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GPU ACCELERATED INTUITIONISTIC FUZZY AND OTSU ALGORITHMS FOR FOREIGN LEAF DETECTION IN COTTON

PAMUKTAKİ YABANCI ELYAFLARIN GPU İLE HIZLANDIRILMIŞ SEZGİSEL BULANIK MANTIK VE OTSU ALGORİTMALARI İLE TESBİTİ

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ABSTRACT

The foreign substances, arising during the production and shaping of wool and cotton raw materials that are used in textile and cotton gin factories or coming from the outside, decrease considerably the quality of the obtained fabric or yarn. Nowadays, a different methods are used to separate foreign substances in the textile sector, most of these methods are not efficient in terms of speed and quality. Computerized vision systems play a vital role in the field of textiles as in other fields. In this study, Intuitionistic Fuzzy Algorithm is used to define the foreign substances in the images that obtained from a camera. CPU (Central Processing Unit) based applications have speed problems due to the structure of the algorithm. For this reason, GPU (Graphics Processing Unit) technology was used to overcome the speed problem. The otsu algorithm generates a dynamic threshold from the numerical values of the image obtained using the Intuitionistic fuzzy algorithm. By this means, the threshold value of each frame obtained from the camera was calculated on real time and implemented on the image timely. These algorithms were accelerated maximum 262 times using NVIDIA GTX 480 GPU supported display card.

Keywords: GPU Programming, Intuitionistic Fuzzy, Otsu, CUDA, Foreign Fibre Detection.

ÖZET

Tekstil, pamuk ve çırçır fabrikalarında kullanılan veya dışarıdan gelen yün ve pamuk ham maddelerinin üretimi ve şekillendirilmesinde ortaya çıkan yabancı maddeler, elde edilen kumaş veya ipliğin kalitesini önemli ölçüde azaltır. Günümüzde tekstil sektöründeki yabancı maddeleri ayırmak için farklı yöntemler kullanılmaktadır, ancak bu yöntemlerin çoğu hız ve kalite açısından verimli değildir. Bilgisayarlı görme sistemleri, diğer alanlarda olduğu gibi tekstil alanında da hayati bir rol oynamaktadır. Bu çalışmada, kameradan elde edilen görüntülerdeki yabancı maddeleri tanımlamak için Sezgisel Bulanık Mantık kullanılmıştır. CPU tabanlı uygulamalar ilgili algoritmanın yapısı gereği hız problemlerine yol açmaktadır. Bu hız problemini gidermek için ise GPU teknolojisi kullanılmıştır. Otsu algoritması kullanarak Sezgisel bulanık mantık algoritmasıyla elde edilen görüntüler için dinamik bir eşik değeri hesaplanmıştır. Bu sayede, kameradan elde edilen her karenin eşik değeri gerçek zamanlı olarak hesaplanmış ve görüntüye aynı anda uygulanmıştır. Bu algoritmalar, NVIDIA GTX 480 GPU destekli ekran kartı kullanılarak maksimum 262 kez hızlandırılmıştır.

Anahtar Kelimeler: GPU Programlama, Sezgisel Bulanık Mantık, Otsu, CUDA, Yabancı Elyaf Tespit Etme.

INTRODUCTION

The different fibre and soil, arising during the production and shaping of wool and cotton raw materials used in textile and cotton gin factories or coming from the outside, decrease the quality of the obtained fabric or yarn considerably.

In general, this filthy in cotton may be caused by black pigment fibres, color which may come from sheep, foreign material and filthy overlooked while picking plants (Yang, 2009).

In modern-day textile business, the methods used to separate these substances are not efficient in terms of speed and quality (Ji, 2010). There are various techniques to clean the foreign fibers in lint. Some of those are ultrasonic-based, sensor-based and machine vision-based inspection (Zhang, 2011). The present day computerized vision systems have affected textile field clearly as well as all other fields. For the first time, Liberman and colleagues built a machine vision system to overcome this problem in textile factories (Liberman, 1998). Tastaswadi and colleagues have developed a real-time system for images taken from cameras has 3D-LUT technology with the help of edge extraction algorithms (Tastaswadi, 1999). Millman and colleagues have designed a system with two options as high resolution / low speed and low resolution / high speed to solve speed problems in these systems (Millman, 2001). However, this system was not quite efficient due to the differences between the chemical and physical characteristics of wool and cotton. The two problems of quality and speed, encountered in other previous studies, are an important distinguishing factor (Wang, 2015), (Chen, 2010). In this study, using GPU technology which can run hundreds of times faster than CPU were tried to solve this speed problem (NVIDIA, 2019).

In the literature, many different algorithms have been used to clean foreign leaf (Zhang, 2014). One of these algorithms, the Intuitionistic Fuzzy Algorithm, is effective for finding the foreign substance in the images using a specified threshold value. However, since the fixed threshold value cannot give the same quality for each frame, it has been observed that the thresholding of the obtained images cannot be performed properly. Otsu method was used determined the threshold value in order to solve this issue. Thus, the threshold value of each frame obtained from the camera was calculated automatically and implemented on the image timely. Afterwards, for only the soiled part to be cleaned, the calculated image was divided into 8 parts. After many trials, using the threshold value method, an average value was calculated for the histogram values of these parts and afterwards, the parts and amount of foreign leaf were determined. After the many experience, it was confirmed that the used methods gave the needed results completely. Besides, in this study, the Intuitionistic Fuzzy Algorithm and Otsu Method were used for the first time together with GPU to process images. Thanks to these methods, unlike in previous studies, the computerized vision system has provided a vital advantage in terms of speed and quality.

