A Model for Assessing the Reliability of Document Text Field Recognition

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Abstract. In this paper, we propose a model for assessing the reliability of simultaneous recognition for two text fields with the same content in a printed document. An example of such pairs could be the fields «amount» and «amount in words». The model analytically assesses the probability of independent recognition results in several fields to be coherent, while the fields in reality may be coherent and not coherent. We suggest a method for evaluating a single character recognition reliability that allows for a given multi-character word recognition reliability threshold.

Keywords: document recognition, error probability evaluation, probabilistic model for document text field recognition, character recognition, document authentication.

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Introduction

The sheer number of recently published papers, as well non-outdated papers dedicated to document image recognition confirms the relevance of this problem. The most successful development in terms of methods is observed for the analysis of documents with rigid structure [1] as well as documents with flexible layout [2]. Analysis of documents with different layouts includes many methods which either rely on a priori information about document layout or structure («grammar») [3, 4], and methods that do not require prior knowledge of document structure [5]. Another relevant problem is extraction of text from tables [6, 7]. The main tools which are utilized to solve such problems are:

- artificial neural networks (NNs): either convolutional NNs with many parameters [8] or low bit NNs with small parameter counts [9, 10] (for object detection and image classification to identify the characters);
- methods based on feature points (for object detection [11] and image classification [12]);
- methods based on Viola–Jones object detection framework, geometric primitives detection [13], and methods based on spectral analysis of image pixels [14].

Algorithms and recognition systems can be characterized by various criteria. The most important recognition quality criteria are accuracy, precision, recall, algorithmic complexity, and computational complexity of algorithm implementation. Another important criterion, the assessment of recognition reliability, determines if the recognition results can be used in the information system. An important aspect of document image processing is the verification of document authenticity. This process determines whether a document is genuine or fraudulent. Nowadays, document authentication issues draw even more attention since remote identification becomes ubiquitous while countless tools that allow for alteration of images or physical documents are easily available. The fundamental challenges of document authentication primarily include verifying the authenticity of document field content during remote identification without a human operator. With the increased demand for remote identification, the cost of false document authentication constantly increases [15].

The tasks of forensics of digital images and documents are relevant, since nowadays the tools allowing for the alteration of document images or paper documents are advanced and can be easily utilized. A lot of recent publications [16-20] confirm the relevance of this topic.

This work addresses the reliability assessment of identity document text field recognition in the case of duplicated information within document fields.

1. Problem statement

Object recognition reliability is defined by us as a measure of correspondence between the true class of the object and the proposed mechanism of class recognition. Let us consider several document recognition cases:

- recognition of text information in its entirety: the reliability is evaluated separately for each character and each word to transfer the evaluations, for example, to the graphical editor of the recognition results;
- recognition of the structured document fields: reliability is calculated for each field and can be used to edit and validate the fields of the document and to decide whether the field recognition result can be used without validation;
- authentication of the document.

The latter is a special case of more general structured document fields recognition. Authenticity is checked using a set of features. A representative publicly available set of features is described in the Public Register of Authentic Identity and Travel Documents Online (PRADO) [21]. PRADO contains basic technical descriptions of identity documents, including information about security elements and authentication features. The information presented within PRADO is provided by experts from the European Union, Iceland, Norway, and Switzerland.

The PRADO [22] glossary describes Machine Verifiable Feature (MVF), one of the document security feature classes. MVF includes, in particular, text objects retrieved by document readers. According to the PRADO glossary, MVF class includes machine-readable zones (MRZs) [22]. Text in MRZ zones is printed in a standard monospace font, OCR-B, designed specifically for character recognition.

Characters acquired as a result of text field recognition can be authenticity features. The inaccuracy of these results can be caused by image digitization errors. One way to improve the reliability of recognition results is to combine the results acquired for two or more fields containing the same information. For example, in a travel document (passport) of a Russian Federation citizen, information within the "Surname" field is duplicated as part of the MRZ. Obviously, the coherent recognition results of two images that contain the same information improve the confidence in the analysis.

