

Towards Near-Realtime Identification of Extended Objects in Low-contrast Images

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Abstract: At present criminalists deal with tasks of textile fibers identification. Usually this identification is done manually and takes a long time, that is why automation of this complex process is needed, with the ultimate objective to do it with near-realtime speed. As there could be various primary goals of this identification (e.g. performance, accuracy, precise shape extraction), different identification methods may be developed. This paper presents the typical primary and secondary goals of the identification and describes the algorithms and methods which allow achieving these goals. As well as the positive effects of these algorithms, negative effects are presented. Pros and cons of each algorithm are discussed, and, at last, the most optimal method is proposed for the selected goals.

Keywords : real-time system development, image analysis, identification, extended objects.

1. INTRODUCTION

Since the extended objects are a type of objects which is frequently discovered on digital images, many specialists deal with it. One can mention the following areas where the extended objects are considered as the object of analysis: road and rivers tracking for cartography needs, vascular examination on medical images, handwritten characters recognition, textile fibers identification.

Each of the listed areas has specific purposes for the extended objects identification and that is why each of them deals with the identification in its own way. As a result, a number of methods of identification were developed. Because of the fact that there is no single solid technology of construction of these methods, researches were carried on, classifying extended objects identification goals and algorithms which allow achieving these goals.

Although there could be lots of applications of the identification methods, this paper focuses on the area of textile fibers identification applied to criminal investigations. This area can be a good illustration how special digital images methods can automate complex workflow performed mostly manually, with ultimate goal to achieve near-realtime speed.

The steps of the workflow are: 1) acquire patterns; 2) filter them visually with microscope; 3) perform spectral analysis; 4) investigate them chemically; 5) decide whether the selected fibers are identical.

Firstly, the expert acquires patterns of textile fibers. He uses sticky film to capture fibers from the clothes of the victim

and the suspected persons. The film allows investigating the textile fibers carefully using a microscope on the step two.

Secondly, the expert filters the films in the following way. He searches visually (using the microscope) for the identical fibers on the patterns taken from the clothes of the victim and from the clothes of each suspected person. This is the most difficult and long process conditioned by the actual number of the patterns needed to be filtered. The successful filtering on the step two greatly reduces the amount of textile fibers which need to be specially tested with spectral analysis and chemicals.

And at last, the expert uses special tools to develop the last conclusion whether the fibers taken from the clothes of the victim and from the suspected person are identical. These steps are very responsible because the result of the investigation can impact on the whole life of the suspected person. Therefore these steps are performed only by people and can not be fully automated.

On the subject of automation of textile fibers identification, there could be a special system helping to filter visually the patterns. The system could allow scanning the patterns using a business-class scanner and searching the identical fibers on them (let us assign a limitation: the whole fiber should be monochrome, though fibers of different colors are allowed).

2. METHODS OF IDENTIFICATION OF TEXTILE FIBERS

There are two main attributes of the images acquired using a business-class scanner. They are: low contrast of the objects

comparing to the background and non-uniform uneven background which contains both distortions and noise.

Let us assign the terms.

Primary goal – is the main goal of the method. When the effect is achieved, the method succeeds.

Secondary goal – is an extra goal which may or may not be added to the primary goal.

Derivative effect – is the effect of the particular method, which may be positive or negative depending on the details of the implemented algorithms and the goals.

Any method of the extended objects identification on low-contrast images must include at least two steps: extended object extraction and object's characteristics extraction.

Let us agree that forward way of identification is the method where the extended object extraction goes before the object's characteristics extraction. Thus, backward way is the method of the identification where object's characteristics extraction goes before the extended object extraction.

As we shall see later, the forward way of identification greatly reduces the amount of pixels of the image which should be compared. Hence it may be used when the primary goals focus on the speed of search and correct shape of the extended objects.

The backward way of identification compares all the pixels of the images. Consequently, it will not skip objects of interest and thus it should be used when high accuracy of the identification is requested.

3. PRIMARY GOAL: HIGH SPEED OF FILTERING

It is obvious that if the primary goal is the high speed of filtering, then the images should be prepared for filtering in a special way. The speed of the filtering is conditioned by the amount of filtered data. For that reason the image preprocessing should organize the data in such a way that the filtering algorithm will get reduced amount of data.