The rest of this paper is organized as follows. In section 2, the Intuitionistic fuzzy and edge extraction process which are the basis of the study are explained. In section 3, the experimental results of the study are presented and five examples are given. In the last section, some suggestions are made for future studies.

DEVELOPMENT OF INTUITIONISTIC FUZZY EDGE DETECTION

According to the fuzzy set theory of L.A Zadeh $X = \{x_1, x_2, x_3, ..., x_n\}$ set is mathematically expressed as (Zadeh, 1965):

$$A = \{x, \mu_A(x), \upsilon_A(x) \mid x \in X\} \tag{1}$$

Here in $\mu_A(x)$: X → [0, 1]; is called as membership degree of each x element defined in X set. It is expressed as $\upsilon_A = 1 - \mu_A(x)$ in non- membership degree. Where $\mu_A(x) + \upsilon_A = 1$, fuzzy sets are defined.
In addition to Zadeh's fuzzy set theory, Atanassov added the 3rd parameter hesitation degree (Atanossov, 1986).

$$\pi_A(x) = 1 - \mu_A(x) - \upsilon_A(x) \tag{2}$$

The term indicated by $\pi_A(x)$ are intuitive fuzzy logic index or hesitation value. It was added to the zadeh equation by the Atanasov to minimize user error. Thus, $\pi_A(x)$ is assigned to restrict the real numbers $\mu_A(x), \upsilon_A(x)$.

$$\pi_A(x) = C * [1 - \mu_A(x)] \tag{3}$$

C is the hesitation constant and should be defined without breaking the equality of Eq. 2. In this study, c value was selected as 0.2.

Intuitionistic Fuzzy Edge Detection

In fuzzy set theory, there are three concepts for establishing relationships between images. These are fuzzy entropy, distance measure and similarity measurement. The relationship between these three concepts are detailed in (Xuecheng, 1992). However, entropy and similarity measurement are applied to images similarly in fuzzy set and based on the divergence calculation between the respective pixels of the two images (Fan, 1999). These relationships are defined following:
$\mu_A\left(a_{ij}\right)$ is the membership of $A \in F\left(A\right)$, $v_A\left(a_{ij}\right) = 1 - \mu_A\left(a_{ij}\right)$ is the non-membership of $A^c \in F\left(A\right)$ and c is the complement of A. $d\left(A,B\right)$ is the distance between A and B fuzzy sets. $e\left(A\right)$ is the entropy of A and $s\left(A,B\right)$ is the similarity measurement of the A and B.

The relation between d and s is the $d = 1 - s$. The fuzzy entropy defined as:

$$e\left(A\right) = s\left(A, A^c\right) \text{ or } e\left(A\right) = 1 - d\left(A, A^c\right) \tag{4}$$

As can be seen from the Eq.4, it can be used by similarity or distance measurement to calculate the entropy. Since $\mu_A + v_A = 1$ in the fuzzy set theory, entropy, distance and similarity measurement calculations can made over these two variables.

Exponential entropy is described by Pal and Pal using Shannon's information entropy (Pal, 1992). $P = \left\{p_0, p_1, \ldots, p_{L-1}\right\}$ is the probability distribution set of image size MxM with L grey level and its exponential entropy is defined as:

$$H = \sum_{i=0}^{L-1} p_i . e^{1-p_i} \tag{5}$$

In fuzzy set theory, Fuzzy entropy of image A having size MxM is defined as:

$$H\left(A\right) = \frac{1}{n\left(\sqrt{e}-1\right)} \sum_{i=0}^{M-1} \sum_{j=0}^{M-1} \left[\left(\mu_A\left(a_{ij}\right) e^{1-\mu_A\left(a_{ij}\right)}\right) + \left(1 - \mu_A\left(a_{ij}\right)\right) e^{\mu_A\left(a_{ij}\right)} - 1\right] \tag{6}$$

This entropy was found taking into account the $\mu_A\left(a_{ij}\right)$ degree of membership and the $v_A\left(a_{ij}\right) = 1 - \mu_A\left(a_{ij}\right)$ degree of non-membership.

For two image A and B (at the (ij)th pixel), amount of information between $\mu_A\left(a_{ij}\right)$ and $\mu_B\left(b_{ij}\right)$:

$$I_1\left(A, B; ij\right) = \frac{e^{\mu_A\left(a_{ij}\right)}}{e^{\mu_B\left(b_{ij}\right)}} = e^{\mu_A\left(a_{ij}\right) - \mu_B\left(b_{ij}\right)} \tag{7}$$

The fuzzy expected information of image A against the image B (for $\mu_A\left(a_{ij}\right) = 0.5$)

$$I_1\left(A, B\right) = \sum_{i=0}^{M-1} \sum_{j=0}^{M-1} \left(\frac{1}{2} - \left(1 - \mu_A\left(a_{ij}\right)\right) e^{\mu_A\left(a_{ij}\right) - \mu_B\left(b_{ij}\right)}\right) \tag{8}$$

Similarly, the fuzzy expected information of image A^c against the image B^c (for $v_A = 0.5$).

$$I_1\left(A^c, B^c\right) = \sum_{i=0}^{M-1} \sum_{j=0}^{M-1} \left(\frac{1}{2} - \left(\mu_A\left(a_{ij}\right)\right) e^{\mu_B\left(b_{ij}\right) - \mu_A\left(a_{ij}\right)}\right) \tag{9}$$

Eq. (8) and Eq. (9) may appear equal. But in general, $I_1\left(A,B\right) \neq I_1\left(A^c,B^c\right)$. Therefore, the two expected values should be taken into account together.

