

DESCRIPTION

TITLE: Method using inter-ridge distances in pixels relating to fingerprints

FIELD OF THE INVENTION

5 The present invention relates to the field of processing operations applied to images showing fingerprints.

PRIOR ART

10 Methods for identifying or authenticating an individual using their fingerprints are known, these methods comprising the following steps. Conventionally, a test image showing a test fingerprint of an individual is acquired, and this image is compared with a reference image showing a reference fingerprint, so as to verify whether the test fingerprint and the reference fingerprint match. If such a match is found, then the individual is considered to have been recorded beforehand.

The reliability of these methods is based on the prior knowledge of the resolution of the test image (generally expressed in pixels per inch, abbreviated to ppi).

15 However, there are some situations in which the resolution of the test image is not known.

DESCRIPTION OF THE INVENTION

One aim of the invention is to verify whether or not a test fingerprint corresponds to a reference fingerprint reliably and without needing to know the resolution of the image.

20 This aim is achieved by way of a method for processing a test image showing a test fingerprint, the method comprising the following computer-implemented steps: estimating a first test inter-ridge distance relating to the test fingerprint, the first test inter-ridge distance being a distance in pixels; obtaining a reference inter-ridge distance relating to a reference fingerprint shown in a reference image, the reference inter-ridge distance being a distance in pixels; resizing the test image into a resized test image such that the first test
25 inter-ridge distance in pixels corresponds to the reference inter-ridge distance in pixels; and commanding a comparison between the resized test image and the reference image, so as to verify whether the test fingerprint and the reference fingerprint match.

This method may also comprise the following optional features, taken alone or in combination whenever technically possible.

30 Preferably, the method furthermore comprises steps of: estimating a second test inter-ridge distance relating to the test fingerprint, the second test inter-ridge distance being a distance

in pixels; and repeating the steps of resizing and of commanding a comparison for the second test inter-ridge distance instead of the first test inter-ridge distance.

Preferably, the steps of resizing and of commanding a comparison are repeated only on the condition that the comparison between the resized test image and the reference image led to a result indicating that the test fingerprint and the reference fingerprint do not match.

Preferably, the method comprises the following steps: generating a classification map from the test image, the classification map comprising, for each block forming part of a plurality of blocks of the test image and for each class of a plurality of classes of distances in pixels, a score associated with the block and with the class, the score associated with the block and with the class being indicative of a probability of existence in the test image of a segment passing through the block and the length of which in pixels constitutes an inter-ridge distance of the fingerprint included in the class; generating a local inter-ridge distance map on the basis of the classification map, the local inter-ridge distance map comprising, for each block of the plurality of blocks, a local inter-ridge distance in pixels estimated for the block; and estimating the test inter-ridge distance on the basis of the local inter-ridge distance map and of a class of interest forming part of the plurality of classes of distance in pixels, the estimation comprising selecting, from the local inter-ridge distance map, local inter-ridge distances of interest according to a criterion of proximity to the class of interest, and computing an average of the local inter-ridge distances of interest.

Preferably, the local inter-ridge distance in pixels estimated for a block is computed on the basis of: a first score indicative of a maximum probability of existence among the scores associated with the block, the first score being associated with a first class forming part of the plurality of classes of distances, and a first distance value in pixels included in the first class; optionally, a second score associated with a second class, the second class being adjacent to the first class in the plurality of classes of distances in pixels, and a second distance value in pixels included in the second class; and optionally, a third score associated with a third class, the third class being adjacent to the first class in the plurality of classes of distances in pixels, and the third class being distinct from the second class, and a third distance value in pixels included in the third class.

Preferably, the local inter-ridge distance in pixels estimated for a block is computed as an average of the first distance value, of the second distance value and of the third distance value, weighted by the first score, the second score and the third score, respectively.

Preferably, the method comprises steps of: generating a preliminary classification map from the test image, the preliminary classification map comprising, for each block of a set of

- blocks covering the entire test image and for each class of the plurality of classes of distances in pixels, a preliminary score associated with the block and with the class, the preliminary score associated with the block and with the class being indicative of a probability of existence in the test image of a segment passing through the block and the length of which in pixels constitutes an inter-ridge distance of the fingerprint included in the class; on the basis of the test image, generating a binary mask estimating, for each block of the set of blocks, whether or not the block contains a fingerprint; applying the binary mask to the preliminary classification map so as to generate the classification map, the plurality of blocks being restricted to each block that the binary mask deems to contain a fingerprint.
- 10 Preferably, the preliminary classification map is generated using a first neural network, and the binary mask is generated using a second neural network operating in parallel with the first neural network, applying the binary mask to the preliminary classification map comprising for example a Hadamard product of the preliminary classification map and of the binary mask.
- 15 Preferably, the method furthermore comprises extracting features from the test image using a neural network without any normalization layer, the classification map being derived from the extracted features.