Let us use the forward way of identification. Firstly, we extract the extended objects from the low-contrast non-uniform background. Secondly, we extract invariant objects' characteristics. The filtering algorithm will compare only the objects' characteristics, and their amount is noticeably less than the image pixels.

There are many clustering algorithms which are able to extract objects from the low-contrast image and certain algorithms may be applied to the task of extraction of textile fibers from the low-contrast images with non-uniform background.

3.1 Adaptive Thresholding for Textile Fibers Extraction

Because of its intuitive properties and simplicity of implementation, image thresholding enjoys a central position in applications of image segmentation (Gonzalez(2001)). The

simplest of all thresholding techniques is to partition the image histogram by using a single global threshold T . Segmentation is then accomplished by scanning the image pixel by pixel and labeling each pixel as object or background, depending on whether the gray level of that pixel is greater or less than that level of T . The success of this method depends entirely on how well the histogram may be partitioned.

As shown on Fig.1, the histogram of an image with textile fibers contains two peaks separated by a small valley. The biggest peak corresponds to the brightness level of the background; the lowest peak corresponds to the brightness level of the textile fibers. The presence of the valley between the peaks means that the image is contrast enough, and the thresholding will succeed. But the images acquired from a business-class scanner are mostly low-contrast, containing no valley between the peaks. That is why the global thresholding will not succeed here.

An approach for segmentation of low-contrast images is to divide the original image into subimages and then utilize a different threshold to segment each subimage. But applying this approach to extract extended objects produces results of low quality. Unequal thresholds produce extended objects of uneven width if the fiber extends over two or more regions with different threshold.

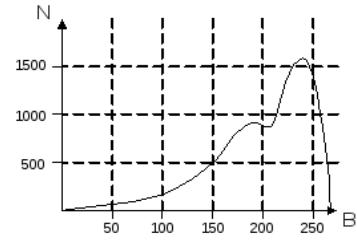


Fig. 1. Histogram of an image acquired by the business-class scanner. B stands for brightness, N – number of pixels.

A further development of the adaptive thresholding is the thresholding with an optimal threshold. As discussed earlier, it is intuitively evident that the chances of selecting a “good” threshold are enhanced considerably if the histogram peaks are tall, narrow, symmetric, and separated by deep valleys. One approach for improving the shape of the histogram is to consider only those pixels which lie on or near the edges between objects and the background. This approach allows acquiring an optimal threshold and extract objects from uneven background.

But when this algorithm is applied to extract the extended objects, the “spilt figure” effect appears (Fig.2). If the image is too low-contrast, and the object is an extended and long one, then the mean brightness threshold of the object may be equal to the background general brightness. For instance, on the Fig. 2, the brightness threshold of the object is 2, and there are 16 pixels of the background, which form the mentioned “spilt figure” effect.

In other words, as it is proved in Bushenko et al. (2008), this algorithm can not be used to extract the extended objects from the non-uniform background.

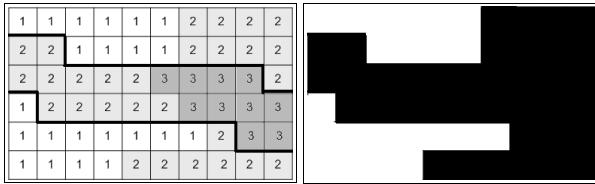


Fig. 2. Spilt figure effect.

3.2 K-Means for Textile Fibers Extraction

Another well-known clustering technique is the K-means algorithm (Baldock et al. (2000)). Basically it defines the centers of clusters and marks each pixel of the image with the cluster label depending on which cluster center is the nearest to the pixel. This algorithm iteratively adjusts the cluster centers and repeats the clustering until the cluster centers become stable. It is evident that this algorithm fits best for the data which is structured as bunches around their cluster centers.

As it was defined earlier, the main objective of this paper is the extended objects identification. The attempt to apply the K-means algorithm to extract the extended objects using their geometric characteristics failed. This is because of their form which is far from the form of a bunch.

One more way to apply the K-means clustering algorithm here is to cluster the image histogram. This technique allows defining just two clusters: object and background; and when the two peaks of the histogram are separated by the valley, the technique succeeds. Nevertheless, on most low-contrast images this algorithm produces the extended objects of blurred form (Fig. 3).