Here we will consider a model for assessing the reliability of recognition for two or more fields under the assumption that coherent recognition results are independent (see example in Fig. 1). Fields can be of either fixed or variable lengths. The model is based on the evaluation of the single character recognition reliability.

2. Probabilistic model

Let us introduce a model of document text recognition. Let there be a finite alphabet A of the valid characters set. We assume that the image of a character is an element within some set I_A of possible character images. Let us introduce two operators.

$T: I_A \to A$ maps images of characters into characters.

$G: I_A \to A$ is a recognition operator. It maps images of characters into recognized characters.

Let us assume that the operators G and T are defined and determined, there is such sigma-algebra on a set I_A so that T and G can be measured, and the probability measure is defined on this sigma-algebra.

Let us denote a set of words of fixed length composed of characters within the alphabet A as S, and set I_S includes the images of words within the document. We consider elements of S as ordered sets of fixed

Fig. 1. An example of an ID where three fields (marked in green) contain the same information
The image is taken from the dataset [23]

length containing the elements of A, and elements of I_S as ordered sets of fixed length containing the elements of I_A. Sigma-algebra on I_S is induced by cylinder sets formed by elements of the sigma-algebra for I_A and by selected positions. Let us extend the definition of the operators G and T to words.

$T: I_S \to S$ maps images of words into words.

$G: I_S \to S$ maps images of words into recognized words.

Let us define the coherence condition for images of words and images of characters. Let

$$is = (ia_1, ia_2, \dots, ia_n),\ is \in I_S,\ ia_k \in I_A,\ \ k = 1, \dots, n,$$

then

$$T(is) = s = (a_1, a_2, \dots, a_n) \Leftrightarrow T(ia_1) = a_1, T(ia_2) = a_2, \dots, T(ia_n) = a_n,$$

$$s \in S, \qquad a_k \in A, \qquad k = 1, \dots, n.$$

Additionally, let us assume that word recognition is performed character by character and independently:

$$G(is) = (G(ia_1), G(ia_2), \dots, G(ia_n)),$$

$$is \in I_S, \qquad ia_k \in I_A, \qquad k = 1, \dots, n.$$

Now we can begin to study the model.

2.1. Word recognition

Let us consider a simplified probability measure on the set I_S. Assume that the images of characters in words and the length of the words in images – are mutually independent. We also assume that the images of characters in words have the same distribution. Suppose that for any b and a from the alphabet A we know the following probabilities:

$$P(G(ia) = b | T(ia) = a), \qquad i_a \in I_A.$$

We will assume for simplicity that

$$P(G(ia) = a | T(ia) = a) = p, \qquad p \in [0,1], \forall a \in A.$$

Let us formulate the first statement.

Statement 1. *For given image is of a word and the word length n,*

$$P(G(is) = s | T(is) = s) = p^n.$$

Proof. Let us rewrite

$$is = (ia_1, ia_2, \dots, ia_n),\ s = (a_1, a_2, \dots, a_n),$$

then

$$P(G(is) = s | T(is) = s) = P(G(ia_1) = a_1, \dots, G(ia_n) = a_n).$$

Under the assumption that the images of characters are independent, the following is true

$$P(G(ia_1) = a_1, \dots, G(ia_n) = a_n) = P(G(ia_1) = a_1)P(G(ia_2) = a_2) \dots P(G(ia_n) = a_n) = p^n.$$

The statement is proven.

Hence, the probability of correct word recognition exponentially decreases with increasing word length within this probabilistic model. Note that in the latter, the probability of correct recognition does not depend on the characters themselves, but only on the length of a word.

2.2. Multiple field recognition

Let us consider the probability of the recognition results coherence in several fields.

Statement 2. *Let us consider k images of a word $is_1, is_2, \dots, is_k$, where word s of length n is captured. Let us denote*

$$\{T(is_1) = T(is_2) = \dots = T(is_k) = s\} \text{ as } H.$$

Then the following is true for the probability of the recognition results coherence

1) $P(G(is_1) = G(is_2) = \dots = G(is_k)|H) \leq (p^k + (1-p)^k)^n$,
2) $P(G(is_1) = G(is_2) = \dots = G(is_k)|H) \geq \left(p^k + \frac{(1-p)^k}{(|A|-1)^{k-1}}\right)^n$.