20 Preferably, the local inter-ridge distances of interest selected according to the criterion of proximity to the class of interest are local inter-ridge distances within an interval having bounds determined on the basis of a distance value included in the reference class, the interval forming a neighborhood around the distance value.

25 Preferably, the method comprises steps of: computing a histogram on the basis of the classification map, the histogram comprising, for each class forming part of the plurality of classes of distances in pixels, an aggregated score obtained by aggregating the scores associated with the class; and detecting at least one local maximum of the histogram, the class of interest being associated with a local maximum detected in the histogram.

Preferably, each block is one pixel of the image.

30 Preferably, the plurality of classes of distances respects the following rule: the higher a median value of a class of the plurality of classes of distances, the larger a size of the class.

Also proposed is a computer program product comprising program code instructions for executing the steps of the above method when this program is executed by a computer.

Also proposed is a computer-readable memory storing instructions that are executable by the computer in order to execute the steps of the above method.

DESCRIPTION OF THE FIGURES

Further features, aims and advantages of the invention will become apparent from the following description, which is purely illustrative and non-limiting, and which should be read with reference to the appended drawings, in which:

Figure 1 schematically illustrates an image-processing device according to one embodiment.

Figure 2 is a flowchart of steps of an image-processing method according to one embodiment.

Figure 3 contains two images: on the left, an image showing a latent fingerprint, and, on the right, a visual representation of a local inter-ridge distance map that was produced by applying the method of figure 2 to the image on the left.

Figure 4 is an image portion annotated so as to show an inter-ridge distance.

Figure 5 contains two images: on the left, another image showing a latent fingerprint, and, on the right, a histogram derived from the image on the left.

Figure 6a shows a series of results obtained by applying to images a method using a neural network comprising normalization layers.

Figure 6b shows a series of results obtained by applying to images a method using a neural network without any normalization layer.

In all of the figures, elements that are similar have been designated by identical references.

DETAILED DESCRIPTION OF THE INVENTION

With reference to **figure 1**, an image-processing device 1 comprises a processor 10, a communication interface 12 and a memory 14.

The processor 10 is configured to implement certain steps of an image-processing method that will be described below. The processor 10 may have any structure. The processor comprises one or more cores, each core being configured to execute the code instructions of a program so as to implement the aforementioned steps. It will be seen below that this program uses neural networks.

The communication interface 12 is configured to allow the image-processing device 1 to receive images to be processed and to communicate with a server 2. The communication interface 12 is of any type. It is for example a wired (Ethernet) interface or a wireless radio interface using any communication protocol (Wi-Fi, Bluetooth, etc.).

The memory 14 is configured to store data manipulated or produced by the processor 10. The memory 14 is of any type. Conventionally, the memory 14 comprises a volatile memory for storing data temporarily, and a non-volatile memory for storing data persistently, that is to say in a manner that preserves the data when the non-volatile memory is turned off.

- 5 The memory 14 is in particular configured to store an image received by the processing device 1 and intended to be processed by the processor.

The image-processing device 1 may also comprise a sensor 16 of images containing fingerprints. The sensor may optionally comprise a transparent surface that serves as a medium against which a finger may be pressed, so as to stabilize the finger and thus allow
10 a fingerprint of the finger to be clearly seen in an image delivered by the sensor.

The server 2 stores a database of reference images showing reference fingerprints relating to previously recorded reference individuals.

Classes of distances in pixels

As will be seen below, the processing device 1, and more particularly the processor 10, is
15 configured to implement processing operations based on a plurality of N predefined classes of distances in pixels.

Each of the N classes includes a set of distance values in pixels that is specific thereto, this set of values being defined in advance.

As indicated above, the distances are expressed in pixels, and not in a unit of length (such
20 as inches or meters) or in a unit dependent on a unit of length (as is the case with resolution, which is generally expressed in pixels/inch, abbreviated to ppi). In the present text, it is assumed that a distance in pixels may be a decimal value, and is therefore not necessarily an integer value.

Each class has a size that characterizes the amount of distance values in pixels included in
25 the class. Moreover, each class has a median distance value in pixels.

Within the plurality of N classes, the classes are ordered according to their respective median values. Thus, the plurality of N classes comprises two end classes, and possibly N-2 intermediate classes if $N > 2$. Each intermediate class has two classes adjacent to it within the plurality of N classes. In contrast, each end class has a single class adjacent to it.

