported to yield a more consistent PRNU extraction on large data sets compared to other denoising filters.

Four different source camera clustering techniques, based on three distinct clustering principles, are investigated in this work:

- **Agglomerative clustering**: Blind Camera Fingerprinting and Image Clustering (BCF)[5]
- **Hierarchical clustering**: Unsupervised Clustering of Digital Images (UCDI)[2], Fast Image Clustering (FICL)[3]
- **Spectral clustering**: Multi-Class Spectral Clustering (MCSC) [16]

The outcome of all algorithms is a list of clusters with associated images. More details on the algorithms can be found in the corresponding papers. The clustering results of the various source camera clustering algorithms are evaluated in form of a cluster validity assessment, as described in Section I. The internal CVIs used in this work, all computed using the CVAP toolbox [10], are:

- **Davies-Bouldin Index (DBI)** [17]: Reflects the average similarity between a cluster and its most similar one.
- **Silhouette Index (SI)** [18]: Index measuring the compactness and separation of clusters.
- **Calinski-Harabasz index (CHI)** [19]: Measures between-cluster isolation and within-cluster coherence.
- **Dunn Index (DI)** [20]: Index that maximises inter-cluster distances, while minimising intra-cluster ones.

For DBI, smaller values indicate compact and well-separated clusters, while for CHI and DI this is indicated by larger values. For SI, negative values indicate an incorrect clustering, values around 0 overlapping clusters and positive values a dense clustering with high compactness and separation. Furthermore, the following external CVIs have been computed using the Scikit-learn toolbox (https://scikit-learn.org):

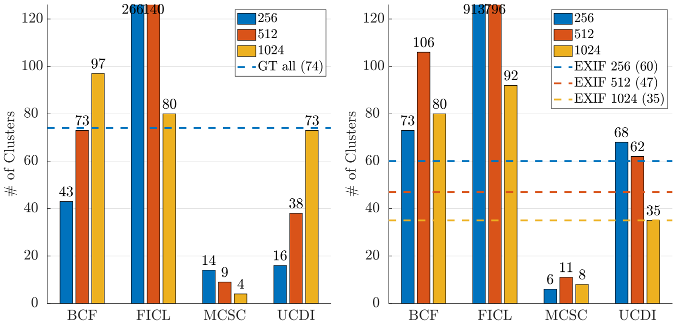
- **Homogeneity (HOM)** [21]: Measures if only members of the same class are assigned to a cluster.
- **Completeness (COM)** [21]: Measures if all members of the same class are assigned to the same cluster.
- **Adjusted Mutual Information (AMI)** [22]: Measures the agreements of two clusterings ignoring permutations and normalised against chance.
- **Adjusted Rand Index (ARI)** [23]: Measures the similarity of two clusterings with adjustment for chance.

For all external indices, higher values (closer to 1) indicate better results. AMI and ARI furthermore are adjusted against chance, which means that they have a score of 0 when the result could also be obtained by chance alone. For further details on the various indices, the reader is referred to the corresponding papers.

In order to assess the general performance of the used source camera clustering algorithms and validity and reliability of the CVIs, a source camera clustering has been performed on a subset of the Dresden Image Database [24] first, where 30 images have been randomly selected for each of the 74 distinct cameras.

V. Results and Discussion

As described in the previous section, two different experiments have been conducted in this work: First, the clustering algorithms and CVIs are evaluated on a subset of the Dresden Image Database with known ground truth. With the knowledge gained from the first experiment, the same algorithms and metrics are applied to the criminal case data. The results of both experiments are presented in the remainder of this section together with a discussion of the results.



