New Content Based Forensic Metrics for Judicial Disputes Concerning the Graphic Symbols Similarity

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Abstract - **This paper proposes new forensic criteria for matching assessment of two-dimensional (2D) multimedia content in judicial processes. An authorship of two companies' trademark symbols is needed to proof by exact measures, avoiding undefined or ambiguous perceptual criteria. Our algorithm includes several content based wavelets image processing methods for image similarity matching and shape recognition. The result is a new metric, obtained from accurate computations of basic digital image features.**

Keywords – **2-D shape, digital image, forensic and security, shape recognition, trademark similarity assessment, wavelets.**

I. Introduction

Judicial or litigation processes regarding to a determination of authorship or user rights on multimedia or graphic symbols, often need an expert evidence to determine a "similarity" / "difference" of such a digital content. The essence of mentioned multimedia symbols makes the problem of determining an analogy non-trivial, whether it comes from digital audio recordings, analogue and digital photographs, video clips, and more recently three-dimensional (3D) models. In fact, all estimates of this content type are reduced to a factor of a human perception and its metrics. In addition, the most evidence procedures actually rely on an opinion of non-multimedia field experts. Therefore, this paper introduces a new exact metrics that solve a problem of the digital forensics in the field of multimedia, or more precisely in the area of digital images and trademarks.

A comparison of multimedia content are generally based on well-known techniques for *Content Based Image Retrieval* (CBIR) that extract several important image features, mapping a visual content into a new descriptor space. Success of matching picture retrieval or in our case an images similarity determination depends of choosing unique features for the image descriptor. However, in general case there is no unique image feature that is sufficient to characterize an object in picture, thus CBIR uses three basic types of features: color features, texture features and shape features. For example, the both standards QBIC [1] from IBM and Photobook [2] from MIT use all features, whereby QBIC deals with color histogram and shape features that are based on moments, and texture descriptors. Photobook uses all visual features, but also texture and 2D shapes characteristics. SIMBA [3], SIMPLIcity [4], CIRES [5], IRMA [6], FIRE [7] are also important modern methods that deal with one or even all mentioned features. Researchers propose different methods for accurate feature extraction, whereas other deal with optimization of the number of bins that descriptor uses. Using a great number of data descriptors accurately compute similarity and thus achieve required quality of mage retrieval. However, deficiency of the big descriptor content is a slow matching process, and also lot of memory using. The Moving Picture Expert Group (MPEG-7) [8] standard identifies set of descriptors that maintains the equilibrium of descriptor size and quality of achieved result.

The approach of our research relies at existing mentioned methods in a segment of a texture recognizing and color features description, but also suggests using a new curvature feature of extracted shapes and contours. Specifically, our research result [9] has shown an important influence of curvature for the shapes characterization of three-dimensional (3D) meshes, thus we introduce a new 2D shape descriptor feature based at accurate computations of Gaussian and mean curvature of the extracted contours.

This paper is organized as follows. Section II represents notions and notations of main multimedia content features, and also briefly explains descriptors and their functionality. Theoretical and mathematical background of all descriptor features that is used in image matching and retrieving systems is defined in Section III. The main idea of our *similarity measuring* method is exposed in Section IV where is explained also the proposed algorithm through all of its steps. Section V gives numerical results of comparison of two concrete trademark features and explicitly shows values of calculated similarity. Result is discussed in Section VI with conclusions and direction of future work.

II. Image Descriptors

A. Visual Color Descriptor

Color is a feature that is commonly used in the picture description. This feature is invariant to transformations such as rotation and uniform scaling. However, note that there is no feature that could uniquely define a similarity of images; hence several features are used for characterization, simultaneously or by user request.

Scalable color descriptor (SCD) represents color distribution in pictures. Generally speaking, the histogram [10] of digital photos is obtained by color discretization through the number of bins and counting the number of pixels in each bin. The uniqueness of the image is always represented by color histogram, even when perceptual similarity is obvious. During the histogram calculation methods of quantization and the number of bins are different in applications and can be distributed uniformly or non-uniformly at the quality or computational speed request.

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Dominant color descriptor defines local and global color distribution over the image, mostly for fast matching and online retrieving. Colors in certain picture regions are grouped into several clusters as their color representatives. Thereby, descriptor contains representative colors, the percentage of color values per regions, spatial coherence and color variation.

