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Edge detection of aerial images using artificial bee colony algorithm

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ABSTRACT

Edge detection techniques are the one of the best popular and significant implementation areas of the image processing. Moreover, image processing is very widely used in so many fields. Therefore, lots of methods are used in the development and the developed studies provide a variety of solutions to problems of computer vision systems. In many studies, metaheuristic algorithms have been used for obtaining better results. In this paper, aerial images are used for edge information extraction by using Artificial Bee Colony (ABC) Optimization Algorithm. Procedures were performed on gray scale aerial images which are taken from RADIUS/DARPA-IU Fort Hood database. Initially bee colony size was specified according to sizes of images. Then a threshold value was set for each image, which related with images' standard deviation of gray scale values. After the bees were distributed, fitness values and probability values were computed according to gray scale value. While appropriate pixels were specified, the other ones were being abandoned and labeled as banned pixels therefore bees never located on these pixels again. So the edges were found without the need to examine all pixels in the image. Our improved method's results are compared with other results found in the literature according to detection error and similarity calculations'. All the experimental results show that ABC can be used for obtaining edge information from images.

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1 Introduction

Nowadays, image processing techniques are quite advanced with the development of technology. Image is a concept that may be encountered in each area. Camera Systems are used in wide area such as military technology, education and training techniques, space science and in many areas like these ones. This system used in many different areas is open to continuous improvement.

Computer vision systems are also changed by the views of the nature of the images obtained in the field. For example, gray scale images, thresholded images and so on. On each image dependent upon the nature of the operations performed can be varied. All of these operations encountered appears as "**image processing**" in the literature. Image processing is being used also in many areas such as the industry of military, oil exploration, medical technology, security, criminal laboratories, satellite imagery, remote sensing applications, farming (for example; determination of the quality of meat), robotics, radar, astronomy [1-7]. Edge detection is one of the most important and indispensable step in image processing. Therefore, edge detection algorithms can be used wherever image processing is used [8-14].

In this paper, an "**edge detection method**" which is one of basic step of these operations, is used. Edges are the borders that are generated by abrupt diversities in the pixels of between two different areas [8-9, 11, 14]. Edge detection is so important because of the characterize the boundaries. Detecting the edges of an image preserves the major structural properties of the image. The recognition of edges of views is so important for human visual system because of the strong association between edge information and object attributes. For this reason, in image processing, edge detection algorithms try to identify where the object is. Edge detection reduces the amount of data to process in the image while provides important information about the shapes of objects [12]. It must be effective and trustworthy because it is very important for determining how successful following operation steps will be [15].

The existing edge extraction methods which are still used today, most of the common point is that they are dependent on a mask. Without this mask information, edge detection process cannot be done. Derivative methods such as Laplacian, Canny, Roberts, Prewitt and Sobel are the common masks used for edge detection. Marr and Hildreth's method was developed by using edges of zero crossings with Gauss's Laplacian operator [9]. Haralick used the value of the gradient of the derivative to find a gradient of zero crossings in an image [8]. Canny's approach was based on the implementation of the Gaussian mask operator, which reduces the noise level on the image. This mask operator is produced by a sigma value. Then before the derivate process, a smoothing filter is applies on image. This method uses gradient value to find edge directions [16]. Roberts, Prewitt and Sobel methods are the some common techniques used in the image processing area. There is abundant literature [8-9, 11, 13, 16-18] on the subject of edge detection.

Optimization is to use available limited resources in the most optimal ways. Mathematically, it can be defined as maximizing or minimizing a function. It is a collection of processes comprising the best results. Optimization algorithms aim is to obtain the best results in the present circumstances. Because of the technology development and become more complex with each passing day, the problems raised by the optimization of the system also becomes more difficult to perform. For this reason, optimization algorithms must evolve with technology [19]. In the last years, new methods are developed by using modern global optimization algorithms such as the Genetic Algorithm (GA), Differential Evolution Algorithm (DE) and Simulated Annealing (SA). These kinds of algorithms are known as "**stochastic algorithms**". Yang describes the name of the all stochastic algorithms based on the randomization as "**metaheuristic**" [20].