30 By convention, the classes are assigned respective indices ranging from 1 to N, in order of median value. Thus, an intermediate class of index i is adjacent to the classes of indices i-1 and i+1.

Preferably, the classes are contiguous, in the sense that for any value of i ranging from 1 to $N-1$ the upper bound of the class of index i is equal to the lower bound of the class of index $i+1$. In this way, the respective intervals of the classes when put end to end cover a continuous interval, without much redundancy (neglecting the bounds in the case where the intervals are closed).

Preferably, the plurality of N classes respects the following rule: the higher a median value of a class, the larger a size of the class. In other words, for any value of i ranging from 1 to $N-1$, the class of index $i+1$ has a size larger than the size of the class of index i . It will be seen below that this feature is advantageous.

- 10 In one non-limiting embodiment, each class of distance in pixels is an interval of distance values in pixels. This interval comprises a lower bound (minimum distance value in pixels) and an upper bound (maximum distance value in pixels). In this embodiment, the size of a class is the length of the interval (from the lower bound to the upper bound). Moreover, the median value of the class is, in this embodiment, the central value of the interval, that is to say a value located equidistant from the lower bound and from the upper bound.

For example, a plurality of classes respecting all the principles defined above is detailed in the following table (in which $N = 5$):

Index of the class	Values included in the class (expressed in pixels)	Class size (expressed in pixels)
1	[10, 11]	1
2	[11, 12.1]	11.1
3	[12.1, 13.31]	1.21
4	[13.31, 14.64]	1.33
5	[14.64, 16.11]	1.47

- 20 This plurality of 5 classes covers an overall interval extending from 10 to 16.11 pixels. This interval makes sense, because it covers a range of inter-ridge distances in pixels measurable in a bank of fingerprint images having various resolutions (about 500 ppi to about 1000 ppi).

Image-processing method

With reference to the flowchart of figure 2, a method implemented by the device 1 comprises the following steps.

In a step 102, the processing device 1 receives a test image showing a test fingerprint of an individual. Here, the qualifier "test" is just intended to make it possible to distinguish between the received image and the reference images stored by the server.

Two types of fingerprints are distinguished between: fingerprints shown in images acquired by a dedicated image sensor (these are referred to as "tenprints") and so-called "latent" fingerprints, which are shown in photographs acquired by a generic device, that is to say a device not dedicated specifically to the acquisition of fingerprints. For example, in the context of a police investigation, it is possible to use as test image a photograph of a fingerprint left on a medium, this photograph being acquired by such a generic device. The medium on which the latent print was left may comprise interfering patterns liable to compromise the accuracy of the estimation of the aforementioned methods.

The test image may have been acquired by the image sensor (if present) or by another image sensor, in which case the test fingerprint is of tenprint type. As a variant, the test image may be received via the communication interface, and may be latent.

The test image contains a plurality of pixels forming a two-dimensional grid. Each pixel has a specific position in this grid, and contains light-related information. Its color information is of any type: it may be one-component (grayscale), three-component (red, green, blue for example), etc.

All or some of the pixels in the test image show the test fingerprint.

Figure 3 shows on the left an example of a test image showing a latent fingerprint capable of being processed by the device 1. It may be seen that the latent fingerprint does not cover all of the image, and indeed that it is only partially visible.

It will be recalled that a fingerprint is a pattern drawn by ridges formed on the finger of an individual. Two adjacent ridges are separated by an inter-ridge distance. The inter-ridge distances are different from one fingerprint to another. Figure 4 shows an inter-ridge distance appearing in a magnified image portion. As may be seen in this figure, an inter-ridge distance extends over a certain number of pixels.

The resolution of the test image is not known to the processing device 1.

Returning to figure 2, the processor 10 implements the following steps on the basis of the test image.

In a step 104, the processor extracts features from the test image by means of an extraction neural network. The extracted features are generally called "feature maps" in the literature.

Conventionally, a neural network comprises a succession of layers. Each layer contains neurons that receive input from neurons of the preceding layer. Layers having various functions are known. In particular, as known, the function of a normalization layer is to normalize data that it receives as input, so as to limit dispersion in the data output from the neural network.

The extraction neural network may be convolutional, in which case at least one of the layers of the neural network is a convolutional layer.

The extraction neural network has the particularity of not having any normalization layer. It will be seen in the following that this absence of a normalization layer is advantageous, contrary to what might be thought at first glance.