Proof. With

$$is_j = \left(ia_{j,1}, ia_{j,2}, \dots, ia_{j,n}\right), j \in \{1,2,\dots,k\}, s = (a_1, a_2, \dots, a_n),$$

then

$$P(G(is_1) = G(is_2) = \dots = G(is_k)|H) = \prod_{j=1}^{n} P\big(G(ia_{1,j}) = G(ia_{2,j}) = \dots = G(ia_{k,j})|H\big).$$

Each term in the product can be expanded as follows

$$P\big(G(ia_{1,l}) = G(ia_{2,l}) = \dots = G(ia_{k,l})|H\big) = \sum_{j \in A} P\big(G(ia_{1,l}) = j, \dots, G(ia_{k,l}) = j\big|H\big) =$$

$$= p^k + \sum_{j \in A \setminus \{a_l\}} P(G(ia_{1,l}) = j|H) \dots P(G(ia_{k,l}) = j|H).$$

Note that the probabilities $P(G(ia_{i,l}) = j|H)$ are equal for all $i \in \{1, \dots, k\}$ since the distribution of character images is the same. Let us solve the following optimization problem:

$$f(x_1, x_2, \dots, x_{|A|-1}) = \sum_{j=1}^{|A|-1} x_j^k \to \min,$$

$$x_j \geq 0, \qquad j = 1, \dots, |A|-1,$$

$$\sum_{j=1}^{|A|-1} x_j = 1 - p.$$

The Lagrange function can be represented as follows

$$L(x, \lambda, \mu) = \sum_{j=1}^{|A|-1} x_j^k + \sum_{j=1}^{|A|-1} \mu_j x_j + \lambda\left(\sum_{j=1}^{|A|-1} x_j - (1-p)\right).$$

Kuhn–Tucker conditions are as follows [24]:

1) $\mu_j x_j = 0, \qquad j = 1, \dots, |A| - 1;$

2) $L'_\lambda = \sum_{j=1}^{|A|-1} x_j - (1-p) = 0;$

3) $L'_{x_j} = k x_j^{k-1} + \mu_j + \lambda = 0, \qquad j = 1, \dots, |A| - 1; \;\; x_j \neq 0.$

By solving the system and obtaining the minimum, we obtain the solution to a problem

$$x_1 = x_2 = \dots = x_{|A|-1} = \frac{1-p}{|A|-1},$$

hence,

$$\sum_{j \in A \setminus \{a_l\}} P\big(G(ia_{1,l}) = j \big| H\big) \dots P\big(G(ia_{k,l}) = j \big| H\big) \geq (|A| - 1)\left(\frac{1-p}{|A|-1}\right)^k,$$

thus we proved the inequality 2).
Moreover, maximization

$$f(x_1, x_2, \dots, x_{|A|-1}) = \sum_{j=1}^{|A|-1} x_j^k \to \max$$

yields

$$\sum_{j \in A \setminus \{a_l\}} P(G(ia_{1,l}) = j|H) \dots P(G(ia_{k,l}) = j|H) \leq (1-p)^k.$$

Finally,

$$P\big(G(ia_{1,l}) = G(ia_{2,l}) = \dots = G(ia_{k,l})|H\big) \leq \prod_{j=1}^{n} (p^k + (1-p)^k) = (p^k + (1-p)^k)^n.$$

Thus, the inequality 1) is proved.

2.3. Probability of the Type II error

Let us assess the probability of false coherence of the field recognition results.

