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Research Article

Recognition of the Script in Serbian Documents Using Frequency Occurrence and Co-Occurrence Analysis

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Any document in Serbian language can be written in two different scripts: Latin or Cyrillic. Although characteristics of these scripts are similar, some of their statistical measures are quite different. The paper proposed a method for the extraction of certain script from document according to the occurrence and co-occurrence of the script types. First, each letter is modeled with the certain script type according to characteristics concerning its position in baseline area. Then, the frequency analysis of the script types occurrence is performed. Due to diversity of Latin and Cyrillic script, the occurrence of modeled letters shows substantial statistics dissimilarity. Furthermore, the co-occurrence matrix is computed. The analysis of the co-occurrence matrix draws a strong margin as a criteria to distinguish and recognize the certain script. The proposed method is analyzed on the case of a database which includes different types of printed and web documents. The experiments gave encouraging results.

1. Introduction

Cryptography studies the problems concerning the conversion of information from a readable to some other state. It deals with information which is changing from one to another state. The initial information represents a plain text. When the information becomes encrypted, it is referred as a cipher text [1]. A substitution cipher is a method of encoding. According to it, the units of plain text are replaced with cipher text [2]. They can be single letters, pairs of letters, triplets of letters, mixtures of the above, and so forth. In our application the encryption function is not needed to be injective [3] due to nature of further statistical analysis. It does not matter if it will encrypt two different plain texts into the same cipher text, because decryption of the cipher text is not considered. Hence, the cryptography is used only as a basis for modeling and analyzing documents written in Serbian language. Serbian language represents the European minority language. However, it is distinct due to its capability to be written in Latin and Cyrillic script, interchangeably. According to the baseline characteristics [4], each letter in the text file is replaced with the cipher which is taken from the set of four counterparts only. The basic idea is to distinguish the script (Latin or Cyrillic) according to statistical analysis of the cipher text. It is accomplished with frequency analysis concerning occurrence [5] as well as with the method using statistical measures extracted from gray-level co-occurrence matrix [6]. The letter frequency distribution is a function which assigns each letter a frequency of its occurrence in the text sample [7]. The gray-level co-occurrence matrix (GLCM) have used for the extraction of features needed for texture classification [8]. Nevertheless, it can be exploited for a letter co-occurrence in a text document [9]. At the final stage, the experiment is made on a custom oriented database containing text from printed and Web documents.

The rest of the paper is organized as follows. Section 2 describes the full procedure of the proposed algorithm. Section 3 defines the experiment. Section 4 presents the results from experiment and discusses them. Section 5 makes a conclusion.

2. Proposed Algorithm

The proposed algorithm converts document written in Latin and Cyrillic script which represent the plain text into cipher

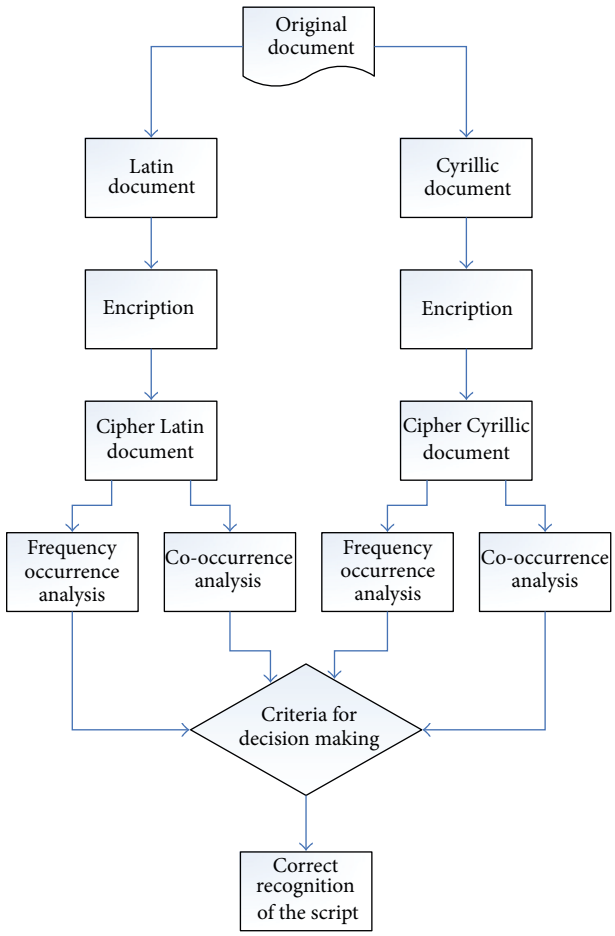


Figure 1: The flow of proposed algorithm.

text according to predefined encryption based on text line structure definition. Then, the equivalent cipher texts are subjected to the frequency and co-occurrence analysis. The results of frequency analysis indicated a substantial difference between cipher texts obtained from Latin and Cyrillic text. Similarly, co-occurrence analysis shows obvious quantitative disparity in some measures. This draws a strong margin as a criterion in order to distinguish and recognize a certain script type (Figure 1).

2.1. Text Line Structure. Text in printed and Web documents is defined as well-formed text type. It is characterized by strong regularity in shape. The distances between the text lines are adequate to be split up. The words are formed regularly with similar distance. Their inter word spacing is decent as well. However, in certain script, the letters or signs have different position according to its baseline. It is shown in Figure 2.

From Figure 2 four virtual lines can be defined [4]:

(i) The top-line,

(ii) The upper-line,

(iii) The base-line, and

(iv) The bottom-line.

Table 1: Definition of script types according to the baseline characteristics.

Script example	Type of script	Designation
a	Short	S
b	Ascender	A
j	Descender	D
lj	Full	F

Accordingly, a text line can be considered as being composed of three vertical zones [4]:

(i) The upper zone,

(ii) The middle zone, and

(iii) The lower zone.

Each text line has at least a middle zone. The upper zone depends on capital letters and letters with ascenders, while the lower zone depends on letters with descenders. Only a few letters occupy the upper and lower zone.

2.2. Encryption. Two different sets are produced. They are A_L and A_C for Latin and Cyrillic alphabet, respectively:

$$A_L = \{\text{A, B, C, } \ldots \text{, Ž, a, b, c, } \ldots \text{, ž}\},$$
$$A_C = \{\text{А, Б, Ц, } \ldots \text{, Ш, а, б, ц, } \ldots \text{, ш}\}. \quad (1)$$

Each of them consists of 60 elements that is, letters, which are valid for Serbian language. Furthermore, both sets A_L and A_C are mapped into set C.

$$f_L : A_L \longmapsto C,$$
$$f_C : A_C \longmapsto C. \quad (2)$$

These mappings are achieved in accordance with the text line area definition. The structure of text line allows definition of following script types [4].

(i) Full letter (F), where letter is present in all three zones.

(ii) Ascender letter (A), where character parts are present in the upper and middle zones.

(iii) Descender letter (D), where character parts are present in the lower and middle zones, and

(iv) Short letter (S), where character parts are present in the middle zone only.

Accordingly, all letters will be replaced with the cipher from the following set:

$$C = \{\text{S, A, D, F}\}. \quad (3)$$

All letters can reach certain position, which belongs to set C with a unique designation according to Table 1.

It should be noted that above mappings are surjective.

Serbian language contains 30 letters. Each letter in Latin has a corresponding equivalent letter in Cyrillic. Table 2 shows Latin and Cyrillic letters as well as theirs designation according to Table 1.

Statistical analysis of the letters and theirs corresponding type for Latin and Cyrillic scripts is shown in Table 3.