In a step 106, the processor 10 generates a preliminary classification map from the test image. More precisely, the preliminary classification map is generated by the processor 10 using a classification neural network into which the features extracted by the extraction neural network are input, the classification neural network having been trained beforehand.

The classification neural network classifies the N classes of inter-ridge distances in pixels discussed above, and the classification map reflects the result of this classification.

The preliminary classification map comprises, for each block of a set of blocks covering the entire test image and for each class forming part of the plurality of N classes, a preliminary score associated with the block and with the class.

In the present text, a "block" of an image is a region of the image that is unitary and contains one or more pixels of the image. In one preferred embodiment, each block in question is in fact one pixel of the test image. In this case, the set of blocks covering the entire image is the set of the pixels of the test image, and hence the number of preliminary scores is equal to N multiplied by the number of pixels in the test image.

The preliminary score p_i associated with a block and with the class of index i is indicative of a probability of existence, in the test image, of a segment passing through the block and the length of which constitutes an inter-ridge distance of the fingerprint included in the class of index i.

In one embodiment, the preliminary score p_i associated with a block and the class of index i is directly the probability of existence such as defined above. The preliminary score p_i then has a value between 0 and 1. In this case, the higher the value of the preliminary score, the higher the probability of existence. However, it will be understood that the preliminary score p_i may be indicative of such a probability of existence, without however directly taking

the form of this probability. Specifically, the preliminary score may be a datum on the basis of which such a probability of existence may be deduced.

To summarize, the operation carried out by the classification neural network may be considered to be that of partitioning the test image into blocks, and of assigning, to each
 5 block, a discrete distribution of N scores $p_1, \dots, p_N$ associated with the classes of indices ranging from 1 to N , respectively. These scores p_i indicate which inter-ridge distance values are most probably contained in the corresponding block.

In the vast majority of images showing a fingerprint, the fingerprint does not cover the entire image, but is visible in only one section of the image (this is in particular the case in the
 10 image shown on the left of figure 3). Thus, the test fingerprint may be visible only in certain blocks of the test image, which by convention are referred to as "blocks of interest", the other blocks of the test image providing no relevant information on the test fingerprint. To summarize, the initial set of blocks, covering the entire image, comprises a plurality of blocks of interest, this plurality of blocks of interest forming a subset of the initial set of
 15 blocks.

To take this aspect into account, the processor 10 generates, in a step 108, a binary mask estimating, for each block of the set of blocks, whether the block is a block of interest (that is to say a block showing a fingerprint) or not (that is to say a block not showing a fingerprint).

20 The binary mask is generated by a semantic segmentation neural network into which the features extracted by the extraction neural network are input, the semantic segmentation neural network having been trained beforehand. The semantic segmentation neural network operates in parallel with the classification neural network.

For example, the binary mask assigns the value 1 to each block of interest (considered to
 25 show a fingerprint), and the value 0 to the other blocks (considered not to show a fingerprint).

To assign a value 0 or 1, the semantic segmentation neural network may implement the following sub-steps.

In a first sub-step, the segmentation neural network generates a segmentation map on the
 30 basis of the features previously extracted from the test image. The segmentation map comprises, for each block, a probability that the block shows a fingerprint. This probability has a value between 0 and 1.

In a second sub-step, the segmentation neural network determines a threshold to be applied to the segmentation map. Preferably, the threshold is equal to the maximum probability of the segmentation map multiplied by a predefined coefficient strictly lower than 1, for example 0.65.

- 5 In a third sub-step, the segmentation neural network thresholds the segmentation map using the determined threshold, so as to produce the binary mask. During this sub-step, any probability below the threshold is set to zero, while any probability above the threshold is set to 1.

10 In a step 110, the processor applies the binary mask to the preliminary classification map so as to generate a masked classification map.

For example, applying the binary mask to the preliminary classification map comprises obtaining a Hadamard product of the preliminary classification map and of the binary mask (this product being represented in figure 2 by the sign X).

15 The masked classification map comprises, for each block of interest and for each class of the plurality of N classes, a score associated with the block of interest and with the class. The score associated with a block and a class is indicative of a probability of existence, in the reference image, of a segment passing through the block and the length of which constitutes an inter-ridge distance of the fingerprint included in the class.

20 It will be understood that the masked classification map has a content similar to that of the classification map generated by the classification neural network used upstream.

Each score of the masked classification map, which score is associated with one block of interest and with one given class, is derived from the preliminary score associated with this block of interest and with this class.