Statement 3. *Let* 2 *images of the words* is_1, is_2 *be of length* n. *Let* $p > 0.5$. *Let us denote*

$$\{T(is_1) \neq T(is_2)\} \text{ as } H.$$

Then the following is true for the probability of coherence of the recognition results

$$P(G(is_1) = G(is_2)|H) \leq 2p(1-p)(p^2 + (1-p)^2)^{n-1}.$$

Proof. With

$$is_j = \big(ia_{j,1}, ia_{j,2}, \dots, ia_{j,n}\big), \; s_j = (a_{j,1}, a_{j,2}, \dots, a_{j,n}), \qquad j \in \{1,2\}.$$

Let us evaluate the probabilities of the recognition results coherence for different characters at the same positions in two different images.

$$P\big(G(ia_{1,l}) = G(ia_{2,l})|H\big) =$$
$$= \sum_{j \in A} P\big(G(ia_{1,l}) = j, G(ia_{2,l}) = j \big| H\big) = \sum_{j \in A} P(G(ia_{1,l}) = j|H) P(G(ia_{2,l}) = j|H) =$$
$$= p\big(P(G(ia_{1,l}) = a_{2,l}|H) + P(G(ia_{2,l}) = a_{1,l}|H)\big) + \sum_{j \in A \setminus \{a_{1,l}, a_{2,l}\}} P(G(ia_{1,l}) = j|H) P(G(ia_{2,l}) = j|H).$$

Let us estimate from above under the assumption $p > 0.5$. Similarly to the proof of the second inequality from statement 2

$$\sum_{j \in A \setminus \{a_{1,l}, a_{2,l}\}} P(G(ia_{1,l}) = j|H)P(G(ia_{2,l}) = j|H) \leq$$
$$\leq \quad (1 - p - P(G(ia_{1,l}) = a_{2,l}|H))(1 - p - P(G(ia_{2,l}) = a_{1,l}|H)).$$

Then

$$P\big(G(ia_{1,l}) = G(ia_{2,l})|H\big) \leq p\big(P(G(ia_{1,l}) = a_{2,l}|H) + P(G(ia_{2,l}) = a_{1,l}|H)\big) +$$
$$+(1 - p - P(G(ia_{1,l}) = a_{2,l}|H))(1 - p - P(G(ia_{2,l}) = a_{1,l}|H)).$$

Let us introduce the notation

$$P(G(ia_{1,l}) = a_{2,l}|H) = p_1 \in [0,1-p],$$
$$P(G(ia_{2,l}) = a_{1,l}|H) = p_2 \in [0,1-p],$$
$$F(p_1, p_2) = p(p_1 + p_2) + (1 - p - p_1)(1 - p - p_2).$$

For the function $F(p_1, p_2)$, the following is true

$$F(p_1, p_2)'_{p_1} = p - (1 - p - p_2) = 2p - 1 + p_2 \geq 0,$$

because $2p - 1 > 0;\ p_2 \geq 0.$

Similarly, $F(p_1, p_2)'_{p_2} \geq 0.$

Hence, the function F has maximum within the rightmost borders of values p_1 and p_2. Hence,

$$P\big(G(ia_{1,l}) = G(ia_{2,l})|H\big) = F(p_1, p_2) \leq F(1 - p, 1 - p) = 2p(1 - p).$$

Since the probability of the recognition results $ia_{1,j}$ and $ia_{2,j}$ to be coherent is greater if $T(ia_{1,j}) = T(ia_{2,j})$, $p > 0.5$, thus when estimating from above, we can assume that the words have matching characters at all positions except for a single one. The estimate from above of $p^2 + (1-p)^2$ if $T(ia_{1,j}) = T(ia_{2,j})$ was achieved in statement 2. Then

$$P(G(is_1) = G(is_2)|H) \leq 2p(1 - p)(p^2 + (1 - p)^2)^{n-1}.$$

Thus the statement is proven.

2.4. Application of estimations to the probability of date recognition

Let us apply the estimates obtained above to date recognition in multiple fields. Assume that the date is a word of length six (i.e. two characters denote the day, two characters denote the month, two characters denote the year) and the corresponding alphabet has the cardinality of ten. Then according to statement 1, the probability of correct date recognition in a single field is p^6 which is illustrated in Fig. 2: the value of the parameter p is marked on the horizontal axis, and the desired probability according to our model is marked on the vertical axis.

The plot shows that even if the total probability of correct recognition for the digits individually is 0.98, the probability of correct recognition of the field is only 0.8858. In order to correctly recognize a date field with a probability of at least 0.98, according to our model, it is necessary to correctly recognize each character with a probability of at least 0.9967. The inverse plot to the plot in Fig. 2 is illustrated in Fig. 3.