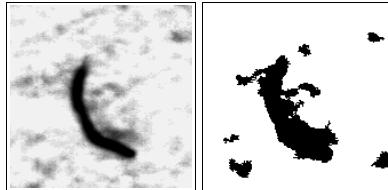


Fig. 3. K-Means clustering.

Overall, K-means algorithm does not fit entirely for the task of extended objects extracting from the uneven non-uniform background of the low-contrast images.

3.3 Morphological Analysis for Textile Fibers Extraction

Morphological analysis of the image includes many algorithms of segmentation. As it is observed in Jahne (2002), best known representatives of these group of algorithms are the following:

- 1.Region filling;
- 2.Region growing.

The main idea of these techniques is to connect pixels based on some rule using various methods, such as dilation. When

the algorithm stops, the bunches of connected pixels will represent the bodies of the extracted objects.

The most promising modification of these techniques is the following algorithm:

1. Extract objects' borders.
2. For each border iteratively dilate it from the darker side.
3. Stop the dilation according to some condition.

This modification of the morphological analysis uses the main property of the extended object: its length is much longer than its width.

Basically, the weak-point of the algorithm is its stopping condition. Among others we can mention the following:

1. Opposite border is met;
2. Maximum fiber width achieved;
3. The brightness of the object in the dilation direction started growing.

However in most cases the quality of this technique will fit the needs of the extended objects extracting.

3.4 Modified Adaptive Thresholding for Textile Fibers Extraction

The best algorithm among the discussed techniques is the modified adaptive thresholding algorithm, presented in Bushenko et al. (2008). It succeeds as follows:

1. Detect objects borders.
2. Define the maximum fiber width around the border.
3. Calculate the optimal threshold value.
4. Extract the object using the computer graphics algorithm of filling the closed contour. Start filling from the border and mark all the pixels whose brightness exceeds the computed threshold.

Although the described algorithm is rather slow, it extracts the objects with comparatively high accuracy (Fig. 4). In experiments on the database with images containing about 10.000 fibers, 81.35% of objects were extracted correctly.

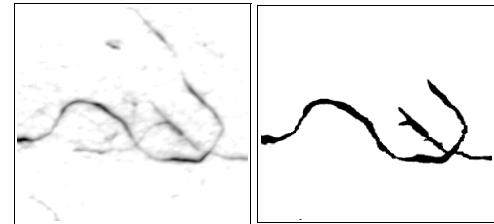


Fig. 4. Modified adaptive thresholding.

The method of verification was as follows.

1. The software processes all the images and marks the borders of the extracted fibers on the source images.
2. Several experts investigate the extracted fibers simultaneously. Two types of software errors are possible here:
 - a) The extracted object is considered as a false object if it is not a a textile fiber or if its skeleton does not fit the real fibers body.

b) An object is considered as not extracted if it is a textile fiber, but the applied algorithm has not extracted it.

The verification by the humans is crucial here because only human is the ultimate authority when taking a decision about the quality of the extraction of extended objects on low-contrast images.

3.5 Extracting Characteristics

The second step of the identification using the forward way is the extracting of invariant characteristics of the objects. When an expert compares visually two fibers, he utilizes the fiber's color. That is why the hue of the fiber, calculated over all the pixels of its body, will be the best characteristic for identification. We can use the mean hue value, $M(H_{\text{Body}})$, or central value of the hue distribution, as defined in Korn et al. (1968). This one number will be treated as the object descriptor.

4. PRIMARY GOAL: HIGH SPEED OF FILTERING

When an object was extracted, the system should check whether it is an extended object. The extended object's length is much longer than its width (this is the main attribute of the extended objects which moves such objects as textile fibers to a special class of objects).

If the shape of an object is known, then we can measure its length and width as follows:

1. Obtaining the object's skeleton.
2. L , the length of the object is the number of pixels of its skeleton.
3. For each pixel of the object's border find the minimum distance to the nearest skeleton point.
4. W , object's width is the mean value of the distances, calculated on step 3.

Skeleton of an object is a set of centers of the circles inscribed in this object.

Basically, the rule for determining whether the object is extended will be the next:

$$L \ll W$$

and

$$D(W) < T$$

where $D(W)$ is the width variance and T is the threshold usually is defined as $T = 0.75W$.