So, the fuzzy entropy, the total divergence between image A against the image B defined by:

$$I\left(A,B\right) = I_1\left(A,B\right) + I_1\left(A^c,B^c\right) = \sum_i \sum_j \left(1 - \left(\left(1-\mu_A\left(a_{ij}\right)\right)e^{\left(\mu_A\left(a_{ij}\right)-\mu_B\left(b_{ij}\right)\right)}\right) - \left(\mu_A\left(a_{ij}\right)e^{\left(\mu_B\left(b_{ij}\right)-\mu_A\left(a_{ij}\right)\right)}\right)\right) \tag{10}$$

Similarly, the total divergence between image of B against the image of A defined by:

$$I\left(B,A\right) = \sum_i \sum_j \left(1 - \left(\left(1-\mu_B\left(b_{ij}\right)\right)e^{\left(\mu_B\left(a_{ij}\right)-\mu_A\left(b_{ij}\right)\right)}\right) - \left(\mu_B\left(b_{ij}\right)e^{\left(\mu_A\left(b_{ij}\right)-\mu_B\left(a_{ij}\right)\right)}\right)\right) \tag{11}$$

For fuzzy sets A and B, total fuzzy divergence between image of A and image of B can be defined by:

$$I(A,B)+I(B,A) = \sum_i \sum_j \left(2 - \left(\left(1-\mu_A\left(a_{ij}\right)+\mu_B\left(b_{ij}\right)\right)e^{\left(\mu_A\left(a_{ij}\right) - \mu_B\left(b_{ij}\right)\right)}\right) - \left(\left(1-\mu_B\left(b_{ij}\right)+\mu_A\left(a_{ij}\right)\right)e^{\left(\mu_B\left(b_{ij}\right) - \mu_A\left(a_{ij}\right)\right)}\right) \right) \tag{12}$$

As seen Eq. (12) , in fuzzy entropy, the divergence value between A and B is calculated taking into account the degree of membership and non-membership.

In addition to the fuzzy set theory, T. Chaira suggested that should be taken into account the π_A value, which is the hesitation degree in Intuitionistic fuzzy logic theory (Chaira, 2008). This value is added directly to the equation Eq. (12). So, $v_A = 1 - \mu_A - \pi_A$ is written instead of $v_A\left(a_{ij}\right) = 1 - \mu_A\left(a_{ij}\right)$ in the fuzzy set theory.

In Instuistic fuzzy theory, for the two image of A, B (at the (ij)th pixel) amount of information defined by:

$$I_2\left(A,B;ij\right) = e^{\mu_A\left(a_{ij}\right)+\pi_A\left(a_{ij}\right)} / e^{\mu_B\left(b_{ij}\right)+\pi_B\left(b_{ij}\right)} \tag{13}$$

Intuitionistic Fuzzy Entropy calculation is the same as Fuzzy Entropy case, so Intuitionistic Fuzzy Entropy can be written directly as follows:

$$\begin{pmatrix} I_2(A,B) \\ + I_2(B,A) \end{pmatrix} = \sum_i \sum_j \left(2 - \left(\left[1 - \begin{pmatrix} \mu_A\left(a_{ij}\right) \\ -\mu_B\left(b_{ij}\right) \end{pmatrix} + \begin{pmatrix} \pi_B\left(b_{ij}\right) \\ -\pi_A\left(a_{ij}\right) \end{pmatrix}\right] e^{\left(\mu_A\left(a_{ij}\right)-\mu_B\left(b_{ij}\right)-\left(\pi_B\left(b_{ij}\right)-\pi_A\left(a_{ij}\right)\right)\right)}\right) - \left(\left[1 - \begin{pmatrix} \pi_B\left(b_{ij}\right) \\ -\pi_A\left(a_{ij}\right) \end{pmatrix} + \begin{pmatrix} \mu_A\left(a_{ij}\right) \\ -\mu_B\left(b_{ij}\right) \end{pmatrix}\right] e^{\left(\pi_B\left(b_{ij}\right)-\pi_A\left(a_{ij}\right)-\left(\mu_A\left(a_{ij}\right)-\mu_B\left(b_{ij}\right)\right)\right)}\right) \right) \tag{14}$$

The overall Intuitionistic Fuzzy Divergence, IFD, between image A and image B.