B. Shape and Contour Descriptor

Shape descriptors provides credible proof of the similarity of two pictures that contain information based on textual characters, vector shapes, and drawings, but also color and texture information that actually is not the most important image information. Note that descriptors from this group should be also invariant to image scaling, rotation and translation.

3D shape descriptor is based on the concept of the shape spectrum. Roughly speaking spectrum is defined as a histogram of shape index, calculated over the entire 3D surface. The shape index measures the convexity of each local 3D surface.

Region based descriptor belongs to the *moment invariant* group of methods for shape characterization. This type of descriptor uses moments that are invariant to transformation. For example MPEG-7 is based on complex Angular Radial Transformation (ART), which is defined at unit disc in polar coordinates system.

Contour based descriptor represents contours by the curvature space increment co-called *Curvature Scale-Space (CSS)*, including values of a circularity and eccentricity. CSS indicates most prominent peak values and horizontal and vertical position of peaks on CSS picture.

C. Texture Descriptor

Texture refers to visual patterns that could have homogenous / inhomogeneous properties, which is a consequence of the multitude colors and intensity existence / absence in image structure. In our case this type of descriptor can be powerful for a comparison of textured trademarks, which are usually homogenous.

Homogenous texture descriptor characterizes orientation, roughness and regularity of patterns in images. This type of descriptors is the best suited for a quantitative characterization of the homogeneous texture. In order to describe features such as texture and deviation energy, values are extracted from the frequency domain of the image by extraction of the main and standard deviation of frequency coefficients. Fourier transform and wavelets are commonly used for image transformation into the frequency domain after which descriptor practically applies filters that are sensitive to values and orientation.

Inhomogeneous texture descriptor or *Edges Histogram* [11] detects spatial edges distribution and based on this feature detects similarity. Recent scientific approaches usually suggest the image division at several parts of equal size, after which detected edges are classified into five categories: *vertical*, *horizontal*, *45*^{0}, *135*^{0}, and *no edge*. Blocks, featured by the five bins histogram, form the descriptor that is invariant to image scaling. Rotation and translation can be computed.

III. Background

A. Integrated Region Matching

We assume that regions of two pictures are represented by two sets of regions $R_1 = \{r_1, r_2, ..., r_m\}$ and $R_2 = \{r_1', r_2', ..., r_n'\}$ where r_i and r_i' are descriptors of i-th region. Distance between regions r_i and r_j' is denoted as $d(r_i, r_j')$, and shortly as $d_{i,j}$. In order to determine a similarity of regions R_1 and R_2, $d(R_1,R_2)$ we have to compare all regions of the both images [4]

$$d(R_1, R_2) = \sum_{i,j} s_{i,j} w_{i,j} d_{i,j} \tag{1}$$

where $s_{i,j} \geq 0$ is a credit of an importance and denoted the importance of matching for similarity determination, and $w_{i,j}$ adjusts effects of regions *i* and *j* to a similarity measure.

B. Region Distance

Let we consider a distance between the region pair $d(r_i, r_i')$. Because trademarks are usually homogenous, our case requires an exception of the texture matching, thus we briefly give a mathematic formulation that we use for computations of *no textured* regions. Thus, the region distance $d(r,r')=g(d_s(r,r'))d_t(r,r')$ is given as:

$$d(r, r') = \sum_{i=7}^{9} w_i (f_i - f_i')^2 \tag{2}$$

For a region H in k dimenzional Eucledian space where $\hat{x}$ is centroid, $V(H)$ volume of the region H, L_γ is γ-th order normalized inertia of spheres, and functions f are given as $f_7=l(H,1)/L_1$, $f_8=l(H,2)/L_2$, and $f_9=l(H,3)/L_3$, a discrete normalized inertia l with the order $\gamma \in [1,2,3]$ is defined as:

$$l(H, \gamma) = \frac{\sum_{x:x \in H} \|x - \hat{x}\|^\gamma}{[V(H)]^{1+\gamma/k}} \tag{3}$$

