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Endoscopy video analysis algorithms and their independence of rotation, brightness, contrast, color and blur

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ABSTRACT: The article presents selected image analysis algorithms for endoscopy videos. Mathematical methods that are part of these algorithms are described, and authors' claims about the characteristics of these algorithms, such as the independence of rotation, brightness, contrast, etc. are mentioned. Using the common test on the real endoscopic image database and a set of image transformations, the validity of these claims was checked and compared between algorithms. Many of the results seem to differ from the declaration of the authors, sometimes even strongly denying them. In addition, some algorithms were found extraordinary sensitive to blurring of the images, which indicates the possibility of using them for the detection of blurry frames, not just diseases.

KEYWORDS: endoscopy, video analysis, independence, rotation, brightness, contrast, color, blur

I. Introduction

In the past several years, endoscopic movie analysis algorithms (obtained by gastroscopy, colonoscopy or capsule endoscopy) were gaining popularity. These algorithms are used to recognize informative and non-informative frames, and various diseases or healthy tissues. Unfortunately, the algorithms described in the literature do not have any larger comparative tests, which makes a comparison between them almost impossible. In addition, the authors of mathematical methods used in these algorithms do not provide evidence for their claims (e.g. on the algorithms' independence of transformations such as rotation or brightness change). [1]

This article focuses on a comparison of selected endoscopic image analysis algorithms and mathematical tools used in them. The algorithms were tested with a special comparator to check if their authors' claims about the independence of image transformations like rotation, brightness, contrast, blur and color change are trustworthy.

II. Test procedure

All tests were carried out on a common database of real colonoscopy videos [2]. For the tests, 100 random images from the database were selected. The algorithms' classification part was removed, leaving only the kernel of the algorithms - the calculation of the feature vectors. In the next step, every feature was normalized so that the average (calculated over all the images in the database) was equal to 0 and standard deviation to 1.

Only the normalized feature vectors were analyzed in the article (ignoring the classification component, such as neural networks or support vector machines). In the literature it is often claimed that the algorithms are dependent or independent of the various image transformations. For comparison and test purposes, 5 popular transformations that occur naturally in endoscopy were selected, as in table I.

A. Comparison measure

In the first place, feature vectors from original images were compared with each other using the metrics described below.

Let $F(a)$ be a feature vector of image a for algorithm F, and $f_i(a)$ be its i-th normalized value:

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Table I: Image transformations

ID	Transform	Description	Values
1	brightness	Change of brightness by a multiplying factor	$1.3-2$ or $0.5-0.8$
2	Contrast	Change of contrast by a multiplying factor	$1.2-2$ or $0.5-0.8$
3	Color	Change of pixels' hue and saturation	$\pm\ 20-301$
4	Rotation	Rotation of the image from its center	$45°-315°$
5	Blur	Box filter blur	Kernel size $3-7$

$$F(a) = [f_1(a), f_2(a), ...]$$

To obtain a common comparing base for algorithm F, feature vectors of all original images $(a, b, c, ...)$ were compared with each other. Then, the average base feature difference was calculated as follows::

$$d_i(a,b) = \begin{cases} 0 & \text{if } f_i(a) = f_i(b) = 0 \\ \frac{|f_i(a)-f_i(b)|}{\max(|f_i(a)|,|f_i(b)|)} & \text{otherwise} \end{cases}$$

$$D_0 = \text{mean}\big(d_i(a,b) \text{ for each } i, a, b, \text{ where } a \neq b\big)$$

$$\sigma_0 = \text{std.dev.}\big(d_i(a,b) \text{ for each } i, a, b, \text{ where } a \neq b\big)$$

The difference between the feature vector between original and transformed images was defined analogously, with additional normalization in regard of typical not-transformed image feature vector differences:

$$T(a) = \text{image } a \text{ modified with transform } T$$

$$D_T = \frac{\text{mean}\{d_i(a, T(a)) \text{ for each } i, a\}}{D_0}$$

$$\sigma_T = \frac{\text{std.dev.}\{d_i(a, T(a)) \text{ for each } i, a\}}{\sigma_0}$$

III. Mathematical operations

In this section, mathematical operations used in the analyzed algorithms are described. Most of them focus on the spatial features of the images, brightness changes and edge detection. This is due to the fact that these features are similar to human vision methods of seeing objects, which allows humans to recognize textural anomalies in the image. Some transformations, however, focus more on the color features, as they are the second most characteristic phenomenon differencing healthy tissue from cancer (e.g. shades of gray, black or bright red are found almost only in cancerous tissue).