$$IFD(A,B) = I_1(A,B) + I_1(B,A) + I_2(A,B) + I_2(B,A) \tag{15}$$

$$IFD(A,B) = \sum_i \sum_j \left(\begin{array}{l} \left(\begin{array}{l} 2 - \left(\left[1 - \mu_A(a_{ij}) + \mu_B(b_{ij}) \right] e^{\left(\mu_A(a_{ij}) - \mu_B(b_{ij}) \right)} \right) \\ - \left(\left[1 - \mu_B(b_{ij}) + \mu_A(a_{ij}) \right] e^{\left(\mu_B(b_{ij}) - \mu_A(a_{ij}) \right)} \right) \end{array} \right) \\ + \left(\begin{array}{l} 2 - \left(\left[\begin{array}{l} 1 - \left(\mu_A(a_{ij}) - \mu_B(b_{ij}) \right) \\ + \left(\pi_B(b_{ij}) - \pi_A(a_{ij}) \right) \end{array} \right] e^{\left(\mu_A(a_{ij}) - \mu_B(b_{ij}) - \left(\pi_B(b_{ij}) - \pi_A(a_{ij}) \right) \right)} \right) \\ - \left(\left[\begin{array}{l} 1 - \left(\pi_B(b_{ij}) - \pi_A(a_{ij}) \right) \\ + \left(\mu_A(a_{ij}) - \mu_B(b_{ij}) \right) \end{array} \right] e^{\left(\pi_B(b_{ij}) - \pi_A(a_{ij}) - \left(\mu_A(a_{ij}) - \mu_B(b_{ij}) \right) \right)} \right) \end{array} \right) \end{array} \right) \tag{16}$$

Object Extraction Method

It is defined A={x, $\mu_A(x)$, $\upsilon_A(x)$ |x ε X} and B={x, $\mu_B(x)$, $\upsilon_B(x)$ |x ε X} as intuitive two fuzzy sets. Here in;

A: 3x3 display matrix obtained from the image
B: Sixteen 3x3 matrices including edge templates
In order to use in intuitive fuzzy logic object extraction algorithm, 3x3 matrix including 16 different states is created.

$$\begin{pmatrix} 0 & b & a \\ 0 & b & a \\ 0 & b & a \end{pmatrix} \begin{pmatrix} a & a & a \\ 0 & 0 & 0 \\ b & b & b \end{pmatrix} \begin{pmatrix} a & a & b \\ a & b & 0 \\ b & 0 & 0 \end{pmatrix} \begin{pmatrix} b & b & b \\ 0 & 0 & 0 \\ a & a & a \end{pmatrix} \begin{pmatrix} b & a & a \\ 0 & b & a \\ 0 & 0 & b \end{pmatrix} \begin{pmatrix} b & a & 0 \\ b & a & 0 \\ b & a & 0 \end{pmatrix} \begin{pmatrix} a & 0 & b \\ a & 0 & b \\ a & 0 & b \end{pmatrix} \begin{pmatrix} 0 & 0 & 0 \\ b & b & b \\ a & a & a \end{pmatrix}$$

$$\begin{pmatrix} a & a & a \\ b & b & b \\ 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} a & b & 0 \\ a & b & 0 \\ a & b & 0 \end{pmatrix} \begin{pmatrix} 0 & 0 & 0 \\ a & a & a \\ b & b & b \end{pmatrix} \begin{pmatrix} 0 & a & b \\ 0 & a & b \\ 0 & a & b \end{pmatrix} \begin{pmatrix} b & b & b \\ a & a & a \\ 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} b & 0 & a \\ b & 0 & a \\ b & 0 & a \end{pmatrix} \begin{pmatrix} b & 0 & 0 \\ a & b & 0 \\ a & a & b \end{pmatrix} \begin{pmatrix} 0 & 0 & b \\ 0 & b & a \\ b & a & a \end{pmatrix}$$

Figure 1: Intuitionistic Fuzzy Extraction Sets

The selection of fuzzy extraction sets are very importance. Because, it indicates the type and direction of the edge. These sets expresses examples of the edge and the images also. In the literature there are state matrix applications in different dimensions (Alam, 2013). In general, when the template size increases, the edges are missed and the algorithm is less efficient. However, if the size of the template is reduced, the algorithm takes a lot of time. Therefore, the most suitable template size was chosen as 3x3. *"a", "b"* and *"0"* refer to pixel equivalent of edge samples; *"a"* and *"b"* values are completely found by trial and error method. However, in literature survey, the most convenient estimation is obtained by *a*=0.3 and *b*=0.8 (Chaira, 2008), (Kaushik, 2015). To the center of each fuzzy inference set, it is placed over normalized image to (i, j)th position. IFD (intuitionistic fuzzy divergence) is measured in each pixel (i, j)th position. IFD (i, j)th value is obtained by the same size image with fuzzy inference set and MAX-MIN relationship of fuzzy inference sets from the Eq. (17).

$$IFD(i,j) = \underset{N}{MAX}\left[\underset{r}{MIN}\left(\underset{z}{IFD}(A,B) \right) \right] \tag{17}$$

In Eq. (17), IFD (i, j)th value between A and B is calculated by a_{ij} element of an image matrix and b_{ij} element of B template matrix. N represents the number of sets in fuzzy inference template and r represents the number of elements obtained like 3x3 image matrix. IFD (i, j)th is obtained after processing all pixel positions of the image.

In literature studies, in order to define threshold method, a fixed threshold value is applied by determining trial and error method. The fixed threshold value can't work well because it uses the same value for different images. Therefore, a determination of a dynamic threshold value by the numerical values of image is required. In this study, it is clear that Otsu method or the calculation method of the automatic threshold value with respect to numerical values of the image is more appropriate to developed system (Otsu, 1979).

In this study, it is aimed to calculate the threshold value in each frame by using the Otsu method instead of using a fixed threshold value. In this way, each frame has its own threshold value.