As a result, the whole technique of determining whether the object is extended, depends on the underlying skeletonization algorithm. Many of them could be applied here.

4.1 Vectorization

The most known vectorization techniques which could be utilized to extract the skeletons of the extended objects are: triangulation and the Voronoi diagram (Barber et al. (1996)). To obtain the skeleton from the triangulated object, one should extract the points laying on the centers of the triangle sides inside the object. Correspondingly, the skeletons are acquired from the Voronoi diagram.

The main drawback of the vectorization technique is that it is inaccurate.

4.2 Thinning

Probably, the most popular skeletonization technique is binary thinning, such as presented in Zhang et al. (1984). It utilizes the following procedure applied to a binary image:

1. Start erosion of the source object by 1-pixel pattern.
2. For each pixel of the object decide whether it could be removed.
3. If the pixel is removable, remove it.
4. Continue from step 2 for the next pixel.

On the step 2 it's supposed to investigate the 3x3 pixel area. As the image is binary, it contains only the following values:

a) 0's which stand for background;

b) 1's which stand for objects.

Let us assign the 3x3 pixel area as a set of P_0 - P_8 pixels as shown on Fig. 5.

P_1	P_2	P_3
P_8	P_0	P_4
P_7	P_6	P_5

Fig. 5. Area of the pixel P_0 .

On the first subiteration the pixel is removed if applies for the following conditions:

$$2 \leq B(P_1) \leq 6$$

$$B(P_i) = \sum_{i=1}^8 P_i$$

$$A(P_1) = 1$$

$$P_2 \cdot P_4 \cdot P_6 = 0$$

$$P_4 \cdot P_6 \cdot P_8 = 0$$

where $A(P_1)$ – is the number of configurations 0/1 in the sequence P_1 - P_8 , finishing with pixel P_1 . $A(P_1) = 1$ means that around pixel P_0 there is only one transition from 0 to 1.

The second subiteration is analogous to the first with the only difference:

$$P_2 \cdot P_4 \cdot P_8 = 0$$

$$P_2 \cdot P_6 \cdot P_8 = 0$$

On the whole, the Zhang and Suen thinning algorithm might fit for skeleton extraction from the extended objects. But it still has the following weak points.

1. It sometimes produces multiple disconnected skeleton parts for a single object.
2. It often produces false branches.
3. It could be applied only for binary images.

4.3 Modified Thinning Algorithm

The modification Bushenko et al. (2009) of the thinning algorithm substitutes the step 2 of the classical thinning algo-

rithm and allows deleting only pixels which are not pixel-connectors.

Pixel-connector is such a pixel, deleting which the object becomes disconnected. Note: the pixel can't be considered as a connector if, when it is removed, only one pixel is remained in its area. The Fig. 6 illustrates the definition of the pixel-connector.

In other words, the second subiteration investigates each pixel and decides whether it is a pixel-connector. If not, this pixel should be deleted. As a result, the skeleton of an object must consist only of the pixels-connectors.

The proposed modified thinning algorithm fits best for extracting the skeletons of the extended objects. Further modification will be presented here allowing thinning of the halftone objects, and the result of the final modification is shown on Fig.7.

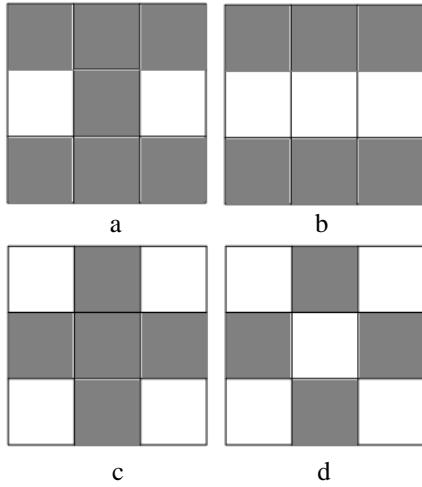


Fig. 6. Source image with pixel-connector (a); source image with deleted pixel connector (b); source image without pixel connector (c); source image with deleted center pixel (d).

5. SECONDARY GOAL: HIGH ACCURACY OF OBJECTS COMPARING

With reference to 3.5, the main characteristic of the object is $M(H_{Body})$, and, to some extent, it fits our needs. But generally the images, acquired using the business-class scanner, possess non-uniform uneven background distorting the fiber bodies mostly around its edges. That is why further modifications of this criteria are needed.