Consider a document authentication system that checks the coherence of multiple field recognition results, and if at least a single non-coherent results pair is observed, the authentication fails. Let us specify the case as a false positive if the ground truth words within fields are coherent, but the recognition results are non-coherent. This case corresponds to the situation when a genuine document was presented, but the system does not confirm its authenticity. Let four date fields be under consideration when analyzing the document. Using statement 2, we can construct the plot in Fig. 4, which illustrates the coherence probability estimation if the dates are indeed coherent in the original document. The «exponential» effect is amplified in this case: when recognizing a character (digit) with 0.98 probability, the probability of false positive is $1 - 0.6158$ at worst.

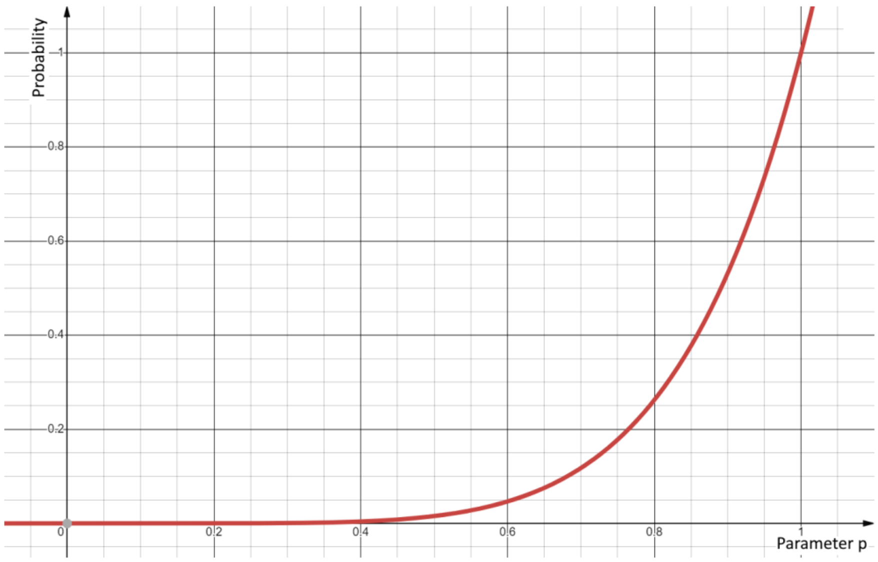

Fig. 2. Probability of correct date recognition in a single field

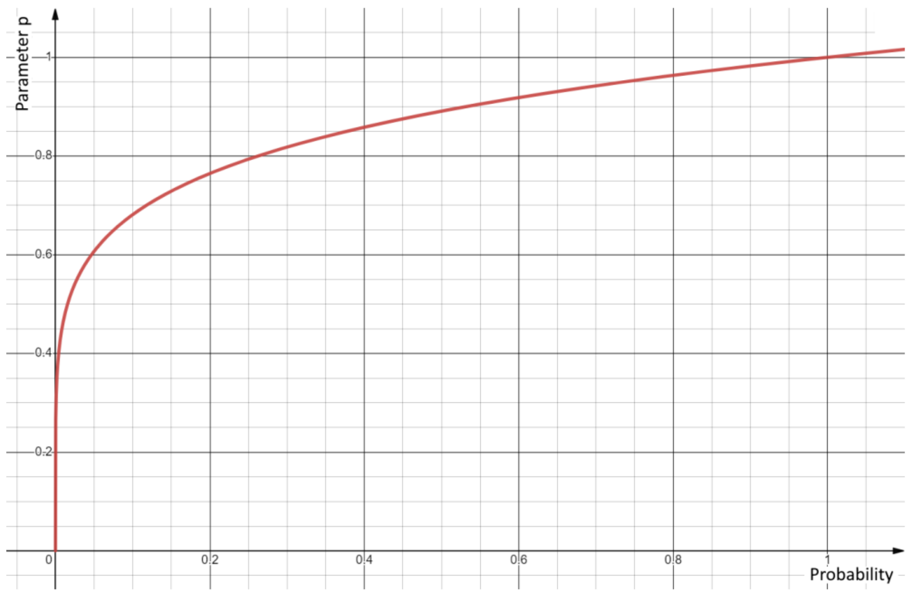

Fig. 3. Digit recognition quality necessary to achieve field recognition within a given probability