C. Shape and Contour Curvatures

In contrary to the main features of 2D pictures, 3D meshes and vector shapes should be characterized by *curvature.* Namely, analogous to contrast of picture i.e., great gradient of intensity in picture, vector shapes, lines and 2D and 3D surfaces are characterized by value of Gaussian curvature and mean curvature. In the discrete case Based on Gauss' research in the field of differential geometry [12], a discrete formula for a Gaussian curvature is given by Mayer *et al.* [13]:

$$\kappa_G(\mathbf{v}_i) = \frac{1}{\mathcal{A}} \left(2\pi - \sum_{j=1}^{\#f} \theta_{ij} \right) \tag{4}$$

where $\#f$ is a number of adjacent surfaces at vertex v_i, and θ_{ij} is the angle of j-th adjacent triangle at v_i. $\mathcal{A}$ is a first-ring area of triangles around vertex v_i. Using this formula in an one-dimensional (1D) or 2D shape case we define unique shape and contour descriptor, whose feature depends only from geometric features of surface, and it is also invariant to all affine transformations.

D. Histogram Euclidian Distance (d_{HE})

If H_1 and H_2 denote two picture histograms, then a distance between them is calculated as [14]:

$$d_{HE}\left(H_1,H_2\right)=\sqrt{\sum_{x\in X,y\in Y,z\in Z}\left(H_1\left(x,y,z\right)-H_2\left(x,y,z\right)\right)^2} \quad (5)$$

where X, Z and Z are palettes of discrete color channels, and distance d_{HE} is L^2- norm of the distance vector.

E. Histogram Intersection Distance (d_{HI})

If H_1 denotes a histogram of a queried image and H_2 histogram of an image for comparison and if $d(H_1,H_2) = 0$ for $H_1 = H_2$, then expression:

$$d_{HI}\left(H_1,H_2\right)=1-\frac{\sum_{x\in X,y\in Y,z\in Z}\min\left[H_1\left(x,y,z\right),H_2\left(x,y,z\right)\right]}{\min\left[\sum_{x\in X,y\in Y,z\in Z}H_1\left(x,y,z\right),\ \sum_{x\in X,y\in Y,z\in Z}H_2\left(x,y,z\right)\right]} \quad (6)$$

represents the Histogram Intersection distance.

F. Histogram Quadric Distance (d_{HQ})

Histogram Quadric distance [14] gives a correlation between histogram bins based on the perceptual similarity of colors that bins represented. The set of correlation values (i, j) [15] is given in a correlation matric A.

$$d_{HQ}\left(H_1,H_2\right)=\sqrt{\left(H_1-H_2\right)^t A\left(H_1-H_2\right)} \quad (7)$$

$$A\left(i,j\right)=1-\frac{d\left(i,j\right)}{\max\left[d\left(i,j\right)\right]},\quad i,j\in\left\{1,2,...,M\right\} \quad (8)$$

where $d(i,j)$ is L^2 norm of the distance between colors i and j in the RGB color space for a number of bins M. In a HSV color space, where (h_i,s_i,v_i) and (h_j,s_j,v_j) are *hue, saturation* and *value* components of two colors, A is expressed as:

$$A\left(i,j\right)=1-\frac{1}{\sqrt{5}}\sqrt{\left(v_i-v_j\right)^2+a^2+b^2} \quad (9)$$
$$a=s_i\cos h_i-s_j\cos h_j\ ,\quad b=s_i\sin h_i-s_j\sin h_j$$

IV. Proposed Algorithm

Flowchart of all proposed algorithm processes is given on Fig. 1. Original and tested trademark are denoted as A and B respectively:

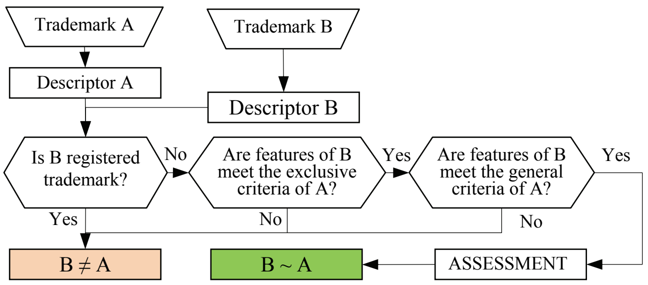


Fig. 1. Flowchart of our algorithm for comparison and assessment of two (A and B) trademarks similarity

Descriptor A forms a list of important features of the trademark A, and then determines their matching priority sorting defined features in three sets of similarity criteria:

1. *Protected characteristics or authorized by the competent institutions*. If the trademark B meets these conditions, it passes to the next set of criteria. Otherwise, the collector is set to state "0" for every feature.