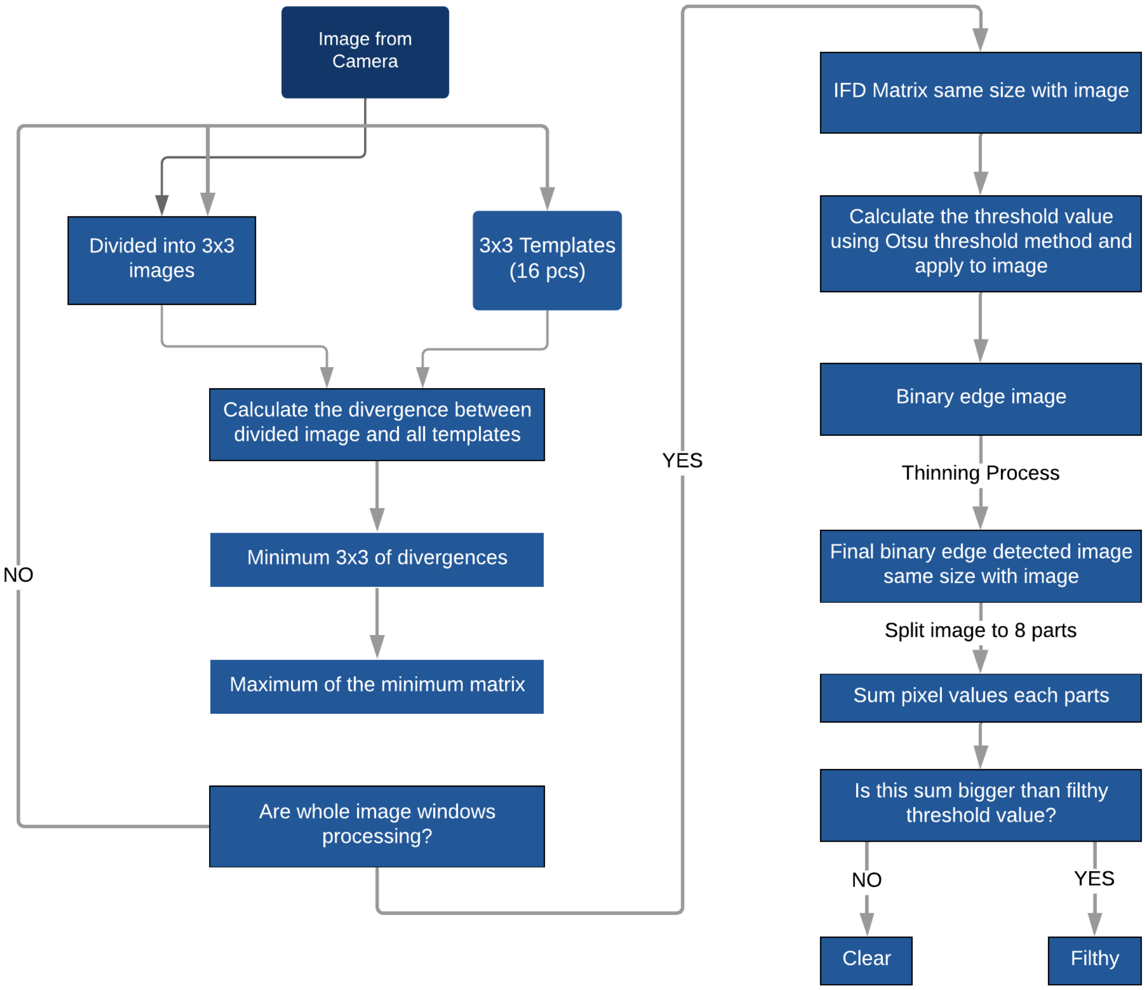
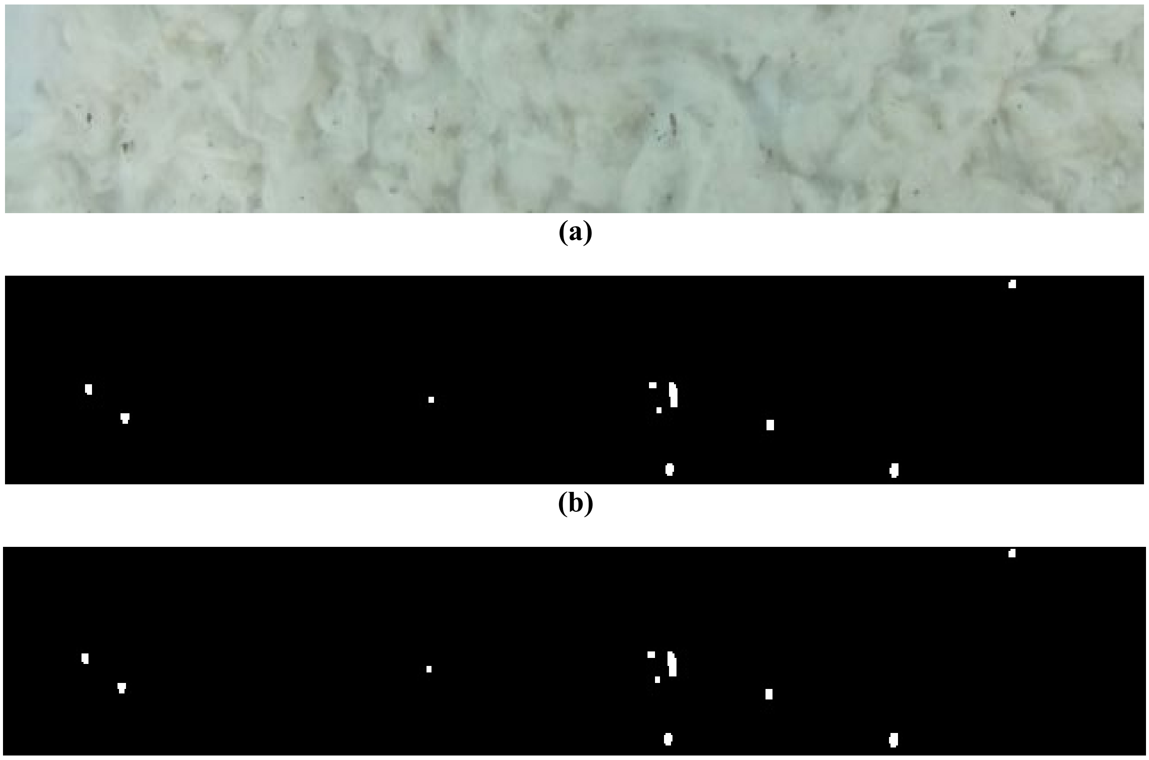