(a) Dresden Image DB

(b) Criminal Case

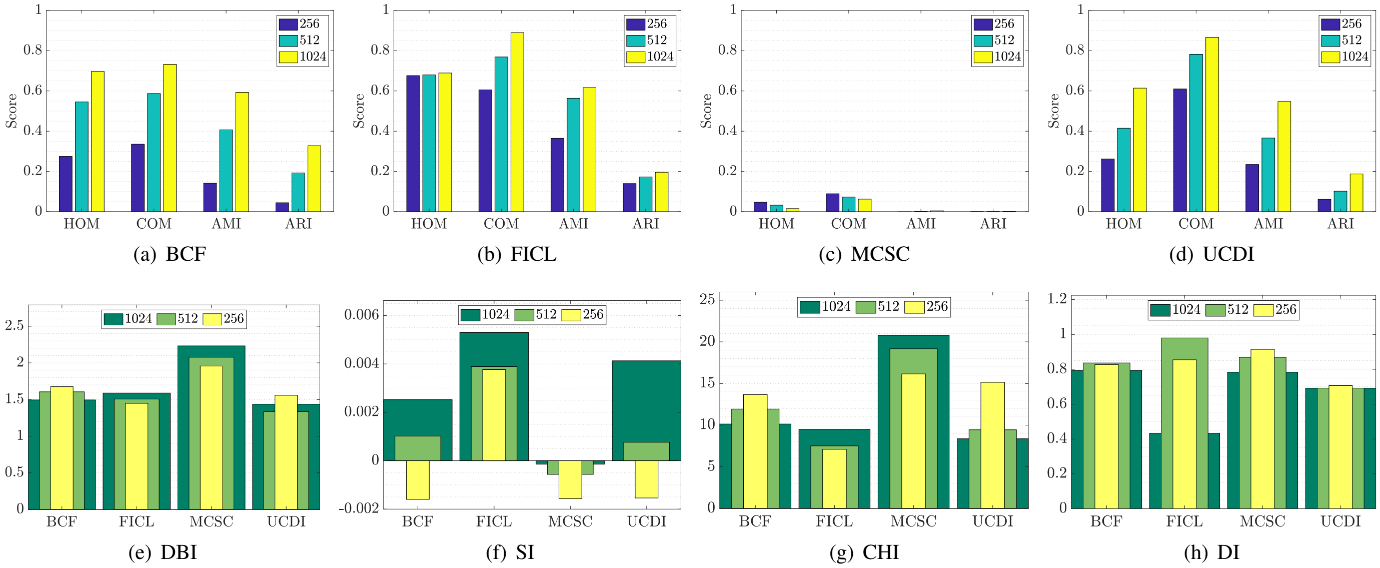
Fig. 2: Number of obtained clusters for the examined data sets.

A. *Dresden Image DB*

To begin with, the number of resulting clusters obtained from applying the various source camera clustering algorithms is illustrated in Figure 2(a). It can be observed, that a larger PRNU size leads to an increase of clusters for BCF and UCDI, while a decrease of the cluster number can be observed for FIC and MCSC. When looking at the ground truth number of 74 clusters, BCF, FICL and UCDI come very close to it with PRNU sizes of 512×512 and 1024×1024, while MCSC yields very low cluster numbers for all PRNU sizes. It can also be observed that FICL produces a very high number of clusters compared to all other algorithms.

Obviously, the quality of the clustering outcome does not rely on the number of resulting clusters alone. Thus, the results of the external CVI are presented in Figure 3(a) to 3(d). As expected from the number of clusters, MCSC shows the lowest metric scores of all algorithms, making this algorithm unable to cluster the data set properly. Since AMI and ARI are almost equal to 0, the resulting cluster structure is almost equivalent to a random assignment. BCF and UCDI show a very similar behaviour: the larger the PRNU size, the better the metric scores. With the largest PRNU size of 1024×1024 pixels, good results can be achieved when looking at all external CVIs, even the ones adjusted for chance. The overall best results are achieved by FICL, which has the highest scores of all investigated algorithms among all external clustering indices. In particular, the stable HOM scores across all PRNU sizes and the growing COM scores with larger PRNU sizes are noteworthy.

Figure 3(e) to 3(h) illustrates the internal CVIs' results. At first glance, DBI and SI seem to reflect the external CVIs' results, while CHI and DI do not. Furthermore, CHI seems to be biased against a low number of clusters because MCSC for all PRNU sizes and UCDI for 256×256 yield high scores. DI indicates that the performance of MCSC is on par or even better than other algorithms, which contradicts the previous external CVIs' results. Hence, CHI and DI do not seem to



(a) BCF

(b) FICL

(c) MCSC

(d) UCDI

(e) DBI

(f) SI

(g) CHI

(h) DI

Fig. 3: External (a-d) and internal (e-h) CVI scores for the Dresden Image DB experiment.

be able to reliably assess the clustering performance in this scenario. The DBI scores are very similar for the different PRNU sizes, though rather large differences can be observed in the previous external CVIs results. Nonetheless, the general performance trends of the various algorithms are resembled in the scores. Contrary to all other internal CVIs, the SI scores have the highest consensus with the external CVIs regarding the algorithm's performance differences for the various PRNU sizes as well as the relation performance differences among the different algorithms themselves. Thus, SI can be considered as the most trustworthy internal CVI in this case.