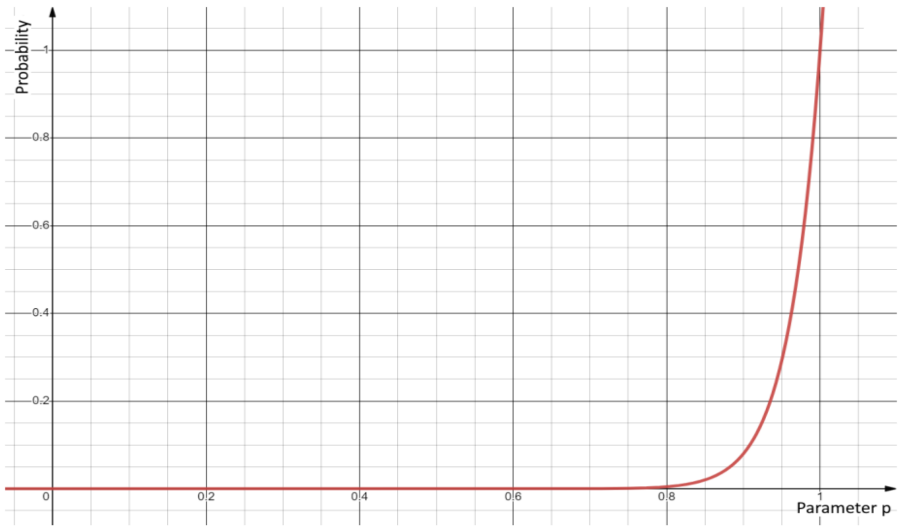

Fig. 4. The probability of coherent recognition results for four date fields if the latter are coherent in the original document

Let two fields contain mismatched dates, the plot of the estimate from above for the recognition results coherence probability is shown in green in Fig. 5. Note that in reality, the probability of observing the identical recognition results for two non-coherent dates will be described by this plot only if the original dates differed by a single character, in accordance with the estimate construction in statement 3. For comparison, Fig. 5 demonstrates a plot of the probability estimate from above if the characters of both dates differ at all positions. This plot corresponds to the equation $y = \left(2x(1-x)\right)^n$ which was obtained using the intermediate constructions from the proof of statement 3. The non-trivial maximum can be explained as follows. When p increases, the probability of confirming equality at $n-1$ positions which actually match increases, but the probability of confirming equality at non-matching positions remains