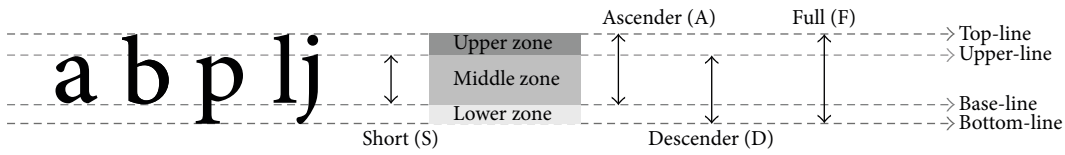


Figure 2: Definitions of the script characteristics.

Table 2: Serbian Latin and equivalent Cyrillic alphabet according to the script types.

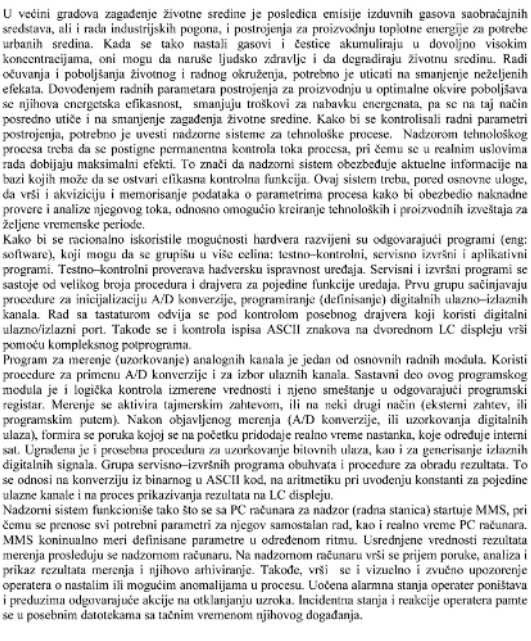
Alphabet	Latin	Script types	Latin	Script types	Cyrillic	Script types	Cyrillic	Script types
1	A	A	a	S	А	A	а	S
2	B	A	b	A	Б	A	б	A
3	C	A	c	S	Ц	F	ц	D
4	Ć	A	ć	A	Ћ	A	ћ	A
5	Č	A	č	A	Ч	A	ч	S
6	D	A	d	A	Д	F	д	S
7	Đ	A	đ	A	Ђ	A	ђ	F
8	Dž	A	dž	A	Џ	F	џ	D
9	E	A	e	S	Е	A	е	S
10	F	A	f	A	Ф	A	ф	F
11	G	A	g	D	Г	A	г	S
12	H	A	h	A	Х	A	х	S
13	I	A	i	S	И	A	и	S
14	J	A	j	D	Ј	A	ј	D
15	K	A	k	A	К	A	к	S
16	L	A	l	A	Л	A	л	S
17	Lj	F	lj	F	Љ	A	љ	S
18	M	A	m	S	М	A	м	S
19	N	A	n	S	Н	A	н	S
20	Nj	F	nj	D	Њ	A	њ	S
21	O	A	o	S	О	A	о	S
22	P	A	p	D	П	A	п	S
23	R	A	r	S	Р	A	р	D
24	S	A	s	S	С	A	с	S
25	Š	A	š	A	Ш	A	ш	S
26	T	A	t	A	Т	A	т	S
27	U	A	u	S	У	A	у	D
28	V	A	v	S	В	A	в	S
29	Z	A	z	S	З	A	з	S
30	Ž	A	ž	A	Ж	A	ж	S

2.3. Frequency Analysis of the Occurrence. In the proposed algorithm, all letters from certain script has been substituted with equivalent members of the set C according to Table 2. These circumstances for Latin document are shown in Figure 3.

Figure 3(b) shows the cipher text which is obtained from Latin documents according to modeling given in Table 2. Figures 3(c)–3(f) shows a subset of cipher text with each element of set C, that is, S, A, D and F, respectively. Statistical analysis of the cipher text shows following: 2217 elements of S, 598 elements of A, 261 elements of D and 8 elements of F types. Accordingly, distribution of C set elements for Latin document is shown in Figure 4.

Currently, the same Latin document is converted into Cyrillic one. Similarly as in Latin document, all letters from Cyrillic document are exchanged with the equivalent members of the set C according to Table 2. These circumstances for Cyrillic document are shown in Figure 5.

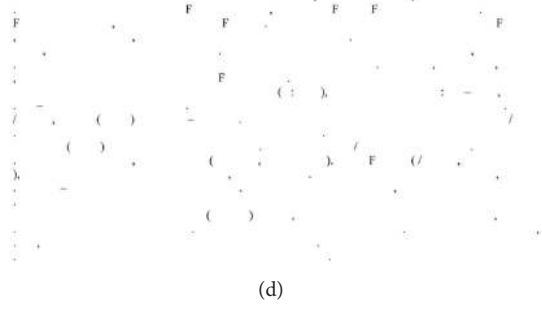
Figure 5(b) shows the cipher text which is obtained from Cyrillic documents according to modeling given in Table 2. Figures 5(c)–5(f) shows a subset of cipher text with each element of set C, that is, S, A, D and F, respectively.



(a)

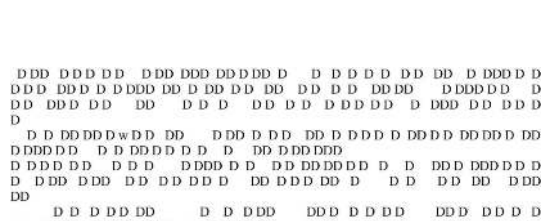
(b)

(c)



(d)

(e)



(f)

Figure 3: Application of the proposed algorithm: (a) Original Latin text, (b) Cipher text according to set C, (c) Only "S" text, (d) Only "F" text, (e) Only "A" text, (f) Only "D" text.

Table 3: Statistical analysis of Latin and Cyrillic script types.

Script	Type of letters	Occurrence of script types				Distribution of script types			
		S	A	D	F	S (%)	A (%)	D (%)	F (%)
Latin	Capital letters	0	28	0	2	0	93.33	0	6.67
Latin	Small letters	12	13	4	1	40.00	43.33	13.33	3.34
Cyrillic	Capital letters	0	27	0	3	0	90.00	0	10.00
Cyrillic	Small letters	21	2	5	2	70.00	6.67	16.66	6.67

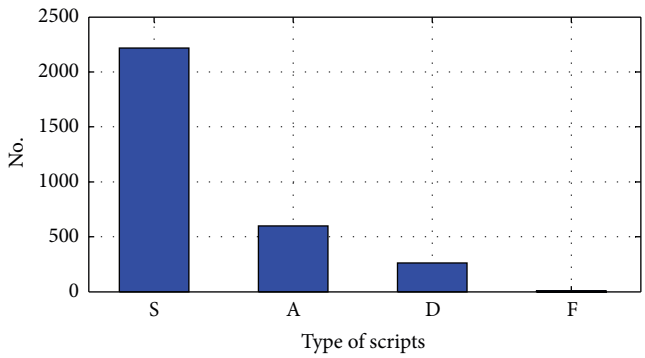


Figure 4: Distribution of C set's elements in cipher text obtained from Latin document.

Statistical analysis of the Cyrillic document image shows following: 2516 elements of S, 53 elements of A, 445 elements of D and 26 elements of F types. It should be noted that the sum of all C set elements in Latin and Cyrillic document is not quite identical. It is valid due to difference in definition of letters in two scripts. In the Cyrillic script, each letter is given one and only one sign. However, in Latin script letters such as dž, lj and nj are represented by two letters. Distribution of C set elements for Cyrillic document is presented in Figure 6.