Figure 2: Block Diagram of Intuitionistic Fuzzy Edge Detection

EXPERIMENTAL RESULTS AND DISCUSSION

The obtained images from the camera using OpenCV software system has been applied on two different hardware to measure the difference in speed between the CPU and GPU. In order to measure the difference of speed, NVIDIA GTX 480 GPU-supported graphics card and Intel E5700 Dual Core processor, 12.8 GB / s with a band speed CPU is used.



(a) **(b)** **(c)**

Figure 3: Image 1 taken by Camera (a) Original, (b) CPU output, (c) GPU output.

Table 1: The Speed Comparison of Image 1

Image 1	**640x100**		**1280x200**		**1920x300**	
	CPU	**GPU**	**CPU**	**GPU**	**CPU**	**GPU**
Threshold value	195	195	195	195	195	195
Otsu Method (ms)	0.501	0.14438	2.172	0.427	3.064	0.292
Intuitive Fuzzy Logic (ms)	1682.317	8.685	7458.596	30.874	17992.239	70.932
Total Response Time (ms)	1682.818	8.82938	7460.768	31.301	17995.303	71.224
Foreign Substance Region	NONE	NONE	NONE	NONE	NONE	NONE
Otsu Method Rate (CPU/GPU)	3.475		5.084		10.481	
Intuitive Fuzzy Logic Rate (CPU/GPU)	193.703		241.581		253.654	
Response Time Rate (CPU/GPU)	190.593		238.353		252.656	

(a)

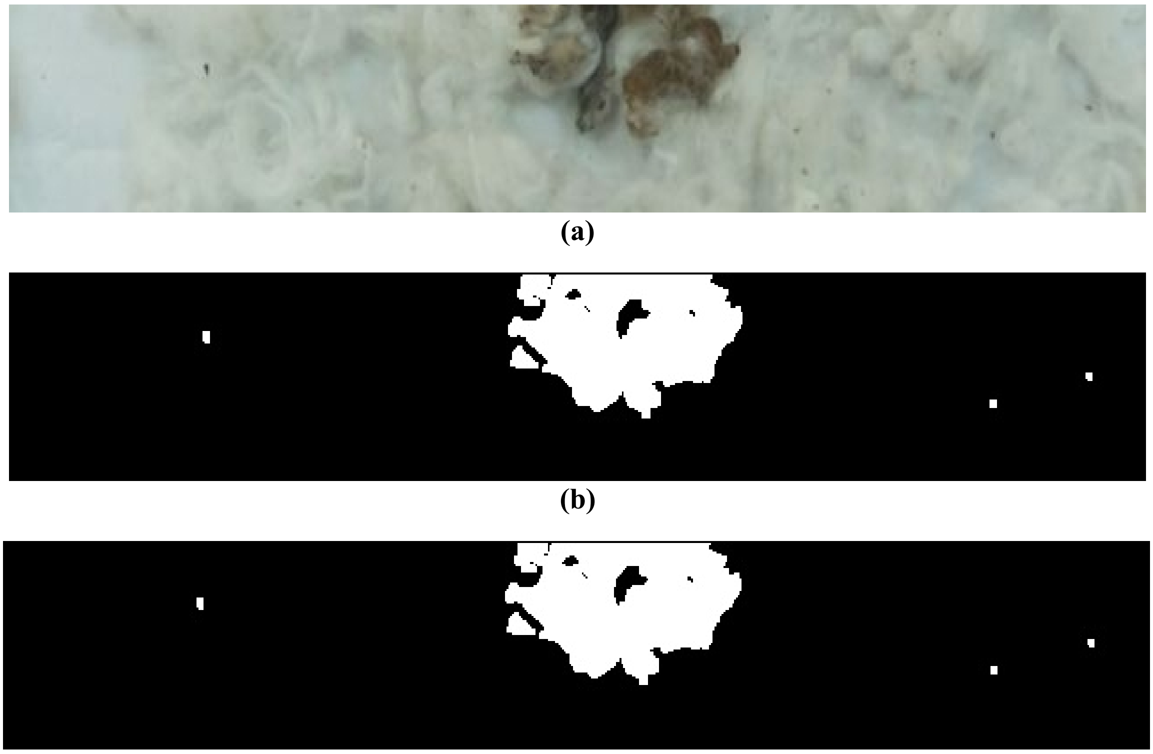
(b)

(c)

Figure 4: Image 2 taken by Camera (a) Original, (b) CPU output, (c) GPU output.