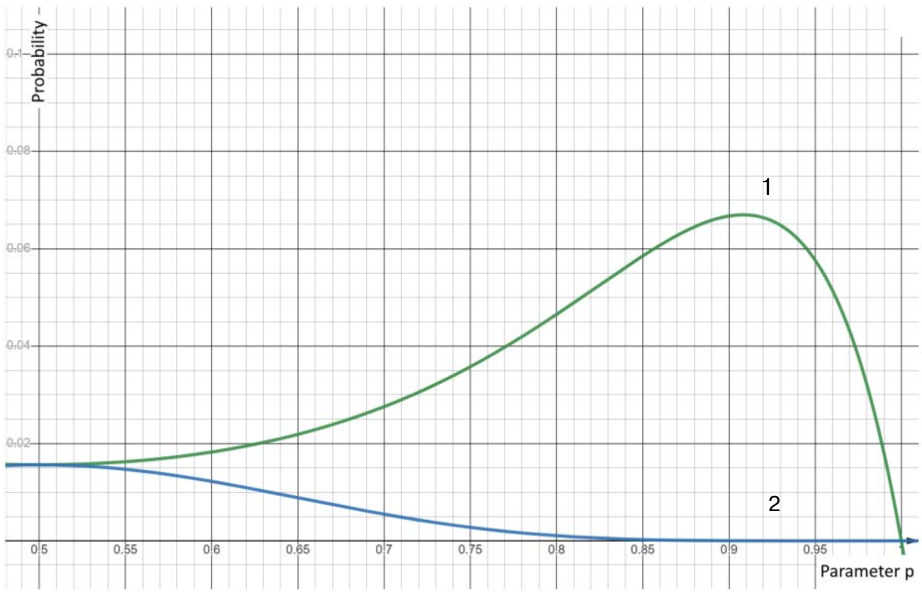

Fig. 5. The probability of recognition results to be coherent for two date fields if the latter are non-coherent in the original document
The plot for a single position mismatch -1, the case of mismatch at all positions of the fields in the original document - 2

substantial, thus the overall probability of dates being coherent increases; but when p becomes too large, we almost certainly do not confirm equality at non-matching positions and the overall probability of dates being coherent tends to zero.

Let us provide an example where we will calculate the necessary accuracy of the character recognition so that the probability of a false positive is less than 0.01 if three document fields are under consideration: each field represents a date which consists of 6 characters. Based on the first inequality of statement 2

$$1 - 0.01 \leq (p^3 + (1-p)^3)^6,$$
$$0.99833 \leq 3p^2 - 3p + 1,$$
$$p \geq 0.99944.$$

Hence, the accuracy of 0.99944 in terms of character recognition is necessary for the overall target probability. The sufficient accuracy is close to the calculated necessary one since the right sides of inequalities 1 and 2 of statement 2 are asymptotically equal if $p \to 1$.

Let us conduct a numerical experiment for ID that contains five text fields (surname, given name, patronymic, sex and date). Every field presents twice on document: as a text field in the visual zone and as a part of MRZ field. Let us denote pairs of images of these fields as

$$(is_1, is_2), (in_1, in_2), (ip_1, ip_2), (ie_1, ie_2), (id_1, id_2)$$

for surname, given name, patronymic, sex and date respectively.

The corresponding alphabet for surname, given name, patronymic has the cardinality of 33, for sex – 2, for 10. Then calculate a sufficient accuracy of one character recognition in order to provide the target quality of 0.01 in terms of false positives. Finally,

$$P(G(is_1) = G(is_2), G(in_1) = G(in_2), \dots, G(id_1) = G(id_2)) =$$
$$= P(G(is_1) = G(is_2)) \dots P(G(id_1) = G(id_2)),$$

because of the independence of recognition. According to the statement 2 we obtain

$$P(G(is_1) = G(is_2)) \dots P(G(id_1) = G(id_2)) \geq \left(p^2 + \frac{(1-p)^2}{32}\right)^l (p^2 + (1-p)^2) \left(p^2 + \frac{(1-p)^2}{9}\right)^6 \geq 0.99,$$

where l is a length of surname in conjunction with given name and patronymic.

Fixing the l, finding the least accuracy of recognition of p from these inequalities and getting the empirical distribution of l, we got the expected value of p of distribution of l, which is equal to 0.99983.

Conclusion

In this work, we proposed a recognition model for several fields containing the same information. The model allows for analytical assessment of the probability for the independent recognition results in several fields to be coherent and the corresponding probability of the Type II error. The proposed model can be utilized when assessing the reliability of document recognition systems in terms of the extracted data. However, a more relevant application is associated with document authentication systems. Such systems classify the document into two categories depending on whether or not the document is genuine. Also, authentication systems are designed to detect anomalies in document images that may indicate potential malicious intent. We also performed the simulations which show that for tasks of digital image forensics, the accuracy of individual character recognition must be very high. The conducted numerical experiments show that in order to provide the target quality of 0.01 in terms of false positives in the case of three fields containing dates that should be coherent in a genuine document, it is necessary to achieve the recognition accuracy of 0.99944 for a single digit. Numerical experiments were also carried out for an ID document consisting of five fields (last name, first name, patronymic, gender, date), each of which is present in two copies directly and as part of the MRZ string). To achieve the target recognition quality for false positives, equal to 0.01, for five fields requires even higher recognition accuracy of a single character, equal to 0.99983.

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