According to Figures 4 and 6, the comparison chart is drawn. It is shown below in Figure 7.

Quantification of the script type appearance in a document written in Latin and Cyrillic is shown in Table 4.

It is obvious that the Latin document compared to Cyrillic one has slightly smaller number of short (S), descender (D) and full (F) letters. Nonetheless, the crucial margin is seen in ascender (A) letters. Hence, it can be a measure of confidence for detection of the script in a document given in Serbian language.

2.4. Co-Occurrence Analysis. Let **I** be the gray scale image which is under consideration. It has M row and N columns, while T is the total number of gray levels. The spatial relationship of gray levels in the image **I** is expressed by the grayscale co-occurrence matrix (GLCM) **C** [6, 10]. Hence, **C** is a matrix that describes the frequency of one gray level appearing in a specified spatial linear relationship with another gray level within the area of investigation [11]. In order to compute a co-occurrence matrix **C**, we considered a central pixel $I(x, y)$ with a neighborhood defined by the window of interest. This window is defined by two parameters: inter-pixel distance (d) and orientation (θ). Typically, the choice of d is 1 (one pixel), while the value of θ depends on the neighborhood. Because of that, each pixel has 8 neighbors given at following angles $\theta = 0^\circ, 45^\circ, 90^\circ, 135^\circ, 180^\circ, 225^\circ, 270^\circ, 315^\circ$. However, the case of neighbors at $\theta = 0^\circ$ or at $\theta = 180^\circ$ is similar to the GLCM definition [12]. So, the choice may fall to 4 neighbors pixels at $\theta = 0^\circ, 45^\circ, 90^\circ$ and 135°, that is, horizontal, right diagonal, vertical and left diagonal [13]. These orientations refer to 4-adjacent pixels at $(x+d, y)$, $(x, y-d)$, $(x-d, y)$ and $(x, y+d)$, where d is 1. For each pixel of the neighborhood, it is counted the number of times a pixel pair appears specified by the distance, and orientation parameters. The (i, j)th entry of **C** represents the number of occasions a pixel with an intensity i is adjacent to a pixel with an intensity j. Hence, for the given image **I**, the co-occurrence matrix **C** is defined as [14]:

$$C(i,j) = \sum_{x=1}^{M} \sum_{y=1}^{N} \begin{cases} 1, & \text{if } I(x,y) = i, \\ & I(x+\Delta x, y+\Delta y) = j \\ 0, & \text{otherwise,} \end{cases} \quad (4)$$

where i and j are the image intensity values of the image, x and y are the spatial positions in the image **I**. The offset $(\Delta x, \Delta y)$ is specifying the distance between the pixel-of-interest and its neighbor. It depends on the direction θ that is used and the distance d at which the matrix is computed. The square matrix **C** is of the order N. Using a statistical approach like GLCM provides a valuable information about the relative position of the neighboring pixels in an image [12]. In order to normalize matrix **C**, matrix **P** is calculated as [10]:

$$P(i,j) = \frac{C(i,j)}{\sum_{i=1}^{N} \sum_{j=1}^{N} C(i,j)}. \quad (5)$$

The normalized co-occurrence matrix **P** is obtained by dividing each element of **C** by the total number of co-occurrence pairs in **C**.

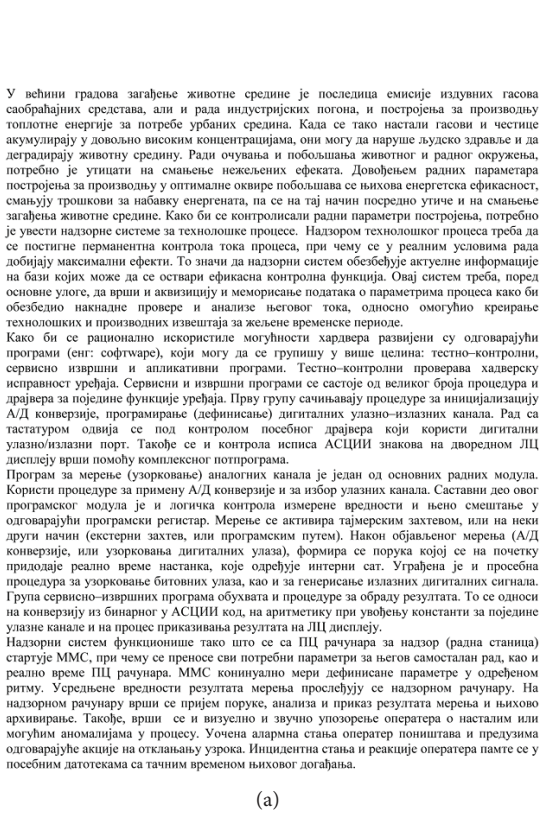
To illustrate the computing of GLCM, a four gray level image **I** is used. The window parameters are $d = 1$ and $\theta = 0^\circ$ (horizontal). Initial matrix **I** is shown in Figure 8.

The procedure of calculating co-occurrence matrix for grayscale matrix **I** ($d = 1$ and $\theta = 0^\circ$) [12] is given in Figure 9.

In order to GLCM be applied in our case, set C is mapped into set C_N by bijective function as:

$$f_C : C \longmapsto C_N, \quad (6)$$

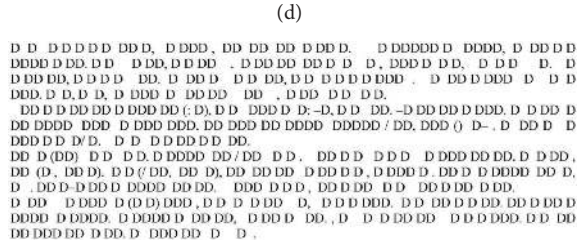
where $C_N = \{0, 1, 2, 3\}$. Furthermore, the neighborhood is given as 2-connected ($x - d$ and $x + d$ around x, where $d = 1$). According to that, the same document in Latin and Cyrillic script is converted into cipher text. It is shown below in Figure 10.



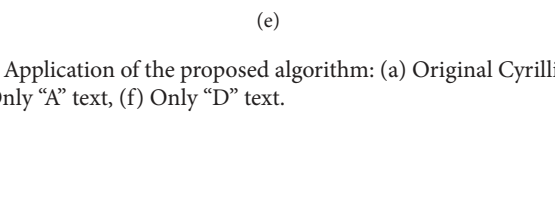
(a)

(b)

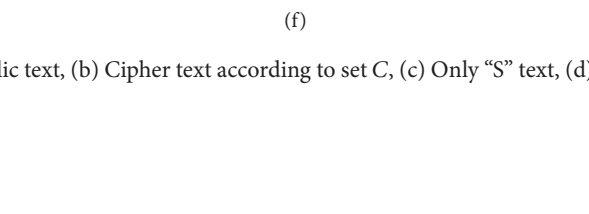
(c)



(d)



(e)



(f)

Figure 5: Application of the proposed algorithm: (a) Original Cyrillic text, (b) Cipher text according to set C, (c) Only "S" text, (d) Only "F" text, (e) Only "A" text, (f) Only "D" text.

Table 4: Percentage of script type occurrence in document.

Type of script (TOS)	Latin	Cyrillic	x times
S	71.88%	82.76%	0.87
A	19.39%	1.74%	11.14
D	8.46%	14.64%	0.57
F	0.27%	0.86%	0.31

It is obvious that the Latin document compared to Cyrillic one has slightly smaller number of short (S), descender (D), and full (F) letters. Nonetheless, the crucial margin is seen in ascender (A) letters. Hence, it can be a measure of confidence for detection of the script in a document given in Serbian language.