2. *Exclusive criteria*. Only if trademark B meets both criteria in a row it passes to the next group of criteria, otherwise the collector is set to state "0".

3. *General criteria* are variable, and an user can set the threshold value of certain parameters. This provides an opportunity to grade the both: "similarities" and "differences".

After all these steps, algorithm introduces parameterization of the similarity degree depending of the collector state.

V. Numerical Results

For following analysis and all computations, we have used *plaintiff* and *respondent* trademark, which we briefly denote as A and B respectively. Both trademarks are shown on Fig. 2.

(A) (B)

Fig. 2. Graphic trademarks of parties to the dispute: (A) trademark of plaintiff, and (B) trademark of respondant

We note that this paper do not consider the first set of criteria given in Section IV 2, because authorities of competent institutions deal with it.

A. Exclusive Criteria

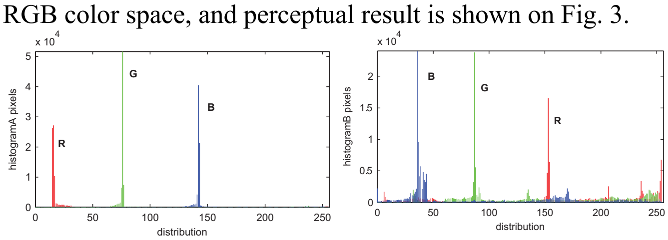
Firstly we define exclusive criteria that uniquely denote a feature as opposite to another. Typical examples are given in the table.

TABLE I
Exclusive feature similarity criteria

Feature	*A*	*B*	*Matching*
Font	Helvetica	Gill Sans MT	0%
Bold / italic	Italic (skew 12%)	Bold	0%
Capitalization	Sentence case	UPERCASE	0%

B. Color Histogram Comparison

The second step of our algorithm is computation of color characteristics such as histograms and all featured histogram distances. Color distributions are obtained using 256 bins in RGB color space, and perceptual result is shown on Fig. 3.



(a) (b)

Fig. 3. Color histograms of trademarks A (a) and B (b) in RGB color space. Due to better visibility white regions are not distributed

Referent maximal distances, for values of perceptual matching, are calculated using two opposite images: black and white, Numerical results for R channel are given in TABLE II.

TABLE II
EUCLIDIAN, SUBTRACTION AND QUADRIC HISTOGRAM DISTANCE

Feature	*A*	*B*	*Matching*
Dominant channel	B = 356357 pix	R = 524158 pix	0%
d_{HE}	0	44289.78 pix	4.0410%
d_{HI}	1	0.156963	15.696%
d_{HQ}	0	-1.396989e-09	21.526%

C. Shape and Contour Comparison

For the shape extraction we use the Laplacian of Gaussian filter that extracts zero crossings after Gaussian filtering of the image. Next picture Fig. 4 shows recognized shapes.

(A)

(B)

Fig. 4. Shape of trademarks A and B recognising by edges extraction

For curvature computations we use our Matlab software [16]. Next table gives numerical results of the shape extraction and curvature estimation, but also the number of horizontal *chdl*, vertical *cvdl* and diagonal *cddl* edges that are obtained using wavelets.

TABLE III
SHAPE AND TEXTURE RECOGNITION RESULTS

Feature	*A*	*B*	*Matching*
Total N^o of contours	24	11	45,833%
N^o of textual contours	23	2	8,696%
Curvature	0.0124567212	-0.31167937	0%
Range *cdd1*-diagonal	96,5	237	0%
Range *chd1*-horizontal	354	414,5	0%
Range *cvd1*-vertical	332,5	404,5	0%

VI. DISCUSSION AND CONCLUSION

This paper solves the problem of measuring the similarity of trademarks, using wavelets image processing methods in combination with the curvature estimation of extracted shapes and contours. Content based image querying methods are widely scientifically studied, but up to our knowledge, this paper first proposes solutions to the problem of proving the similarity or difference of trademarks, symbols and logos. We have also given the new measures for assessments of the similarity and difference values [17], and more results and illustrations are given as technical report in [18]. Our future research will be based on direction of a better shape description and characterization.

ACKNOWLEDGEMENT

The results presented at this paper are achieved as response of the request No 9861 for expertise in real court dispute. We would thank to organization “Evropski pokret” for rights to using logos and trademark symbols in scientific purposes.