25 Preferably, each score of the masked classification map, which score is associated with one block of interest and with one given class, is precisely the preliminary score associated with this block of interest and with this class. In other words, a preliminary score associated with a block of interest is also a score in the masked classification map, its value remaining unchanged.

However, the masked classification map is restricted to blocks of interest.

30 This restriction may be realized in a number of ways.

The restriction may be realized so that the masked classification map comprises N scores p_1 , ..., p_N only for the blocks of interest, that is to say the blocks that have been designated by

the binary mask as showing a fingerprint. In this case, the number of scores contained in the masked classification map is less than the number of preliminary scores contained in the preliminary classification map. In this case, only scores relating to blocks of interest of the test image (only the one or more blocks showing a fingerprint according to the binary mask) are retained, and scores relating to the other blocks of the set of blocks covering the entire image are eliminated.

As a variant, the restriction to blocks of interest is realized by forcing the value of any score relating to a block that is not a block of interest to a value indicating that the score is irrelevant, for example by forcing this value to zero. In the rest of the method, the processor is thus able to recognize an irrelevant score, and thus ignore it.

Whatever the nature of the realized restriction, application of the binary mask may be considered equivalent to filtering the preliminary classification map so as to allow the processor to subsequently limit processing operations to relevant scores. This allows the hardware resources required to subsequently implement the subsequent steps of the method to be decreased. In addition, this restriction improves the accuracy of the estimate delivered by the method, because areas that are not of interest are excluded.

In a step 112, the processor 10 generates a local inter-ridge distance map on the basis of the masked classification map.

The local inter-ridge distance map comprises, for each block of interest, a local inter-ridge distance in pixels estimated for the block of interest. Here, the qualifier "local" is used to illustrate the fact that a local inter-ridge distance is information associated with a block constituting only one portion of the test image, and not more global information.

A local inter-ridge distance in pixels estimated for a block is computed on the basis of selective data derived from the masked classification map and from the plurality of N classes.

These selective data comprise a score p_k indicative of a maximum probability of existence among the N scores $p_1, \dots, p_N$ associated with the block in question. Thus, in the case where the score indicative of a maximum probability of existence is a score p_k of maximum value, the index k of the first score is:

$$k = \underset{i=1, \dots, N}{\operatorname{argmax}}(p_i)$$

The selective data moreover comprise a value C_k included in the class of index k associated with the score p_k . For example, the value C_k is the median value of the class of index k.

Taking the data p_k and C_k into account allows a relevant local inter-ridge distance to be obtained. Specifically, the masked classification map indicates that, if there is in the test image a segment passing through the block in question and the length of which constitutes an inter-ridge distance, then the most probable hypothesis is that this length is included in the class of index k . This is what the score p_k indicative of a maximum probability of existence reflects. Taking this class into account allows a more accurate distance estimation.

If $k > 1$, then the selective data used to compute the local inter-ridge distance associated with a block preferably comprise:

- the score p_{k-1} associated with the class of index $k-1$ (which is therefore a class adjacent to the class of index k in the plurality of N classes),
- a distance value C_{k-1} included in the class of index $k-1$, such as the medial value of the class of index $k-1$.

If $k < N$, then the selective data used to compute the local inter-ridge distance associated with a block preferably comprise:

- the score p_{k+1} associated with the class of index $k+1$ (which is therefore a class adjacent to the class of index k in the plurality of classes),
- a distance value C_{k+1} included in the class of index $k+1$, such as the medial value of the class of index $k+1$.

Thus, the one or more classes adjacent to the most relevant class of index k are preferably taken into account, and other classes are not taken into account. This has the advantage of further refining the estimation of the local inter-ridge distance.

If $1 < k < N$, then the local inter-ridge distance associated with the block in question may be computed in the following way:

$$\frac{p_{k-1}C_{k-1} + p_kC_k + p_{k+1}C_{k+1}}{p_{k-1} + p_k + p_{k+1}}$$

- The local inter-ridge distance is thus an average of the distances C_{k-1} , C_k and C_{k+1} weighted by the corresponding scores p_{k-1} , p_k and p_{k+1} , respectively. With such a computation, an interpolation is carried out that allows values forming part of a continuous and non-discrete space to be obtained as output, this also contributing to refining the estimation.

On the right of figure 3 one example of a local inter-ridge distance map obtained on the basis of the test image on the left of figure 3 has been shown. The black part corresponds to the irrelevant blocks. It may be seen that the blocks of interest cover a specific area of

the image. This area contains various grayscale levels to illustrate the fact that the local inter-ridge distances estimated in this area have different values, with a maximum value equal to 13.