Table 2: The Speed Comparison of Image 2

Image 2	**640x100**		**1280x200**		**1920x300**	
	CPU	**GPU**	**CPU**	**GPU**	**CPU**	**GPU**
Threshold value	146	146	146	146	146	146
Otsu Method(ms)	0.496	0.098	1.530	0.302	3.040	0.349
Intuitive Fuzzy Logic(ms)	1710.541	8.719	8019.5503	30.736	17517.075	71.069
Total Response Time(ms)	1711.038	8.817	8021.081	31.038	17520.11	71.418
Foreign Substance Region	1-2	1-2	1-2	1-2	1-2-3-5-7	1-2-3-5-7
Otsu Method Rate (CPU/GPU)	5.058		5.059		8.698	
Intuitive Fuzzy Logic Rate (CPU/GPU)	196.185		260.917		246.479	
Response Time Rate (CPU/GPU)	194.058		258.423		245.316	



(a)

(b)

(c)

Figure 5: Image 3 taken by Camera (a) Original, (b) CPU output, (c) GPU output.

Table 3: The Speed Comparison of Image 3

Image 3	**640x100**		**1280x200**		**1920x300**	
	CPU	**GPU**	**CPU**	**GPU**	**CPU**	**GPU**
Threshold value	138	138	138	138	138	138
Otsu Method(ms)	0.480	0.098	1.465	0.295	3.043	0.287
Intuitive Fuzzy Logic(ms)	1714.296	8.661	8078.566	30.787	17509.822	70.97
Total Response Time(ms)	1714.777	8.759	8080.032	31.082	17512.8666	71.2573
Foreign Substance Region	4-5	4-5	4-5-6	4-5-6	4-5-6	4-5-6
Otsu Method Rate (CPU/GPU)	4.888		4.966		10.592	
Intuitive Fuzzy Logic Rate (CPU/GPU)	197.932		262.401		246.721	
Response Time Rate (CPU/GPU)	195.766		259.957		245.769	

(a)

(b)

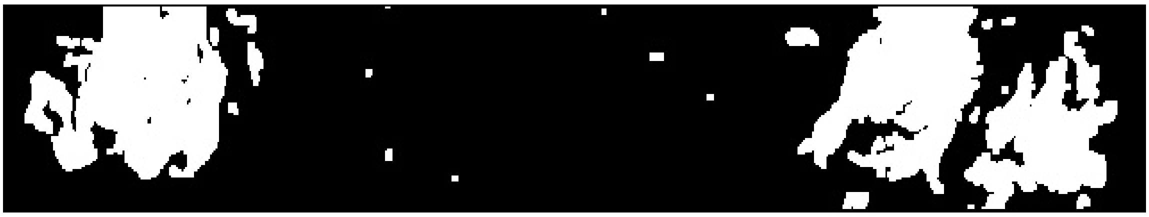
(c)

Figure 6: Image 4 taken by Camera (a) Original, (b) CPU output, (c) GPU output.

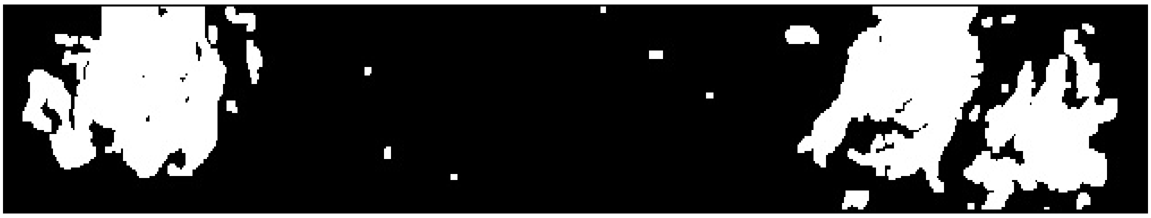
Table 4: The Speed Comparison of Image 4

Image 4	**640x100**		**1280x200**		**1920x300**	
	CPU	**GPU**	**CPU**	**GPU**	**CPU**	**GPU**
Threshold value	145	145	145	145	145	145
Otsu Method (ms)	0.574	0.098	1.451	0.337	3.061	0.321
Intuitive Fuzzy Logic (ms)	1827.948	9.698	7882.1420	32.417	17517.077	71.125
Total Response Time (ms)	1828.5221	9.796	7883.5936	32.75425	17520.1391	71.44676
Foreign Substance Region	2-3-5-6-8	2-3-5-6-8	2-3-5-6-8	2-3-5-6-8	2-3-5-6-8	2-3-5-6-8
Otsu Method Rate (CPU/GPU)	5.842		4.304		9.516	
Intuitive Fuzzy Logic Rate (CPU/GPU)	188.487		243.148		246.285	
Response Time Rate (CPU/GPU)	186.654		240.689		245.219	

(a)



(b)



(c)

Figure 7: Image 5 taken by Camera (a) Original, (b) CPU output, (c) GPU output.