Most of the algorithms include also some form of statistical analysis of the characteristics of the image. Depending on the analyzed image features, this allows to reduce the number of dimensions of the resulting feature vector or make it independent from the scale, rotation, or change of contrast or brightness of the image.

Some of the transformations are commonly known in the field of image analysis (e.g. Gabor filters or discrete wavelet transforms), but some are designed specifically for endoscopic (e.g. AHT, N_{TU}).

Table III provides information about the chosen algorithms for the analysis of endoscopy videos provided by the authors (rot. = rotation, sca. = scale, bri. = brightness, con. = contrast).

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Table II: Mathematical operations

Ref.	Operation	Description	Rot.	Bri.	Con.
	pixel value quantization	data dimension reduction			
	histograms	statistical features of the data	✓		
	colorspace change	matching color spaces to match human vision			
[17]	Local Binary Pattern (LBP)	grayscale local texture pattern numbering		✓	✓
[16]	Texture Unit Number (N_{TU})	similar to LBP, but slightly generalized		✓	✓
[18]	Multi-scale Block LBP (MB-LBP)	block LBP (pixels in blocks are averaged or blurred)		✓	✓
[6]	Rotation Independent Uniform LBP ($LBP^{riu2}_{P,R}$)	rotation-independent LBP; texture homogenity assumed	✓	✓	✓
[10]	Local Color Vector Pattern (LCVP)	similar to LBP, but for color images			
[19]	Canny Edge Detector	grayscale edge detection, based on sharp brightness change	✓	✓	
[20]	Gray-Level Coocurence Matrices (GLCM)	spatial dependencies of pixels		✓	✓
	Discrete Cosine / Transform (DCT)	conversion from raster image to frequency domain		✓	
	Discrete Fourier Transform (DFT)	conversion from raster image to frequency domain		✓	
	Discrete Wavelet Transforms (DWT)	multi-scale frequency-like transforms			
[9]	Color Wavelet Covariance (CWC)	variance and covariance from cooccurance matrices of DWT			
[21]	Gabor Filters	directional image filters (mainly for edge detection)		✓	
[22]	Simple Gabor Feature Space (SGFS)	set of gabor filters for specific scales and directions		✓	
[3]	Autocorrelation Gabor Feature (AGF)	rotation and scale-independent SGFS	✓	✓	
[4]	Homogeneous Texture (HT)	statistics of SGFS for every given direction and scale		✓	
[3]	Autocorrelation Homogeneous Texture (AHT)	statistics of AGF	✓	✓	

IV. TEST RESULTS

The following figures present the results of tests carried out. Figure 1 shows the differences between the untransformed images, i.e. D_0 and σ_0. Figures 2 – 6 present: differences after brightness change $D_{\text{brightness}}$, after contrast change D_{contrast}, after color change D_{color}, after rotation D_{rotation} and after blurring D_{blur}.