5 The processor 10 selects at least one class of interest from the plurality of classes of distances, using the masked classification map. Each class of interest may be selected by the processor 10 by means of steps 114 and 116, which are as follows.

10 In step 114, the processor 10 computes a histogram on the basis of the masked classification map. The histogram comprises, for each of the N classes of distance in pixels, an aggregated score obtained by aggregating the scores associated with the class, these scores being associated with the various blocks of interest retained in the masked classification map. Thus, if the masked classification map contains NM scores, M being the number of blocks of interest identified by the binary mask, then the aggregated score for the class of index i results from aggregation of the M scores p_i associated with the M blocks of interest, respectively. Since there are N classes, N aggregated scores are produced in this step 114.

15 An aggregation that is particularly inexpensive in terms of hardware resources consists simply in summing the M scores p_i respectively associated with the M blocks of interest, to obtain the aggregated score of the class of index i . Other types of aggregation could however be employed instead of a summation in step 114.

20 In step 116, the processor 10 detects at least one score constituting a local maximum of the histogram. Each class of interest is a class associated with a score constituting a detected local maximum.

25 It will be noted that the histogram computed in step 114 may contain a single local maximum or a plurality of local maxima. For example, figure 5 on the left shows another example of a test image, this time one containing interfering signals (the oblique lines), and on the right shows the histogram obtained on the basis of this test image. This histogram contains two local maxima: a principal local maximum of high value (higher than 0.12) associated with a class of interest the values of which are slightly lower than 20 pixels, and a secondary local maximum of lower value (between 0.10 and 0.12) associated with another class the values of which are slightly higher than 10 pixels.

30 For the sake of clarity, it will initially be assumed that a single local maximum is detected in step 116, and therefore that the processor selects only a single class of interest from the plurality of N classes of distance in pixels.

In a step 118, the processor 10 estimates an average inter-ridge distance of the test fingerprint on the basis of the local inter-ridge distance map and the selected class of interest. The estimation 118 comprises the following sub-steps.

5 It will be recalled that the local inter-ridge distance map comprises M local inter-ridge distances in pixels respectively associated with the M blocks of interest previously retained in the masked classification map.

10 In a first sub-step of step 118, the processor 10 selects distances of interest from among the M local inter-ridge distances in pixels respectively associated with the M blocks of interest, based on a criterion of proximity to the class of interest. A local inter-ridge distance the value of which is close to the values of the class of interest is selected here. In contrast, a local inter-ridge distance the value of which is far from the values of the class of interest is not selected.

15 Preferably, the distances of interest are the local inter-ridge distances in pixels having values within an interval the bounds of which are determined on the basis of a distance value included in the class of interest.

For example, the interval is centered on the median value of the class of interest, and has a predefined length. As a variant, the lower bound is equal to $(100 - x) \%$ of the median value of the class of interest, and the upper bound of the interval is equal to $(100 + x) \%$ of the median value of the class of interest, with x between 0 and 100, and for example 35.
20 Regardless of the method used to construct the interval, the interval represents a bounded neighborhood around a value derived from the class of interest.

In another sub-step, the processor computes an average of the distances of interest selected in the preceding sub-step.

25 The result of this averaging is the average inter-ridge distance in pixels estimated for the test fingerprint.

This estimated average inter-ridge distance in pixels is obtained without prior knowledge of the resolution of the test image being required. Specifically, none of steps 102, 104, 106, 108, 110, 112, 114, 116 and 118 had such a resolution as a parameter; the method worked exclusively with distances expressed in pixels.

30 It is possible for the reference images stored by the server to have a different resolution to the resolution of the test image (the latter resolution being unknown). In this case, comparing the test image with the reference images would be liable to lead to false negatives or false positives.

To overcome this problem, the device 1 obtains, in a step 120, a reference inter-ridge distance, expressed in pixels, relating to a reference fingerprint shown in a reference image stored in the database.

To obtain this average inter-ridge distance in step 120, the processing device 1 may send a request to the server 2 via its communication interface 12, the server 2 returning the reference inter-ridge distance in pixels in response to the request.

For example, the reference inter-ridge distance in pixels is computed in advance, that is to say before the request aiming to obtain it is sent, and for example when the reference image is stored on the server 2. As a variant, the server 2 may estimate this reference inter-ridge distance on receipt of the request, for example by means of steps 104 to 118 applied to a reference image stored by the server 2.

In a step 122, the processing device 1 resizes the test image to a resized image, so that the estimated average test inter-ridge distance in pixels corresponds to the reference inter-ridge distance in pixels. This resizing is typically scaling, that is to say a transformation that does not change the aspect ratio of the test image.