B. Criminal Case Data

With previous results on ground truth data in mind, we now focus on the criminal case data presented in Section III. It has to be noted, that for larger PRNU sizes less images can be examined (illustrated in Table I). As it can be observed in Figure 2(b), the various algorithms show a very similar behaviour to the clustering of the Dresden Image DB. FICL exhibits a very high amount of clusters, while MCSC exhibits a very low amount. The number of clusters of UCDI is very close to the number of models, while BCF's one is above it.

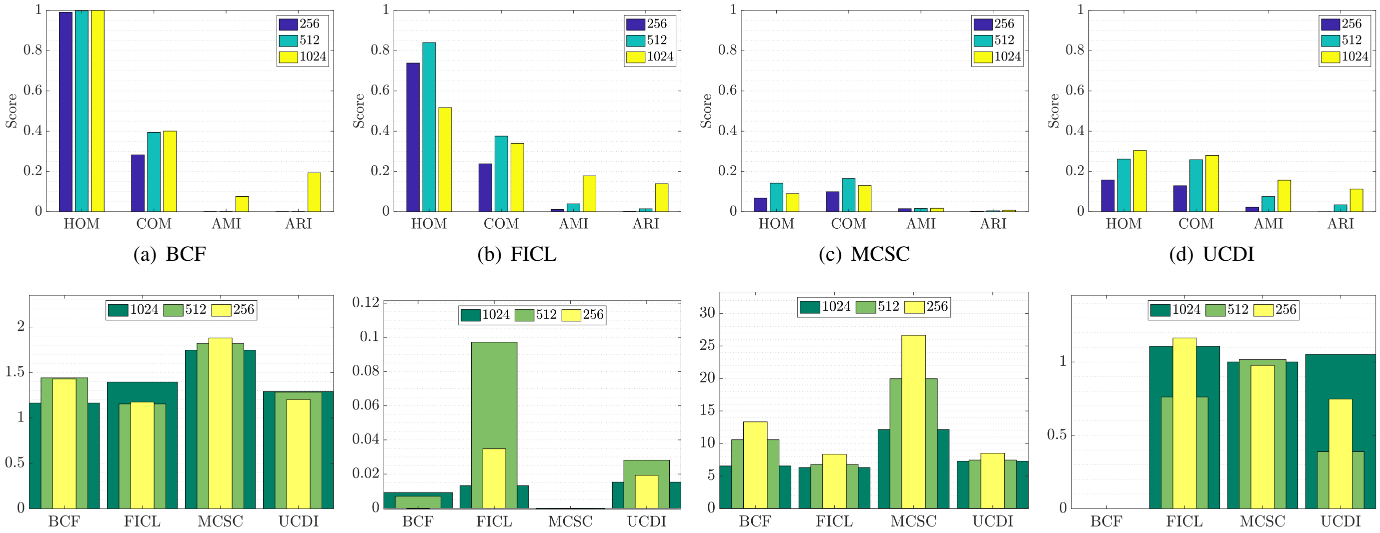
The results of the external CVIs are illustrated in Figure 4(a) to 4(d). In order to evaluate the external CVIs for this data set, some assumptions had to be made: The reference clustering structure was generated with the EXIF data's camera model information, where images without metadata have been excluded. In general, the external CVI scores of all algorithms are significantly lower than the scores obtained on the Dresden Image DB. Only HOM is very high, especially for BCF which did not exhibit such high scores for ground truth data. Considering the overall results, only FICL and BCF seem to produce reasonable results. However, these results have to be interpreted with caution, because the EXIF information might have been manipulated and the reference clustering is based on camera models and not unit level. Though, the number of different camera models in the EXIF metadata could be seen as lower bound for the expected number of clusters.

For the evaluation of the internal CVIs, all examinable images are considered again for computing the internal CVI scores, which are illustrated in Figure 4(e) to 4(h). CHI and DI again show unintuitive results, which contradict all other internal and external CVI results. DBI shows similar scores to the clustering of the Dresden DB and attributes similar performance to all clustering algorithms except MCSC, while SI shows much higher performance gaps between the various algorithms. FICL again yields the highest but highly variable scores in this scenario, while a lower but consistent performance is achieved by UCDI.