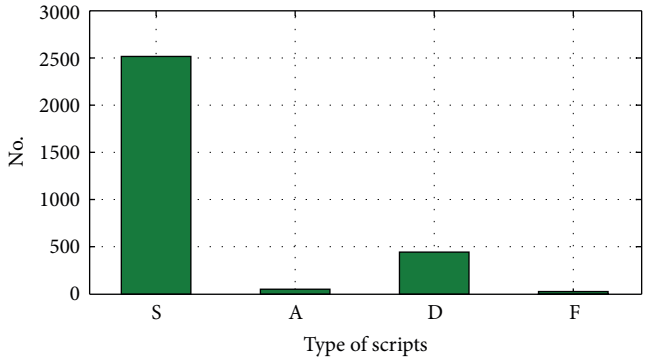


Figure 6: Distribution of C sets elements in cipher text obtained from Cyrillic document.

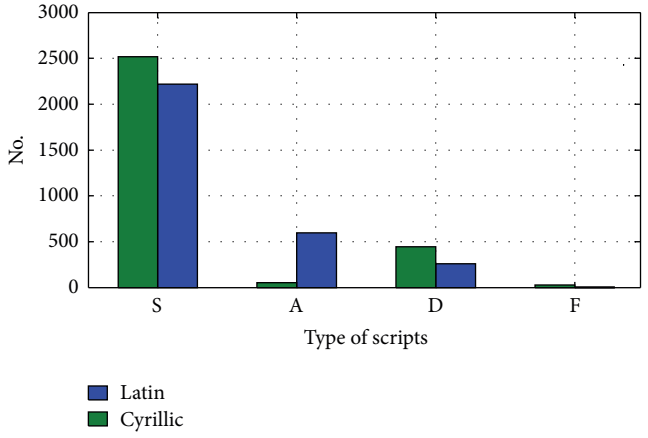


Figure 7: Comparison between distributions of C set elements in Latin and equivalent Cyrillic document.

$$\mathbf{I} = \begin{bmatrix} 1 & 0 & 0 & 2 \\ 0 & 1 & 1 & 1 \\ 2 & 2 & 1 & 1 \\ 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 2 & 3 \\ 0 & 0 & 1 & 1 \end{bmatrix}$$

Figure 8: Initial 4-level grayscale matrix $\mathbf{I}$ (featuring $M = 7$, $N = 4$, and $L = 4$).

Table 5: Normalized cooccurrence matrix.

(a) For cipher text obtained from the Latin text

0.3722	0.2212	0.0623	0.0048
0.2220	0.0343	0.0072	0
0.0623	0.0072	0.0016	0
0.0048	0	0	0

(b) For cipher text obtained from Cyrillic text

0.5863	0.0327	0.1326	0.0064
0.0391	0.0104	0.0144	0
0.1262	0.0200	0.0224	0.0016
0.0072	0	0.0008	0

To evaluate these cipher documents GLCM method is employed. Nevertheless, various statistic measures obtained from the co-occurrence matrix is introduced. The primary goal is to characterize the cipher text. Five descriptors can be used to describe the image [15]:

(i) Uniformity (UNI),

(ii) Entropy (ENT),

(iii) Maximum probability (MAX),

(iv) Dissimilarity (DIS), and

(v) Contrast (CON).

Uniformity (UNI) which is sometimes called angular second moment (ASM) or energy (ENG) measures the image homogeneity. It receives the highest value when GLCM has few entries of large magnitude. In contrast, it is low when all entries are nearly equal. The equation of the uniformity is [15]:

$$\text{UNI} = \sum_{i=1}^{N}\sum_{j=1}^{N} P(i,j)^2. \tag{7}$$

Entropy (ENT) measures the disorder or the complexity of the image. The highest value is found when the values of $P(i, j)$ are allocated quite uniformly throughout the matrix. This happens when the image has no pairs of gray level, with particular preference over others. The equation of the entropy is [15, 16]:

$$\text{ENT} = -\sum_{i=1}^{N}\sum_{j=1}^{N} P(i,j) \cdot \log P(i,j). \tag{8}$$

$j \Rightarrow$

$i \Downarrow$

	0	1	2	3
0	6	4	2	0
1	2	4	0	0
2	0	1	1	1
3	0	0	0	0

(a)

$\gg \mathbf{C} =$

6	4	2	0
2	4	0	0
0	1	1	1
0	0	0	0

(b)

$\gg \mathbf{P} =$

6/21	4/21	2/21	0
2/21	4/21	0	0
0	1/21	1/21	1/21
0	0	0	0

(c)

FIGURE 9: Co-occurrence matrix for grayscale matrix $\mathbf{I}$ ($d = 1$ and $\theta = 0^{\circ}$): (a) The number of occasions a pixel with an intensity I is adjacent to a pixel with intensity j, (b) Co-occurrence matrix $\mathbf{C}$, (c) Normalized matrix $\mathbf{P}$.

FIGURE 10: Document conversion: (a) Original Cyrillic text, (b) Cipher text obtained from Cyrillic text according to set C_N, (c) Original Latin text (equivalent to Cyrillic one), (d) Cipher text obtained from Latin text according to set C_N.

Maximum probability (MAX) extracts the most probable difference between gray scale value in pixels. It is defined as [15]:

$$\mathrm{MAX} = \max\left\{P\left(i, j\right)\right\}. \tag{9}$$

Dissimilarity (DIS) is a measure of the variation in gray level pairs of the image. It depends on distance from the diagonal weighted by its probability. The equation of the dissimilarity is [15]:

$$\mathrm{DIS} = \sum_{i=1}^{N}\sum_{j=1}^{N} P\left(i, j\right) \cdot \left|i - j\right|. \tag{10}$$

PANORAMA

U doba moga detinjstva, dakle vrlo davno, u naš grad je došla stalna panorama. U jednoj od glavnih ulica, njen "direktor", mršav Austrijanac, iznajmio je prazan dućan na uglednom mestu, i u njemu otvorio tu radnju. Iznad vrata je bio solidan natpis, zlatnim slovima na crnom staklu, "Panorama svijeta".
Velika prostorija je lepo urenena i diskretno osvetljena. Ništa tu nije ličilo na jevtine šatre u kojima su dosad boravile prolazne panorame. Sve je odavalo trajnost i stalnost. Unaokolo je išao uzak crven ćilim, u uglovima su bile veštačke palme, ali najveći deo prostora, celu sredinu, zauzimala je – panorama. To je bila drvena granevina u obliku višestrane prizme, od finog drveta koje je bilo tako obojeno da ostavlja utisak mahagonija. Ta poligonska zgradica ličila je na drveno turbe, a krov joj je dopirao do ispod dućanskog plafona. Na njoj su uokrug, u pravilnim razmacima, bili otvori za gledanje: po dva velika durbinska oka s naročitim staklima, uokvirena crnim kaučukom. Pored svakog takvog otvora bila je mala stolica bez naslona, presvučena crvenim plišem. Svega petnaest otvora – na svakoj strani poligona po jedan – i isto toliko sedišta.
U nevidljivoj unutrašnjosti te zgrade bile su kružno rasporenene slike u boji, pomoću naročito postavljenih ogledala i jakog električnog osvetljenja one su pred gledaočevim očima postajale uveličane, jarko osvetljene i veoma žive i plastične. Naročita, i opet nevidljiva, mašinerija pokretala je ceo taj pojas slika uokrug. Svaka slika zadržavala se pred svakim gledaocem dva do tri minuta, a onda se kretala dalje udesno, i na njeno mesto dolazila je nova slika, sleva. Tako, dok svaki gledalac ne vidi sve slike.
Program se sastojao od petnaest slika jedne odrenene zemlje ili jednog velikog grada, i menjao se svake nedelje. Jednom je to bio Rio de Žaneiro, drugi put Lisabon, pa Cejlon, i sve tako redom, iz sedmice u sedmicu, sve daleke zemlje i nepoznati gradovi. Cena ulaznice nije bila visoka, pa ipak je za siromaha naka trećeg razreda realne gimnazije predstavljala znatan novac do koga nije bilo uvek lako doći. Ali taj novac se morao naći. Panorama je za mene postala neka vrsta neophodne droge. Dovijao sam se na sve moguće načine kako da donem do niklenog novca koji otvara vrata "Panorame svijeta", a čim bih uspeo da ga dobijem, trčao sam pravo u glavnu ulicu u predavao ga debeloj ženi za kasom na ulazu u panoramu. A kad bih jednom seo na crveni tabure, za mene je počinjao pravi, veliki i obasjani život. Sve što je dotle značilo moj stvarni život, tonulo je u nepostojanje. A sve što sam čitao u romanima ili želeo i gradio u mašti, sve se moglo povezati sa ovim slikama. Moje vidno polje, a sa njim i cela svest, bilo je potpuno ispunjeno zemljama i gradovima koji su preda mnom klizili i u kojima sam se gubio. Tišina je bila svečana i potpuna, samo je s vremena na vreme fini dečački sluh mogao da uhvati slab šum, jedva čujnu škripu mehanizma.