The resizing step 122 may thus comprise computing a scale factor, namely a ratio of the reference inter-ridge distance in pixels to the average inter-ridge distance in pixels estimated for the test image, and applying this scale factor to the test image to obtain the resized image.

For example, let it be assumed that the average inter-ridge distance estimated for the test image is 5 pixels, and that the obtained reference inter-ridge distance is 10 pixels. In this case, the test image is resized so that the inter-ridge distance of the test image passes from 5 pixels to 10 pixels in the resized image, using a scaling factor equal to 2 (10 divided by 5).

In a step 124, the processor 10 commands a comparison between the resized test image and the reference image, so as to verify whether the test fingerprint and the reference fingerprint match.

The comparison, which is made in a way known in the art, is typically carried out by the server 2. To command this comparison, the processing device 1 may send a comparison request and the resized image to the server 2. The resized image may for example be sent to the server in encrypted form, to increase confidentiality.

It was seen above that the processor 10 may in certain cases select not one but a plurality of classes of interest (in particular if a plurality of local maxima is detected in the histogram in step 116). This may occur in test images containing multiple spatial frequencies, and in

which the test print gets mixed up with other periodic signals, for example as in the example discussed above of figure 5. In this case, step 118 is repeated for each class of interest, so as to produce a plurality of average distances in pixels respectively associated with the classes of interest.

5 Moreover, steps 122 and 124 are first implemented based on the average distance in pixels associated with the class of interest for which a local maximum having the highest value among the detected local maxima was found. If it is observed that the resized image and the test image do not match, then steps 122 and 124 are implemented again based on another average distance. Thus, the various local maxima are successively tested in order
10 of decreasing probability.

It was seen above that the N classes have sizes that increase with their median. This is advantageous, since a higher accuracy is obtained for small inter-ridge distances, which are more sensitive to small absolute errors (for example, making an error of 1 is more serious for an expected distance of 3 than for an expected distance of 20).

15 It was also seen above that the extraction neural network preferably does not have any normalization layer. The inventors have discovered that the presence of normalization layers in the extraction neural network leads to biases in the estimation of average distance in pixels, above all when the test fingerprint rests on a noisy background. Specifically, textures appearing in the test image around the test fingerprint may disrupt correct operation of the
20 network in the fingerprint-containing areas and lead to an average distance that is incorrect (excessively over-estimated or under-estimated).

To confirm this discovery, comparative trials consisting in implementing the method with a batch-normalization layer while gradually adding padding in the form of random noise to very visible fingerprints (tenprints) have been carried out. Figure 6a shows a series of results
25 obtained with the normalization layer, and figure 6b shows a series of results obtained without a normalization layer for the same fingerprint. The images on a white background, and with a gray border where appropriate, are the test images input, and the images on a black background are the corresponding local distance maps obtained. In figures 6a and 6b, the padding corresponds to the gray border around the white square containing the test
30 fingerprint. It may be seen that the absence of a normalization layer allows local distance maps that are much more resistant to the injected noise to be obtained.

Moreover, to measure the added value of the resizing step, the inventors carried out comparative tests consisting in implementing comparisons between the test image and the reference image (step 124) with and without prior resizing of the test image. It was then

verified to what extent the comparison results were or were not erroneous (false positive or false negative). An improvement in accuracy of about 14 points was observed when resizing is implemented before comparison. In some cases, the error decreased from 17% to 2.2%, this being almost 8 times less error.

CLAIMS

1. A method for processing a test image showing a test fingerprint, the method comprising the following computer-implemented steps:
 - 5 • estimating (118) a first test inter-ridge distance relating to the test fingerprint, the first test inter-ridge distance being a distance in pixels,
 - obtaining (120) a reference inter-ridge distance relating to a reference fingerprint shown in a reference image, the reference inter-ridge distance being a distance in pixels,
 - 10 • resizing (122) the test image into a resized test image such that the first test inter-ridge distance in pixels corresponds to the reference inter-ridge distance in pixels,
 - commanding (124) a comparison between the resized test image and the reference image, so as to verify whether the test fingerprint and the reference fingerprint match.

- 15 2. The method as claimed in the preceding claim, furthermore comprising steps of
 - estimating (118) a second test inter-ridge distance relating to the test fingerprint, the second test inter-ridge distance being a distance in pixels,
 - repeating the steps of resizing (122) and of commanding a comparison (124) for the second test inter-ridge distance instead of the first test inter-ridge distance.