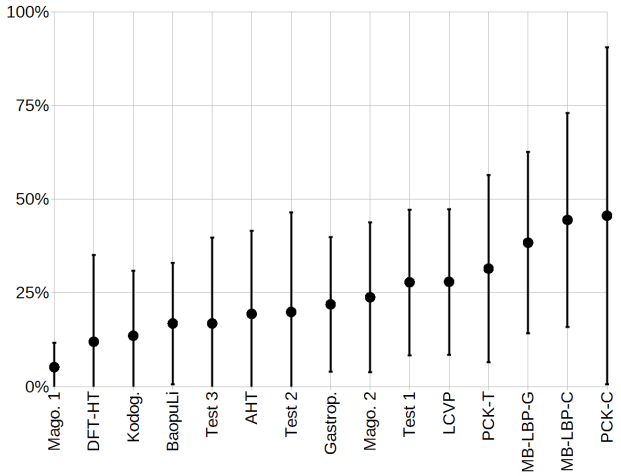

Figure 1: Untransformed images difference D_0

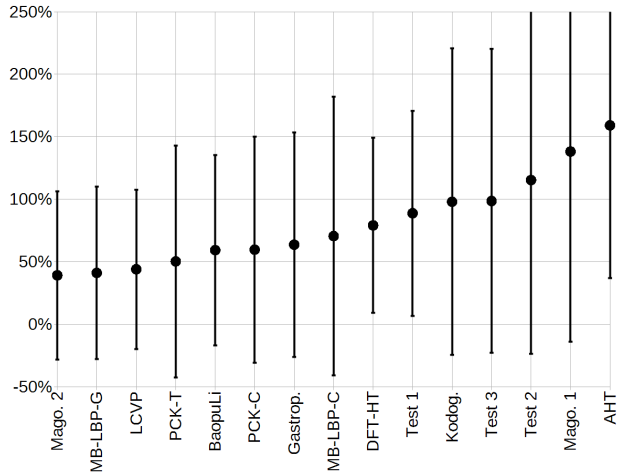

Figure 2: Differences after brightness change $D_{\text{brightness}}$

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Table III: Algorithms' characteristics

Ref.	Algorithm	ID	Objects detected	Color spaces	Independence of					Components	Feature vector
					Rot	Sca	Bri	Con	Hue		
[3]	Autocorrelation Homogeneous Texture	AHT	tumor in chromoendoscopy and narrow-band imaging	gray	✓	✓	✓		✓	Gabor filters, AGF, AHT, SGFS, AHT	AHT
[4]	Discrete Fourier Transform – Homogeneous Texture	DFT-HT	textures	gray	✓	✓			✓	Gabor filters, SGFS, HT, DFT	HT
[5]	Gastropathy	Gastrop.	portal hypertensive gastropathy in gastroscopy	gray, HSV	✓					Canny edge detection, thresholding	% of edge pixels
[6]				gray	✓		✓	✓	✓	$LBP^{riu2}_{P,R}$	histogram P+2 bins (only P=16 tested)
[7]				gray	✓	✓	✓	✓	✓	Local Brightness Maximas, thresholding	% of blocks with maximas
[8]	Baopu Li	BaopuLi	adenoma, adenocarcinoma in Wireless Capsule Endoscopy (WCE)	RGB, HSI, CIE-Lab	✓					DWT (CDF9/7), LBP	10-bin histograms for each channel = 630 values
[9]	Poh Chee Khun	PCK-C	informative frames, bleeding in WCE	HSV	✓					color quantization (H=12, S=5, V=8), 9 blocks, histograms	hisgoram for each block for each quantized value
		PCK-T		HSV	✓		✓	✓		2x DWT (9 channels), GLCM (4 statistics), statistics	CWC – 72 features + 8 additional
[10]	Local Color Vector Pattern	LCVP	textures in magnification endoscopy	RGB lub CIE-Lab	✓		✓	✓	✓	MB-LBP, LCVP, histogram	histogram of LCVP – 256 – features
[11]	Multi-scale Block LBP	MB-LBP-G	patterns for face recognition	GRAY	✓	✓				MB-LBP, histogram	histogram – 256 features
[12]		MB-LBP-C	polyps in endoscopy	RGB	✓	✓				discarding one of the channels, MB-LBP, 2D-histogram	2D-histogram – up to 256^2 features (tested up to 256)
[13]	Test	Test 1	tumor, polyps, informative frames in endoscopy	RGB, HSV	✓	✓		✓		mean value for each channel	6 features
		Test 2		RGB, HSV, Lab	✓	✓				mean, variance, covariance and energy for each channel	36 features
		Test 3		RGB, HSV, Lab	✓	✓				10 statistics for each channel	90 features
[16]	Kodogiannis	Kodog.	normal/abnormal tissue in WCE	RGB, HSV			✓	✓		N_{TU}, 9 statistics for each channel	54 features
[14]	Magoulas	Mago. 1	normal/abnormal tissue in colonoscopy	GRAY	✓		✓	✓	✓	GLCM for 4 directions, 4 statistics	16 features
[15]		Mago. 2		GRAY	✓		✓	✓	✓	DWT, 4x GLCM, 4 statistics for each	48 features

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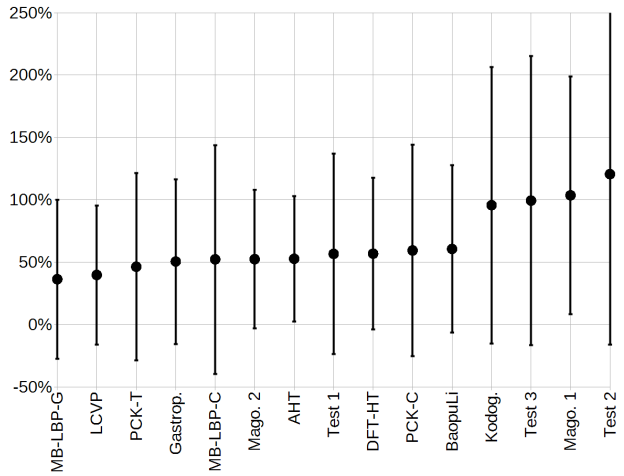