Table 5: The Speed Comparison of Image 5

Image 5	**640x100**		**1280x200**		**1920x300**	
	CPU	**GPU**	**CPU**	**GPU**	**CPU**	**GPU**
Threshold value	136	136	136	136	136	136
Otsu Method (ms)	0.476	0.0980	1.759	0.302	3.053	0.329
Intuitive Fuzzy Logic (ms)	1.724	8.626	8.018	31.606	17575.31	71.332
Total Response Time (ms)	1724.038	8.724	8019.344	31.908	17578.36	71.662
Foreign Substance Region	1-2-6-7-8	1-2-6-7-8	1-2-6-7-8	1-2-6-7-8	1-2-6-7-8	1-2-6-7-8
Otsu Method Rate (CPU/GPU)	4.861		5.820		9.259	
Intuitive Fuzzy Logic Rate (CPU/GPU)	199.810		253.669		246.384	
Response Time Rate (CPU/GPU)	197.618		251.321		245.293	

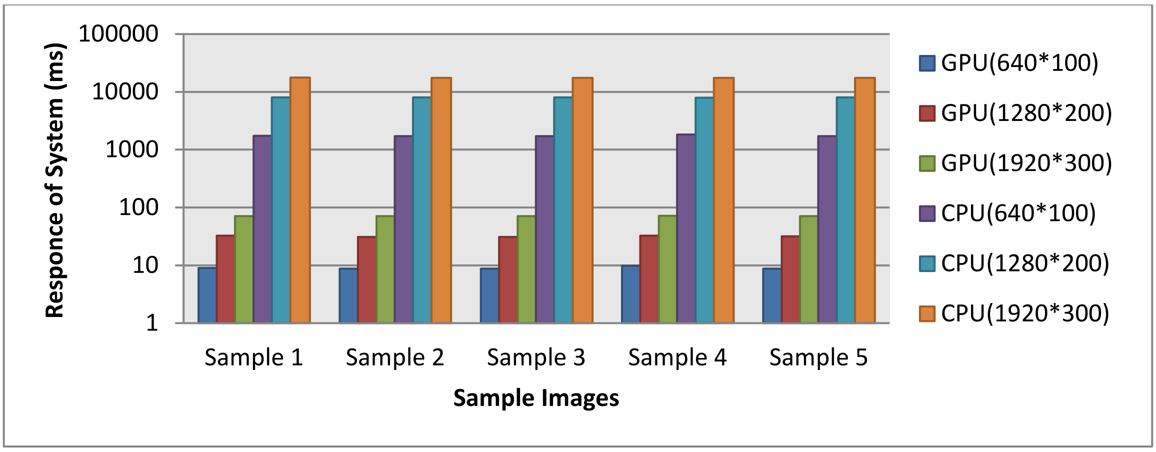


Figure 8: Comparison of Processing Time of Images

In developed algorithm, the aim is to reveal the performance of system by developing either CPU or GPU based application. In result section, when pattern examples in different resolution are analysed, a graphic related to time response of system in Fig. 8 is obtained.

A significant speed difference of GPU based application is seen by analysing the graphic in Fig. 8. The average of results obtained by GPU based application are such like 193 in 640*100 rated images, 249 in 1280*200, 247 times faster in 1920*300. Also, speed ratio in all patterns are obtained between 186 times and 260 times. According to literature studies, the successful systems that hundreds of times accelerated with GPU were found (Bahri, 2017), (Faujdar, 2017), (Gunes, 2016). When 260 times speed is taken into consideration, it is seen that a very successful result is obtained according to the studies in the literature.

CONCLUSION

Nowadays, the used methods to clean filthy in textile sector are not efficient in terms of speed and quality. In recent years, computer vision systems clearly show its effect in textile sector as in other sectors. In this study, intuitive fuzzy logic algorithm developed by Atanossov was preferred in order to determine the impurities within the image taken by camera. In intuitive fuzzy logic algorithm, hesitation error is calculated and subtracted from membership value in order to minimize the professional experience error that does not exist in classic fuzzy logic algorithm. This provides more stable and desired results.

Due to the nature of intuitive fuzzy logic algorithm, some speed problems have been seen in real-time CPU based applications. Therefore, GPU technology was utilized to eliminate the speed problem. In the first stage, intuitive fuzzy object extraction method is applied to the image taken from the camera in grey level of OpenCV. Literature research has shown that a fixed value is used as the threshold value in the intuitive fuzzy logic edge detection algorithm. Because of each frame taken from camera will occur in different values, the algorithm was not to perform desired results. In this study, it is first time, dynamic threshold value obtained by Otsu method was used integrally with heuristic fuzzy logic. In this way, the threshold value of each frame from the camera was calculated in real time and currently applied to the image. While the system is developed, by using examples with different resolutions from taken images in study, it was observed that the most appropriate resolution value in terms of either performance or quality is 640*100 rate. This image was divided into 8 equal region with ratio of 80*100. In each region, whether impurity material exists or not is determined by summation of numerical values of related region of the image. Using this summation, a threshold value was defined to determine whether there is any impurity in related region according to negligence availability levels.

In the used algorithms, minimum 168 maximum 262 times faster speed difference is obtained in pattern samples with different resolutions using NVIDIA GTX 480 GPU supported graphics card. At the end of the trials, it is seen that the methods completely provide desired results. Unlike previous methods of removing filthiness from cotton, textile studies in literature, computerized vision system provided much more important advantage due to these methods.

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