(a)

ПАНОРАМА

У доба мога детињства, дакле врло давно, у наш град је дошла стална панорама. У једној од главних улица, њен "директор", мршав Аустријанац, изнајмио је празан дућан на угледном месту, и у њему отворио ту радњу. Изнад врата је био солидан натпис, златним словима на црном стаклу, "Панорама свијета".
Велика просторија је лепо уренена и дискретно осветљена. Ништа ту није личило на јевтине шатре у којима су досад боравиле пролазне панораме. Све је одавало трајност и сталност. Унаоколо је ишао узак црвен ћилим, у угловима су биле вештачке палме, али највећи део простора, целу средину, заузимала је – панорама. То је била дрвена граневина у облику вишестране призме, од финог дрвета које је било тако обојено да оставља утисак махагонија. Та полигонска зградица личила је на дрвено турбе, а кров јој је допирао до испод дућанског плафона. На њој су уокруг, у правилним размацима, били отвори за гледање: по два велика дурбинска ока с нарочитим стаклима, уокирена црним каучуком. Поред сваког таквог отвора била је мала столица без наслона, пресвучена црвеним плишем. Свега петнаест отвора – на свакој страни полигона по један – и исто толико седишта.
У невидљивој унутрашњости те зграде биле су кружно распоренене слике у боји, помоћу нарочито постављених огледала и јаког електричног осветљења оне су пред гледаочевим очима постајале увеличане, јарко осветљене и веома живе и пластичне. Нарочита, и опет невидљива, машинерија покретала је цео тај појас слика уокруг. Свака слика задржавала се пред сваким гледаоцем два до три минута, а онда се кретала даље удесно, и на њено место долазила је нова слика, слева. Тако, док сваки гледалац не види све слике.
Програм се састојао од петнаест слика једне одренене земље или једног великог града, и мењао се сваке недеље. Једном је то био Рио де Жанеиро, други пут Лисабон, па Цејлон, и све тако редом, из седмице у седмицу, све далеке земље и непознати градови. Цена улазнице није била висока, па ипак је за сиромаха нака трећег разреда реалне гимназије представљала знатан новац до кога није било увек лако доћи. Али тај новац се морао наћи. Панорама је за мене постала нека врста неопходне дроге. Довијао сам се на све могуће начине како да донем до никленог новца који отвара врата "Панораме свијета", а чим бих успео да га добијем, трчао сам право у главну улицу у предавао га дебелој жени за касом на улазу у панораму. А кад бих једном сео на црвени табуре, за мене је почињао прави, велики и обасјани живот. Све што је дотле значило мој стварни живот, тонуло је у непостојање. А све што сам читао у романима или желео и градио у машти, све се могло повезати са овим сликама. Моје видно поље, а са њим и цела свест, било је потпуно испуњено земљама и градовима који су преда мном клизили и у којима сам се губио. Тишина је била свечана и потпуна, само је с времена на време фини дечачки слух могао да ухвати слаб шум, једва чујну шкрипу механизма.

(b)

Beograd dobija Pupinov spomenik

Ispred tehničkih fakulteta u Beogradu sledećeg septembra biće postavljen spomenik Mihajlu Pupinu, u okviru programa kojim će se obeležiti 160 godina od rođenja tog naučnika. Značajnu sumu za izgradnju obezbediće Fond "Mladen Selak".

U okviru programa kojim će se obeležiti 160 godina od rođenja Mihajla Pupina, sledećeg septembra će naspram spomenika Nikoli Tesli, ispred zgrade tehničkih fakulteta u Beogradu, biti postavljen spomenik tom naučniku. Spomenik će biti delo profesera Miroljuba Stamenkovića.

Značajnu sumu za izgradnju obezbediće Fond "Mladen Selak". To je Fond jednog od najbogatijih i najuticajnijih Srba u Americi.

"Ja duboko, duboko, verujem u nauku, duboko verujem u moć čoveka, da čovek je tu da stvara, da pomaže, da širi dobro oko sebe. Za mene su Pupin i Tesla ljudi koji zaslužuju naše najveće poštovanje", kaže Mladen Selak.

Selak je i finansirao izložbu o Pupinovim delima u Srpskoj akademiji nauke i umetnosti, a sada objavljuje knjigu koju će podeliti našim školama. Za autobiografiju "Sa pašnjaka do naučenjaka", Pupin je dobio Pulicerovu nagradu.

Selak kaže da je literatura skupa, ali i da je ta knjiga dobro urađena. "Knjiga nosi istorijat čoveka koji je ovaj svet zadužio", kaže Selak.

Prema njegovim rečima, telefoni, koje mi danas upotrebljavamo, su Pupinovo delo.

Fondacija je već obnovila Pupinovu rodnu kuću u Idvoru i izdala prigodnu poštansku marku. Sve u cilju da se delo velikog naučnika otrgne od zaborava, kako bi prave vrednosti bile putokaz mladima.

(c)

Београд добија Пупинов споменик

Испред техничких факултета у Београду следећег септембра биће постављен споменик Михајлу Пупину, у оквиру програма којим ће се обележити 160 година од рођења тог научника. Значајну суму за изградњу обезбедиће Фонд "Младен Селак".

У оквиру програма којим ће се обележити 160 година од рођења Михајла Пупина, следећег септембра ће наспрам споменика Николи Тесли, испред зграде техничких факултета у Београду, бити постављен споменик том научнику. Споменик ће бити дело професера Миролуба Стаменковића.

Значајну суму за изградњу обезбедиће Фонд "Младен Селак". То је Фонд једног од најбогатијих и најутицајнијих Срба у Америци.

"Ја дубоко, дубоко, верујем у науку, дубоко верујем у моћ човека, да човек је ту да ствара, да помаже, да шири добро око себе. За мене су Пупин и Тесла људи који заслужују наше највеће поштовање", каже Младен Селак.

Селак је и финансирао изложбу о Пупиновим делима у Српској академији науке и уметности, а сада објављује књигу коју ће поделити нашим школама. За аутобиографију "Са пашњака до научењака", Пупин је добио Пулицерову награду.