The "**swarm**" definition is used for a group of animals. "Swarm intelligence", one of the metaheuristic approache's term, is an expression for a group behavior of decentralized and self-organized swarms. Artificial Bee Colony (ABC) is a metaheuristic algorithm inspired by the behavior of foraging bees. It was developed in 2005 by Derviş Karaboğa and has been applied in many fields [21-28].

Our improved edge detection method is based on ABC optimization algorithm and detects edges without using any mask operator. By using ABC algorithm, the pixels which are parts of an edge can be detected. This paper is organized as follows. Section 2 concerns used dataset, basic ABC and modified ABC algorithm that will be used in this work. Section 3 includes experimental results are provided by comparing between our implementation and other methods' performance. Conclusions are given in Section 4.

2. Material and methods

2.1. Dataset

In this study, 10 gray level images taken from the RADIUS/DARPA-IU Fort Hood aerial image dataset [29] were used for testing accuracy of the proposed algorithm. All of the images size ranges between 476x477 and 645x667 pixels. The ground truth images of the test images are also included in the dataset. Figure 1 shows the 10 aerial images and their ground truths (GT: Ground Truths) used in this study.

2.2. Artificial Bee Colony (ABC) Optimization Algorithm

Inspection of the occurring intelligent behavior in nature has directed researchers to produce new optimization techniques. Therefore, many metaheuristic algorithms like ABC based on behavior of the swarms are developed.

In nature, honey bees live in colonies. These bees have some features such as foraging, dancing, task sharing, decision making, navigating, positioning, mating and pheromone spreading behaviors. That features can be used as models for intelligent systems. ABC is one of the popular swarm-based algorithms developed by Karaboğa and Baştürk [30-32]. There are a lot of studies with ABC algorithms [21-24, 31, 33].

ABC algorithm has three types of bees consists of employed bees, scout bees and onlooker bees. In the ABC algorithm, there is one worker bee for each food source and the number of employed bees is equal to the number of onlooker bees. The case of the scout bees depends on the conditions of the food sources.

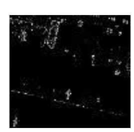
A food source is found randomly by each employed bee in the search space. These locations are found by Eq. (1).

$$x_{i,j} = x_j^{min} + rand(0,1)(x_j^{max} - x_j^{min}) \quad (1)$$

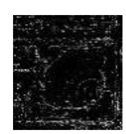
x_i is a D-dimensional vector, $where\ i = 1,2,3, \dots.., SN$ and $j = 1,2,3, \dots., D$ and x_j^{max}, x_j^{min} are the maximum and minimum limits ($SN = number\ of\ the\ food\ source$).

All employed bees should complete their search steps, before they share their source information with the onlooker bees in the dancing area. Additionally this information includes and important data which is related the nectar amounts with onlookers.