- 20 3. The method as claimed in the preceding claim, wherein the steps of resizing (122) and of commanding a comparison (124) are repeated only on the condition that the comparison between the resized test image and the reference image led to a result indicating that the test fingerprint and the reference fingerprint do not match.

- 25 4. The method as claimed in any one of the preceding claims, comprising the following steps:
 - generating (110) a classification map from the test image, the classification map comprising, for each block forming part of a plurality of blocks of the test image and for each class of a plurality of classes of distances in pixels, a score associated with
 - 30 the block and with the class, the score associated with the block and with the class being indicative of a probability of existence in the test image of a segment passing through the block and the length of which in pixels constitutes an inter-ridge distance of the fingerprint included in the class,
 - generating (112) a local inter-ridge distance map on the basis of the classification
 - 35 map, the local inter-ridge distance map comprising, for each block of the plurality of blocks, a local inter-ridge distance in pixels estimated for the block,

- estimating (118) the first test inter-ridge distance on the basis of the local inter-ridge distance map and of a class of interest forming part of the plurality of classes of distance in pixels, the estimation (118) comprising selecting, from the local inter-ridge distance map, local inter-ridge distances of interest according to a criterion of proximity to the class of interest, and computing an average of the local inter-ridge distances of interest.

5. The method as claimed in the preceding claim, wherein the local inter-ridge distance in pixels estimated for a block is computed on the basis of:

- a first score (p_k) indicative of a maximum probability of existence among the scores associated with the block, the first score being associated with a first class forming part of the plurality of classes of distances, and a first distance value in pixels (C_k) included in the first class,
- optionally, a second score (p_{k-1}) associated with a second class, the second class being adjacent to the first class in the plurality of classes of distances in pixels, and a second distance value in pixels (C_{k-1}) included in the second class,
- optionally, a third score (p_{k+1}) associated with a third class, the third class being adjacent to the first class in the plurality of classes of distances in pixels, and the third class being distinct from the second class, and a third distance value in pixels (C_{k+1}) included in the third class.

6. The method as claimed in the preceding claim, wherein the local inter-ridge distance in pixels estimated for a block is computed as an average of the first distance value, of the second distance value and of the third distance value, weighted by the first score, the second score and the third score, respectively.

7. The method as claimed in any one of claims 4 to 6, furthermore comprising steps of:

- generating (106) a preliminary classification map from the test image, the preliminary classification map comprising, for each block of a set of blocks covering the entire test image and for each class of the plurality of classes of distances in pixels, a preliminary score associated with the block and with the class, the preliminary score associated with the block and with the class being indicative of a probability of existence in the test image of a segment passing through the block and the length of which in pixels constitutes an inter-ridge distance of the fingerprint included in the class,

- on the basis of the test image, generating (108) a binary mask estimating, for each block of the set of blocks, whether or not the block contains a fingerprint,
- applying (110) the binary mask to the preliminary classification map so as to generate the classification map, the plurality of blocks being restricted to each block that the binary mask deems to contain a fingerprint.

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8. The method as claimed in the preceding claim, wherein the preliminary classification map is generated using a first neural network, and the binary mask is generated using a second neural network operating in parallel with the first neural network, applying (110) the binary mask to the preliminary classification map comprising for example a Hadamard product of the preliminary classification map and of the binary mask.

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9. The method as claimed in any one of claims 4 to 8, furthermore comprising extracting (104) features from the test image using a neural network without any normalization layer, the classification map being derived from the extracted features.

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10. The method as claimed in any one of claims 4 to 9, wherein the local inter-ridge distances of interest selected according to the criterion of proximity to the class of interest are local inter-ridge distances within an interval having bounds determined on the basis of a distance value included in the reference class, the interval forming a neighborhood around the distance value.

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11. The method as claimed in the preceding claim, comprising steps of

- computing a histogram on the basis of the classification map, the histogram comprising, for each class forming part of the plurality of classes of distances in pixels, an aggregated score obtained by aggregating the scores associated with the class,
- detecting at least one local maximum of the histogram, the class of interest being associated with a local maximum detected in the histogram.

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12. The method as claimed in any one of claims 4 to 11, wherein each block is one pixel of the image.

13. The method as claimed in any one of claims 4 to 12, wherein the plurality of classes of distances respects the following rule: the higher a median value of a class of the plurality of classes of distances, the larger a size of the class.

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14. A computer program product comprising program code instructions for executing the steps of the method as claimed in any one of the preceding claims when this program is executed by a computer.
- 5 15. A computer-readable memory storing instructions that are executable by the computer in order to execute the steps of the method as claimed in any one of claims 1 to 13.