REFERENCES

[1] C. Faloutsos, R. Barber, M. Flickner, J. Hafner, W. Niblack, D. Petkovic, and W. Equitz. “Efficient and effective querying by image content”, *Journal of Intelligent Information Systems*, vol. 3, no 3-4, pp. 231-262, July 1994.

[2] A. Pentland, R. Picard and S. Sclarof, “Photobook: Content-based manipulation of image databases,” *International Journal of Computer Vision*, volume 18, no 3, pp. 233-254, June 1996.

[3] S. Siggelkow, M. Schael and H. Burkhardt, “Search images by appearance,” *Pattern Recognition DAGM 2001*, *Conference* Proceedings Lecture Notes in Computer Science, vol. 2191, pp. 9- 17, Sept. 12–14, 2001.

[4] J. Z. Wang, J. Li and G. Wiederhold, “SIMPLIcity: Semantics-sensitive integrated matching for picture libraries,” *IEEE Trans. Pattern Analysis and Mach. Int.*, vol. 23, no 9, pp. 947 - 963, Sep. 2001.

[5] Q. Iqbal and J. Aggarwal, “CIRES: A system for content-based retrieval in digital image libraries,” *ICARCV' 02*, *Conference Proceedings,* pp. 205 – 210, Dec. 2002.

[6] T. M. Lehmann, M.O. Güld, T. Deselaers, D. Keysers, H. Schubert, K. Spitzer, H. Ney, BB Wein, “Automatic categorization of medical images for content-based retrieval and data mining,” *Comput. Med. Imag. Graph*, vol. 29, no 2, pp. 143 - 155, 2005.

[7] T. Deselaers, T. Weyand, D. Keysers, W. Macherey, and H. Ney, “Combining Content-Based Image Retrieval with Textual Information Retrieval,” *CLEF 2005, Conference Proceedings*, *Lecture Notes in Computer Science*, vol. 4022, 2006, pp. 652 – 661, Sept. 2005

[8] T. Sikora, “The MPEG-7 Visual Standard for Content Description - An Overview,” *IEEE Trans., Circuits and Systems for Video Technology*, vol. 11, no. 6, June 2001.

[9] B. Vasic, “Ordered Statistics Vertex Extraction and Tracing Algorithm (OSVETA),” *Advances in Electrical and Computer Engineering*, vol. 12, no 4, pp. 25 -32, Nov. 2012.

[10] C. L. Novak, S. A. Shafer, “Anatomy of a color histogram,” Computer Vision and Pattern Recognition,” *IEEE - CVPR '92, Conference Proceedings,* pp. 599 – 605, June 1992.

[11] X.Y. Wang, J.F. W.Y. Yang and H.Y. Yang “Robust image retrieval based on color histogram of local feature regions,” Springer Netherlands, 2009

[12] P. Dombrowski, 150 years after Gauss' “Disquisitiones generales circa superficies curvas”: with the original text of Gauss, no 62, Société mathématique de France, 1979.

[13] M. Meyer, M. Desbrun, P. Schröder, and A.H. Barr, “Discrete differential-geometry operators for triangulated 2-manifolds,” *Visualization and Mathematics III*, ED-12, pp. 35 - 57, Springer, August 2003.

[14] S. Jeong, C. S. Wony, and R. M. Gray, “Histogram-based image retrieval using Gauss mixture vector quantization,” *Computer Vision and Image Understanding*, vol. 94, no. 1–3, pp. 44–66, April -June 2004.

[15] J. R. Smith and S. F. Chang, “Tools and Techniques for Color Image Retrieval,” *SPIE ‘96, Conference Proceedings,* vol. 2670, pp. 426-437, 1996.

[16] B. Vasic, Ordered Statistic Vertex Extraction and Tracing Algorithm (OSVETA) - MatLab Software, [Online], Available: http://www.batavasic.com/research/OSVETA.zip

[17] B. Vasic, Similarity calculations for judicial dispute, Matlab file with all numerical results of computations. [Online], Available: http://www.batavasic.com/research/similarity.zip

[18] B. Vasic, “New content based forensic metrics for judicial disputes concerning the graphic symbols similarity”, Technical report N^o 2501/2013”, January 2013, [Online], Available: http://www.batavasic.com/research/treport.zip