Селак каже да је литература скупа, али и да је та књига добро урађена. "Књига носи историјат човека који је овај свет задужио", каже Селак.

Према његовим речима, телефони, које ми данас употребљавамо, су Пупиново дело.

Фондација је већ обновила Пупинову родну кућу у Идвору и издала пригодну поштанску марку. Све у циљу да се дело великог научника отргне од заборава, како би праве вредности биле путоказ младима.

(d)

Figure 11: Custom-oriented database: (a) Printed document in Latin, (b) Printed document in Cyrillic, (c) Web document in Latin, (d) Web document in Cyrillic.

Contrast (CON) or inertia is a measure of the intensity contrast between a pixel and its neighbor over the entire image. Hence, it shows the amount of local variations present in the image. If the image is constant, then the contrast will be equal 0. The highest value of contrast is obtained when the image has random intensity and the pixel intensity and neighbor intensity are very different. The equation of the contrast is [15, 16]:

$$\mathrm{CON} = \sum_{i=1}^{N}\sum_{j=1}^{N} P(i,j)\cdot(i-j)^2. \tag{11}$$

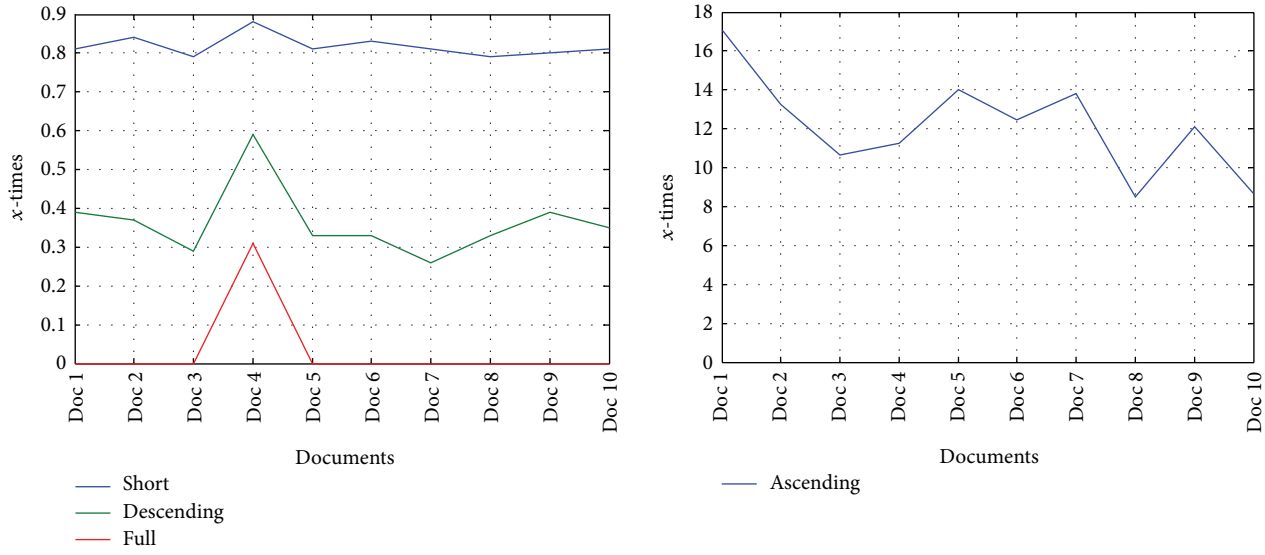


Figure 12: The ratio of the script type occurrence: (a) short, descending and full, (b) ascending.

Table 6: Cooccurrence descriptors for Latin and Cyrillic cipher text.

Serbian language	Latin	Cyrillic	Characterization
Uniformity (energy)	0.2459	0.3811	Latin < Cyrillic
Entropy	−1.6298	−1.4363	Latin > Cyrillic
Maximum probability	0.3722	0.5863	Latin < Cyrillic
Dissimilarity	0.7356	0.6669	Latin > Cyrillic
Contrast	1.0423	1.2660	Latin < Cyrillic

From the above results, it is clear that co-occurrence descriptors can fully characterize the difference between Latin and Cyrillic script. This means that frequency analysis of the occurrence can be supplemented with additional attributes in order to define a strong margin as a criterion to distinguish a certain script.

A brief look at the normalized co-occurrence matrix **P** for the same document written in Latin and Cyrillic scripts (text representing the excerpt of the first four paragraphs from a document given in Figure 10) shows quite a different characterization. The test results are given in Table 5.

Furthermore, the calculation of five co-occurrence descriptors shows the values given in Table 6.

3. Experiments

For the sake of the experiment, a custom-oriented database is created. It consists of 10 documents. These documents represent excerpts from printed and web documents written in Serbian language. The documents are created in both scripts: Latin and Cyrillic. Printed documents are created from PDF documents, while web documents are extracted from web news. The total length of documents given in the database is approx. 75000 letter characters per script (approx. 40 pages). The length of printed documents is from 2273 to 15840 letter characters. Web documents are smaller compared to printed documents. Their length is from 1231 to 2502 letter characters. It should be noted that all documents have more than 1000 letter characters. The example of the printed and web document from the database is shown in Figure 11.

4. Results and Discussion

According to the proposed algorithm, all documents from the database are converted into equivalent cipher texts and subjected to the frequency and co-occurrence analysis. First, the frequency analysis of the script type occurrence in Latin as well as in Cyrillic documents is examined (Table 7). The obtained results for each document are given in Table 8.

The final processing of the results is based on cumulative measures like sum, average, max and min of script type occurrence in the database. According to that the criteria are established. All these are shown in Table 9.

From cumulative results given in Table 10 some criteria can be established. It can be noted that the biggest margin between results are seen in the ratio of ascending letters. This ratio has the value of at least 8. Hence, it is the strongest point of qualitative characterization and recognition of the certain script. Furthermore, the smaller number of short and descending scripts are common in Latin compared to Cyrillic documents. At the and, full letters are quite rare in a Latin document. However, its characterization in criteria form is

Table 7: Frequency analysis of the script type occurrence in documents from database.

Type of script	Printed documents									
	Doc 1		Doc 2		Doc 3		Doc 4		Doc 5	
	Latin	Cyrillic	Latin	Cyrillic	Latin	Cyrillic	Latin	Cyrillic	Latin	Cyrillic
S	2243	2764	11396	13593	1510	1914	2217	2516	2069	2542
A	906	53	4060	306	693	65	598	53	897	64
D	183	468	724	1933	82	286	261	445	151	461
F	0	7	0	8	0	8	8	26	0	12
Type of script	Web documents									
	Doc 6		Doc 7		Doc 8		Doc 9		Doc 10	
	Latin	Cyrillic	Latin	Cyrillic	Latin	Cyrillic	Latin	Cyrillic	Latin	Cyrillic
S	1486	1799	1358	1682	783	996	1657	2078	1328	1637
A	598	48	636	46	408	48	750	62	588	68
D	99	304	75	292	58	174	134	344	99	284
F	0	7	0	9	0	13	0	18	0	9

The above results are further processed in order to calculate the ratio of script type occurrence between Latin and Cyrillic document. Complete results are given in Table 8.

Table 8: The ratio of script type occurrence between Latin and Cyrillic documents.