It is evident, that if most of the distortions are contained around the fiber's edges, then removing this pixels using the erosion would produce the $M(H_{Eroded})$, which is invariant to the effect of the scanner distortions. In most cases $M(H_{Eroded})$ will be a good characteristic for comparing the fibers. But if half of the width of the fiber is equal or less than the width of the erosion pattern, the size of the sample H_{Eroded} will be reduced to 0, and calculating the (H_{eroded}) becomes impossible.

Another way of calculating the invariant fiber's characteristic is to calculate the $M(H_{Skeleton})$, mean hue value of the

fiber's skeleton. The size of the sample $H_{Skeleton}$ is always more than 0. That's why $M(H_{Skeleton})$ is great for comparing the long fibers.

In addition, we would propose to calculate $M(H_{Dilated})$, where $H_{Dilated}$ is the sample of pixels, including the skeleton and the nearest pixels, obtained using the dilation operation. Basically, 1-pixel pattern of dilation fits our needs. Such $H_{Dilated}$ is three times greater than $H_{Skeleton}$, and that is why $M(H_{Dilated})$ is a good invariant characteristic for small fibers, whose $H_{Skeleton}$ is too small.

All the discussed above methods for calculating the invariant characteristics are true only for single fibers. But real-world images usually contain fibers which cross each other (Fig.4). If the crossed fibers have different colors, then the calculated $M(H)$ will be shifted, and the variance $D(H)$ will be too big. In other words, the $M(H)$ will not be the invariant fiber characteristic. Consequently, these fibers must be separated.

In general one can utilize the clustering algorithms to separate the crossed fibers, but each clustering algorithm might cause errors. Regarding the goal of the whole automation system, the expert should have the film with the marked regions, meaning that there some identical fibers are found. It does not matter if a fiber is extracted as a single object or was splitted into parts because when it is drawn on the film, it will look as a single object. Hence, we would propose instead of separating the crossed fibers, just extract the separate skeleton branches and treat them as sole fibers. The proposed technique greatly enhances the accuracy of comparing.

6. PRIMARY GOAL: HIGH ACCURACY OF THE IDENTIFICATION

Although performance of identification in the method discussed above is high, the method lacks accuracy. This is why there should be another goal – maximum accuracy of identification.

The reason why the forward way of identification lacks accuracy is contained in the preliminary objects extracting. As discussed earlier, each method of extraction has its drawback restricting the amount of extracted objects to some percent. It is obvious that when the identification starts, the objects, skipped on the preliminary processing, will not be observed. And thus the accuracy of the whole method will not exceed the accuracy of the objects extracting algorithm.

The backward way of identification does not possess this restriction because the first step is the characteristics extracting. The second step is the filtering itself when the system finds all the pixels whose characteristics are equal to the specified pixels. At last, the system decides whether the found pixels belong to the extended objects.

Using the backward way, the method may be as follows.

1. Calculate hue value of each pixel.
2. Find all the pixels whose hue correspond to the specified pixels' hue.

3. Utilize the region growing algorithm to extract the found objects.

The properties of the algorithm:

1. 100% accuracy, no objects of interest are skipped.
2. Large amount of false pixels found which belong to the background.
3. Filtering algorithm complexity is $O(NE_{mn})$, where

$$E_{mn} = \sum (w_i \cdot h_i) ,$$

w, h – width and height of the subsequent image, and N is the number of distinct hue values specified to be found. That is why the speed of filtering is comparatively long.

7. SECONDARY GOAL: FILTERING PERFORMANCE ENHANCEMENT

It is obvious that if the filtering utilizes each pixel, then the speed of the filtering depends on the size of each image and the images quantity. That is why the backward algorithm lacks performance and needs to be optimized. Number of standard indexing techniques may be applied here (Gaede et al. (1997), Litwin (1980), Samet (1984)).

7.1 Linear Hashing.

Linear hashing is a classical one-dimensional access method. It divides the universe $[A, B]$ of possible values to intervals of size $(B - A)/2^k$ or $(B - A)/2^{k+1}$ for some $k \geq 0$. Each interval corresponds to a bucket, i.e., a collection of records, stored on a disk page. $t \in (A, B)$ is a pointer that separates the smaller intervals from the larger ones: all intervals of size $(B - A)/2^k$ are to the left of t and vice versa. If a bucket reaches its capacity due to an insertion, the source interval is split into two subintervals of equal size, and t is advanced to the next large interval remaining.