Figure 3: Differences after contrast change D_{contrast}

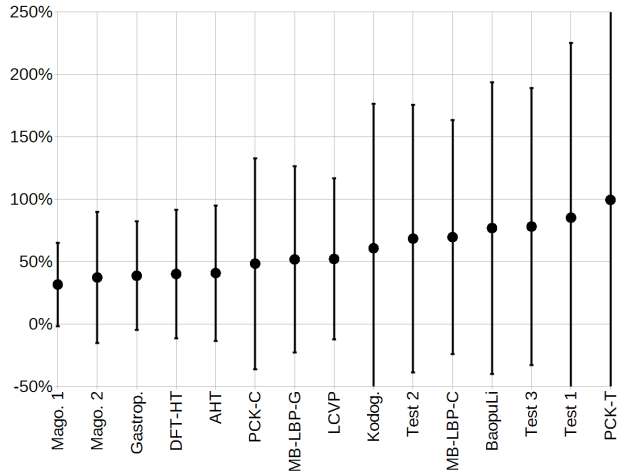

Figure 4: Differences after color change D_{color}

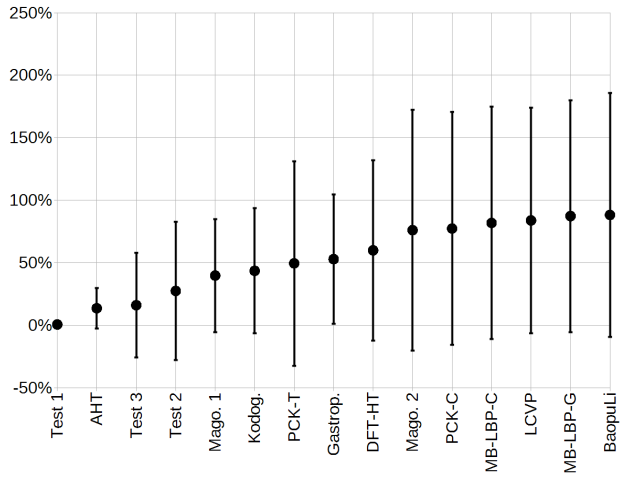

Figure 5: Differences after rotation D_{rotation}

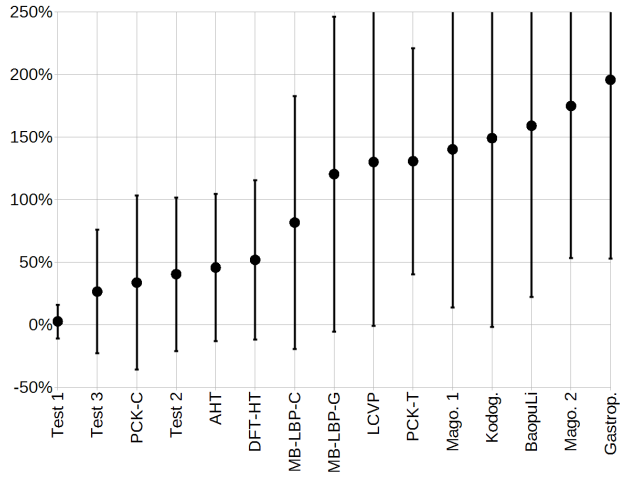

Figure 6: Differences after blurring D_{blur}

V. Conclusion

The article presents mathematical tools used in the gastrointestinal endoscopic video analysis algorithms. The tests show that algorithms' authors' claims about some characteristics of their algorithms about independence from the transformations such as rotation, brightness change, etc. does not always comply with the practical results. Moreover, many of the algorithms are surprisingly sensitive to some transformations – in such cases the difference between the transformed images can be greater than that between the other images. This phenomenon questions the usefulness of these algorithms in provided by the authors applications. However, it is worth noting that some of the algorithm are remarkably sensitive to image blur – this fact indicates these algorithms may perform well in the task of blurry frames recognition, which is also useful in systems supporting digestive system diagnosis.

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