Type of script	Doc 1	Doc 2	Doc 3	Doc 4	Doc 5	Doc 6	Doc 7	Doc 8	Doc 9	Doc 10
S	0.81	0.84	0.79	0.88	0.81	0.83	0.81	0.79	0.80	0.81
A	17.09	13.27	10.66	11.28	14.02	12.46	13.83	8.50	12.10	8.65
D	0.39	0.37	0.29	0.59	0.33	0.33	0.26	0.33	0.39	0.35
F	0.00	0.00	0.00	0.31	0.00	0.00	0.00	0.00	0.00	0.00

The results are presented in Figure 12.

Table 9: The ratio of script type occurrence measures.

Type of script	$\sum$		Ratio			Criteria
	Latin	Cyrillic	Average	Max.	Min.	
S	26047	31521	0.82	0.88	0.79	>0.75
A	10134	813	12.21	17.09	8.50	>8
D	1866	4991	0.36	0.59	0.26	<0.6
F	8	117	0.03	0.31	0.00	?

Table 10: GLCM five descriptors of the script type co-occurrence in documents from database.

	Printed documents									
	Doc 1		Doc 2		Doc 3		Doc 4		Doc 5	
	Latin	Cyrillic	Latin	Cyrillic	Latin	Cyrillic	Latin	Cyrillic	Latin	Cyrillic
Uniformity	0.2885	0.4725	0.2473	0.4167	0.2557	0.4120	0.2759	0.4545	0.2707	0.4498
Entropy	−1.5191	−1.1774	−1.6379	−1.3079	−1.6047	−1.2999	−1.5675	−1.1650	−1.5847	−1.1799
Max. probability	0.4655	0.6636	0.3952	0.6139	0.4120	0.6098	0.4439	0.6457	0.4349	0.6405
Dissimilarity	0.6847	0.5933	0.7469	0.6592	0.7502	0.6427	0.7064	0.6041	0.7117	0.6217
Contrast	1.0324	1.1790	1.1106	1.2859	1.1258	1.2261	1.0577	1.1449	1.0630	1.1949
	Web documents									
	Doc 6		Doc 7		Doc 8		Doc 9		Doc 10	
	Latin	Cyrillic	Latin	Cyrillic	Latin	Cyrillic	Latin	Cyrillic	Latin	Cyrillic
Uniformity	0.2447	0.3714	0.2754	0.3817	0.2533	0.5005	0.2252	0.3147	0.2522	0.3325
Entropy	−1.6524	−1.3738	−1.5725	−1.3412	−1.5990	−1.0779	−1.6778	−1.5650	−1.6144	−1.5059
Max. probability	0.3964	0.5650	0.4409	0.5753	0.3972	0.6844	0.3195	0.5154	0.4016	0.5318
Dissimilarity	0.7723	0.7320	0.6912	0.7209	0.7294	0.5686	0.8317	0.7667	0.7256	0.7416
Contrast	1.1862	1.3869	1.0287	1.3681	1.0459	1.1158	1.2122	1.4220	1.0641	1.3716

The above results are further processed in order to calculate the ratio of script type co-occurrence in between Latin and Cyrillic document. These results are shown in Table 11.

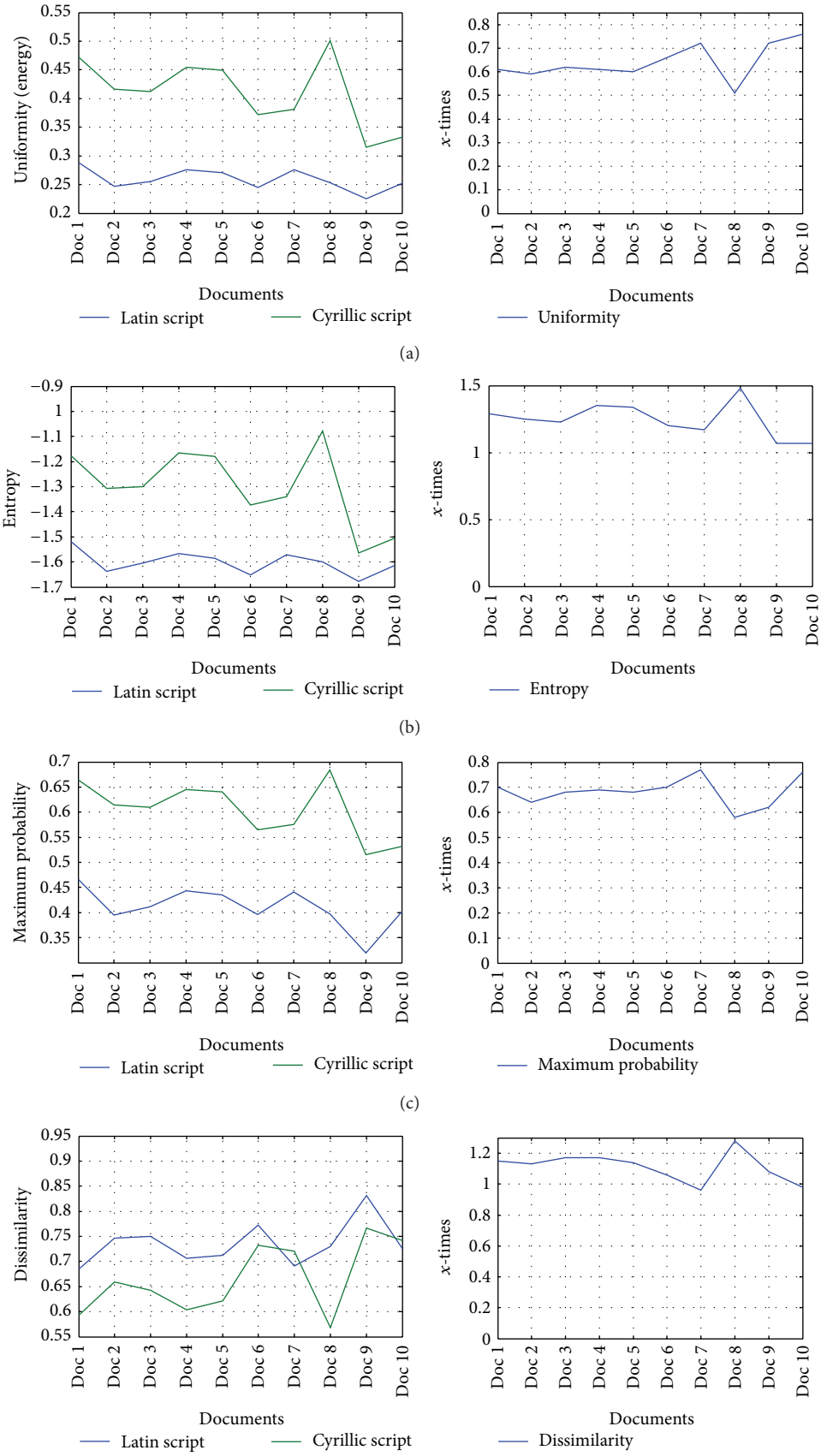
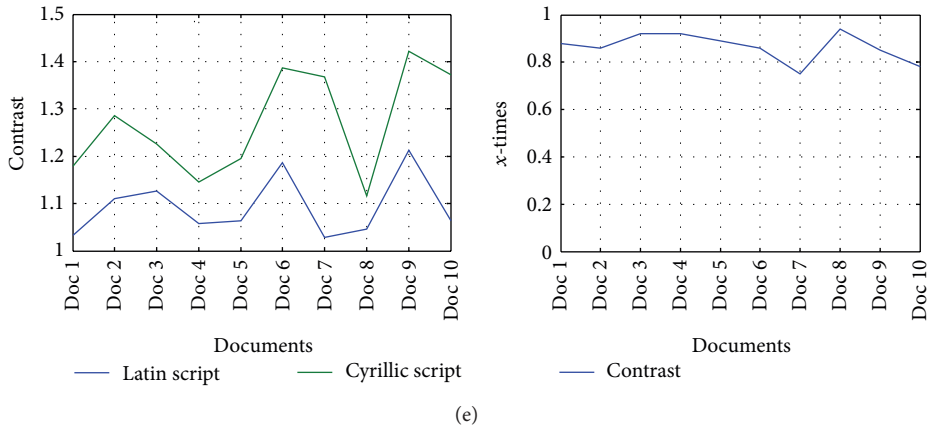


Figure 13: Continued.