C. Discussion and Recommendations

The clustering of the criminal case data set poses many challenges. It contains images from an unknown number of different cameras taken under unknown acquisition conditions and the images might have been subject to unknown post-processings, such as cropping, scaling, rotation, contrast enhancement and other transformations. Datasets used in literature mostly contain images evenly distributed among different cameras, which are acquired under controlled conditions using the base ISO sensitivity of the cameras. In reality, however, images might cover a wide range of different ISO sensitivities, as shown in Figure 1. To the author's best knowledge, there is almost no literature which investigates and, more importantly, proposes a solution to these challenges. Regarding scaling and cropping, a brute force parameter search [25] and the use of a computationally expensive filter (MACE-MRH) have been proposed [26]. Both of these are not feasible for a clustering scenario, since they must be recomputed for every image comparison. Furthermore, the effects of denoising, recompression and demosaicing on the PRNU have been investigated in [27].

The data set furthermore contains images with different resolutions as illustrated in Figure 1. It is well known, that



(a) BCF

(b) FICL

(c) MCSC

(d) UCDI

(e) DBI

(f) SI

(g) CHI

(h) DI

Fig. 4: External (a-d) and internal (e-h) CVI scores for the criminal case data experiment.

a larger PRNU size leads to more reliable results, which we confirmed in the first experiment investigating the Dresden Image DB. However, when working with the criminal case data set investigated in this work a forensic expert has to deal with the trade-off between image size and number of images available for investigation. The decision is made even more difficult due to the fact that most images are of smaller size and would not be examinable when choosing a larger PRNU size.

The examined CVIs are also shown to not be very consistent, especially the internal CVIs show contradicting results. Because only internal CVIs can be used in a scenario with no ground truth data, as in the case of the criminal case data set, this leaves the selection of a reliable CVI an open question. Our results suggest that the Silhouette Index (SI) might be the most reliable index among the examined ones.

An alternative approach would be to use the EXIF metadata to generate a reference clustering on model level and then employ external CVIs to evaluate the resulting clustering, as described in the previous section. However, this metadata could potentially be manipulated and therefore not trustworthy. Furthermore, images with missing EXIF information cannot be examined with this approach. For this approach, we recommend to use either the Adjusted Mutual Information (AMI) or Adjusted Rand Index (ARI) to evaluate the clustering result, due to them being adjusted for chance. This property is valuable, especially when the number of clusters is expected to be high compared to the number of investigated images.

Regarding the examined clustering algorithms, FICL shows the most consistent performance, followed by BCF and UCDI. We cannot recommend the use of MCSC in this scenario because of the obtained results. The selection of the clustering algorithm seems to be less important with increasing PRNU size. For the scenario dealt with in this work, we recommend FICL for the clustering, since the source camera clustering would mainly be used for screening purposes, as described in Section II, where the higher number of clusters compared to the other algorithms is not a substantial issue.

In future work, we plan to investigate more recent clustering algorithms [4, 6–9] as well as making use of the VISION dataset [28] for clustering and CVI performance evaluation.

VI. Conclusion

The main aspect of this work is to examine a data set comprised of a large amount of still images found on a suspect's confiscated computer during a criminal investigation. The data is examined by employing different PRNU-based source camera clustering algorithms, in order to organise the images by their source camera(s). Thereafter, a quantitative analysis of the clustering outcome is conducted by means of different external and internal cluster validity indices (CVIs).

Before examining the criminal data set, we need to assess the reliability and integrity of the clustering algorithms and CVIs. This assessment is performed on a subset of the Dresden Image Database, which enabled us to reveal the inability of certain algorithms and CVIs to properly cluster and quantify the output of this data with known ground truth. The knowledge gained from this preliminary analysis enabled us to better understand the contradicting results obtained when examining the criminal case data. Finally, we gave some recommendations on how to handle this kind of scenario. This challenging data set left many open questions and issues for future work, especially regarding the robustness of PRNU-based algorithms in regard to real world data and how the quality of a clustering can be reliably assessed.

Eventually, a robust and reliable source camera clustering approach could be used to build a database holding PRNU signatures of confiscated images of illicit content. If consistently updated, such a database could reveal potential connections and provide leads for further investigation.

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