One could utilize this algorithm to organize the hue distribution intervals according to the frequency of each particular color. The summary frequency of each interval will be of size $(B - A)/2^k$ or $(B - A)/2^{k+1}$. Then for each interval find the coordinates of all pixels of the image whose hue belong to this interval. Store this coordinates as an attribute of the interval. When the whole image is structured using the linear hashing, searching for pixels of a particular color becomes easier, and performance of filtering grows though the preprocessing time grows also.

7.2 Modified Linear Hashing Algorithm

The discussed earlier linear hashing algorithm mostly fits our needs. But further modification was developed to enhance the performance. Instead dividing the whole hue distribution into intervals, we propose to divide it into separate hue values. The performance boost is conditioned by the immediate availability of the pixel coordinates of the specified color for the whole image.

8. SECONDARY GOAL: EXTENDED OBJECTS EXTRACTION

The overall idea of the discussed method is to perform a search through all the images and to find the pixels of the specified colors. But, occasionally, these pixels may not belong to the extended objects, such as textile fibers. For that reason the method should be adjusted to search only through the extended objects.

The most typical points of an extended object lay on its skeleton. That is why if the system would search only through the skeletons of the objects, then the amount of incorrectly found pixels will be reduced greatly. But most of the known skeletonization methods could be applied only to the binary images. Due to that reason, it is proposed to use the modified halftone skeletonization algorithm as presented in Bushenko et al. (2009). This algorithm produces the skeletons of the extended objects with the best known quality (Fig. 7).

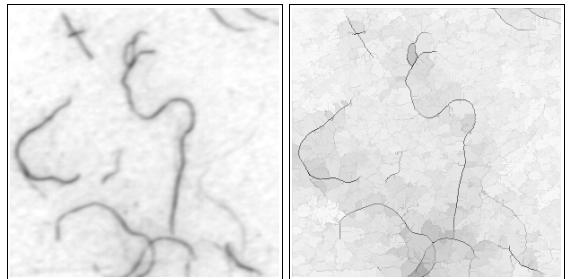


Fig. 7. Halftone skeletonization of the extended objects.

9. PROPOSED METHOD

Finally, we would propose how to utilize the observed algorithms to construct a method of identification of textile fibers for criminal investigations.

Firstly, the primary goal of the method is the best accuracy of identification. That is why the backward way of identification will be used. Secondly, it is desired that the performance of the filtering should be as high as possible for that accuracy.

The method includes the following steps:

1. The system extracts halftone skeletons for all the images using the modified halftone thinning.
2. The system performs indexing of all the extracted skeletons using the modified linear hashing and the $M(H_{Dilated})$ for each skeleton branch as discussed earlier.
3. The user pinpoints the fibers on the image which should be found.
4. The system obtains the invariant characteristic of the fiber which is nearest to the specified point.
5. The system finds all the skeleton branches with the identical $M(H_{Dilated})$ on all the indexed images.

The proposed method is implemented in the digital system, described in Barber et al. (1996). It allows the expert to automate the process of identification of textile fibers, which previously was done using only optical microscopes.

The strong points of the mentioned system are:

1. No extended objects are skipped. All the objects are detected.
2. The system allows setting the desired accuracy of the identification.

The weak point of the system is the continuation of its strong points. The quality of the identification depends on the desired accuracy. That is why if the accuracy is set low values, the system may find all the types of the objects, not only textile fibers.

10. CONCLUSION

Due to the fact that there is no single technology of identification of extended objects on low-contrast non-uniform uneven background, special investigations were carried on, and a number of methods of identification were developed. The paper presents two main methods based on distinct primary goals: high speed of identification and high accuracy of identification. Although the primary goal of the method impacts on all the underlying algorithmic base, there could be secondary goals, adding extra algorithms to the main method. These are: enhanced precession of the fibers comparing, enhanced performance of fibers searching, enhanced detecting of extended objects amongst all the other object types. Finally, the method is presented which is used in digital system of textile fibers identification, showing good results in criminal investigations.

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