(e)

Figure 13: Illustrations of co-occurrence descriptors in Latin and Cyrillic text (left) and its ratio (right): (a) Uniformity, (b) Entropy, (c) Maximum probability, (d) Dissimilarity, (e) Contrast.

Table 11: The ratio of the co-occurrence descriptors between Latin and Cyrillic documents.

	Doc 1	Doc 2	Doc 3	Doc 4	Doc 5	Doc 6	Doc 7	Doc 8	Doc 9	Doc 10
Uniformity	0.61	0.59	0.62	0.61	0.60	0.66	0.72	0.51	0.72	0.76
Entropy	1.29	1.25	1.23	1.35	1.34	1.20	1.17	1.48	1.07	1.07
Max. probability	0.70	0.64	0.68	0.69	0.68	0.70	0.77	0.58	0.62	0.76
Dissimilarity	1.15	1.13	1.17	1.17	1.14	1.06	0.96	1.28	1.08	0.98
Contrast	0.88	0.86	0.92	0.92	0.89	0.86	0.75	0.94	0.85	0.78

The final processing of the above results is based on cumulative measures like average, max. and min. of script type co-occurrence in the database. According to that certain criteria are established. All these are shown in Table 12.

Table 12: The ratio of script type co-occurrence descriptors.

	Latin			Cyrillic			Ratio			Criteria
	Min.	Max.	Average	Min.	Max.	Average	Max.	Min.	Average	
Uniformity	0.23	0.29	0.26	0.31	0.50	0.41	0.76	0.51	0.64	0.3
Entropy	−1.68	−1.52	−1.60	−1.57	−1.08	−1.30	1.48	1.07	1.25	?
Max. probability	0.32	0.47	0.42	0.52	0.68	0.60	0.77	0.58	0.68	0.5
Dissimilarity	0.68	0.83	0.74	0.57	0.77	0.67	1.28	0.96	1.11	?
Contrast	1.03	1.21	1.12	1.12	1.42	1.27	0.94	0.75	0.86	?

quite problematic due to their absence in Latin documents from time to time.

Furthermore, the analysis of the script type co-occurrence in Latin as well as in Cyrillic documents is examined according to GLCM method. The obtained results for each document are given in Table 10.

The co-occurrence descriptor for Latin and Cyrillic text and its ratio is presented in Figure 13.

From the above results, some criteria can be established. It is clear that uniformity and maximum probability receive the most distinct values in Latin and Cyrillic text. Hence, these descriptors are suitable for qualitative characterization of Latin and Cyrillic text as well as for creating criteria to distinguish a certain script type. From the above results, the margin criteria should be uniformity of 0.3 and maximum probability of 0.5. These values of both descriptors represent the strong margin in qualifying the script in certain Serbian text. If we accompany them with the criteria obtained from frequency analysis of the script type occurrence, then the full criteria of decision making can be established. This will lead to correct recognition of the script in Serbian text.

5. Conclusion

The paper proposed the algorithm for recognition of exact script in Serbian document. Documents in Serbian language can be written in two different scripts: Latin or Cyrillic. The proposed algorithm converts document written in Latin and Cyrillic script into cipher text. This way, all alphabetic characters are exchanged with only four different encrypted signs according to predefined encryption based on text line structure definition. Such ciphers texts are then subjected to the frequency and co-occurrence analysis. According to the obtained results a criteria for recognition of the certain script is proposed. The proposed method is applied to the custom-oriented database which includes different types of printed

and web documents. The experiment shows encouraging results. Possible applications can be seen in the area of web page recognition.

Future work will be toward the recognition of related languages as well as different languages written in the same script.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this article ("Recognition of the Script in Serbian Documents using Frequency Occurrence and Co-occurrence Analysis" by Darko Brodić, Zoran N. Milivojević, Čedomir A. Maluckov).

References

[1] C. Smith, "Basic cryptanalysis techniques," Tech. Rep., SANS Institute, 2001.

[2] J. Hoffstein, J. Pipher, and J. H. Silverman, *An Introduction to Mathematical Cryptography*, Springer, New York, NY, USA, 2008.

[3] K. Ruohonen, "Mathematical cryptology," Lecture Notes, 2010.

[4] A. Zramdini and R. Ingold, "Optical font recognition using typographical features," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 20, no. 8, pp. 877–882, 1998.

[5] P. Quaresma, "Frequency analysis of the Portuguese language," TR, 2008/003, University of Coimbra, Portugal, 2008.

[6] R. M. Haralick, K. Shanmugam, and I. Dinstein, "Textural features for image classification," *IEEE Transactions on Systems, Man and Cybernetics*, vol. 3, no. 6, pp. 610–621, 1973.

[7] G. Jaskiewicz, "Analysis of letter frequency distribution in the voynich manuscript," in *Proceedings of the International Workshop (CS&P '11)*, pp. 250–261, Putusk, Poland, 2011.

[8] S. Cagnoni, *Evolutionary Image Analysis and Signal Processing*, vol. 213 of *Studies in Computational Intelligence*, Springer, Berlin, Germany, 2009.

[9] R. Nosaka, C. H. Suryanto, and K. Fukui, "Rotation invariant co-occurrence among adjacent LBPs," in *Proceedings of the 11th International Conference on Computer Vision (ACCV '11)*, vol. 7088 of *Lecture Notes in Computer Science*, pp. 82–91, Daejeon, Republic of Korea, 2011.

[10] D. A. Clausi, "An analysis of co-occurrence texture statistics as a function of grey level quantization," *Canadian Journal of Remote Sensing*, vol. 28, no. 1, pp. 45–62, 2002.

[11] A. Baraldi and F. Parmiggiani, "Investigation of the textural characteristics associated with gray level cooccurrence matrix statistical parameters," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 33, no. 2, pp. 293–304, 1995.

[12] F. R. Renzetti and L. Zortea, "Use of a gray level co-occurrence matrix to characterize duplex stainless steel phases microstructure," *Frattura ed Integrità Strutturale*, vol. 16, no. 5, pp. 43–51, 2011.

[13] R. Susomboon, D. Raicu, J. Furst, and T. B. Johnson, "A Co-occurrence texture semi-invariance to direction, distance and patient size," in *Medical Imaging 2008: Image Processing*, vol. 6914 of *Procedings of SPIE*, San Diego, Calif, USA, February 2008.

[14] A. Eleyan and H. Demirel, "Co-occurrence matrix and its statistical features as a new approach for face recognition," *Turkish Journal of Electrical Engineering and Computer Sciences*, vol. 19, no. 1, pp. 97–107, 2011.

[15] D. A. Clausi and Y. Zhao, "Rapid extraction of image texture by co-occurrence using a hybrid data structure," *Computers and Geosciences*, vol. 28, no. 6, pp. 763–774, 2002.

[16] R. Jobanputra and D. A. Clausi, "Preserving boundaries for image texture segmentation using grey level co-occurring probabilities," *Pattern Recognition*, vol. 39, no. 2, pp. 234–245, 2006.