(a1) Airfield


(b1) GT of Airfield


(a2) Baseball


(b2) GT of Baseball

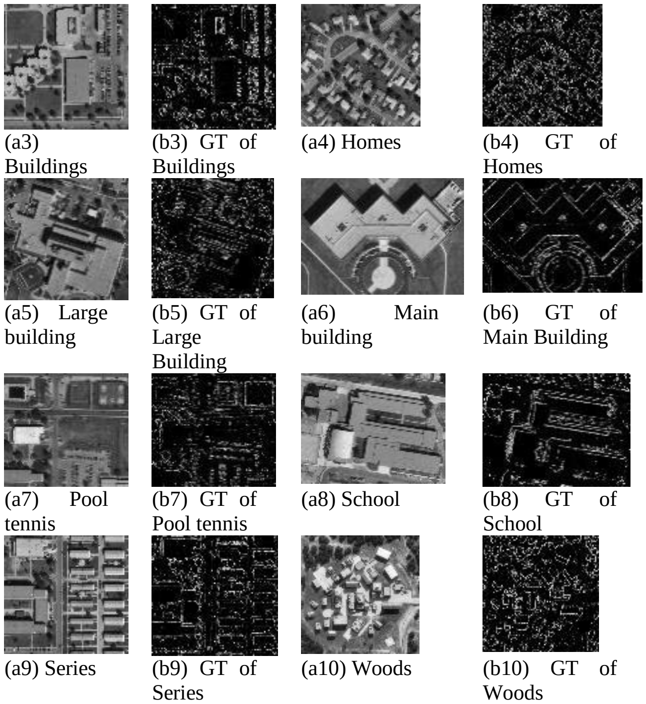


Figure 1. *Images from RADIUS/DARPA-IU with their ground truths.*

Each onlooker bee first selects a food source based on the probability value of the food sources. Then, following the waggle dance, it creates a new candidate solution, a new food source, in the neighborhood of this food source.

Each employed and onlooker bee tries to improve the quality of their food sources by choosing their neighbor by Eq. (2).

$$v_{i,j} = x_{i,j} + \varphi_{i,j}(x_{i,j} - x_{k,j}) \quad (2)$$

v_i is randomly selected from neighbors of x_i and it is called as candidate source. k is a random integer number between [1, SN] and it must be different from i. $\varphi_{i,j}$ is a real random number between [-1, 1] and j represents a random integer number between [1, D].

Works in the employed bees is done again by the greedy selection. If a resource's position cannot be improved after a certain number of cycles, that resource is banned. Meanwhile, the relevant worker bee becomes a scout bee. The banned and abandoned food source is replaced with a random food source [30-32].

The main steps are described below [28]:

1. Initial bee colony is $x = \{x_i | \text{i} = 1, 2,\ldots, \text{n}\}$, where n signify the population size, x_i is the i'th bee in the bee colony.
2. Calculate the fitness f_i of each employed bee x_i, and save the maximum source quality as well as the corresponding food source according to the fitness function.
3. Find a new solution v_i in the neighborhood of the current solution. k is an integer near to i, k ≠i, and φ is a random number between $[-1, 1]$.
4. Greedy criterion is used for update x_i. Compute the fitness of v_i. If v_i is superior to x_i, x_i is replaced with v_i; otherwise x_i is remained.
5. Get the likelihood value P_i by Eq. (3) and Eq. (4) according to the fitness f_i of x_i [34].
6.

$$P_i = \frac{fit_i}{\sum_{i=1}^{n} fit_i} \quad (3)$$

$$fit_i = \begin{Bmatrix} \dfrac{1}{1+f_i}, & f_i \geq 0 \\ 1 + abs(f_i), & f_i < 0 \end{Bmatrix} \quad (4)$$

7. Depending on the probability P_i, onlookers choose food sources, search the neighborhood to generate candidate solutions, and calculate their fitness.
8. For updating the food sources, apply the greedy criteria.
9. Keep the best source data in memory.
10. Check the banned source situation. If located source is an abandoned source, replace it with a new random solution by using (1).
11. Repeat steps 3-9 until stopping criterion is satisfied.

The fitness function is so important factor in ABC algorithm. Also, control parameters of this algorithm, such as the value of limit criteria, the stopping condition and the number of employed bees or onlooker bees must be defined well. Because they affect the performance of convergence directly.

2.3. The proposed method

Our method uses ABC algorithm for edge detection in images. In general, edges of an image are found with masks, and the dependency on masks can be eliminated by this improved method.

The initial image is taken for the process of edge detection with ABC and this image represents the solution space. The initial values for control parameters are set. The limit is the limit value that requires the abandonment of a resource in the ABC algorithm if it cannot be developed.

The maximum number of cycles is the number of iteration. Colony size is the number of individuals in the population and is formulated by Eq. (5) because it should not be a constant value for each image. The colony size is equal to the square root of the product multiplied by the number of rows and columns of the image.

$$K = \sqrt{NxM} \quad (5)$$

K is the total number of sources and is calculated using thee values N and M. N and M are the row and column numbers of the image, respectively [35].

After determining the all parameters' values, the sources are located. First, the number of located sources is equal to half the total number of sources given in Eq. (6). At the same time, emloyee bees are randomly located on the image.

$$LocatedSourceNumber = \frac{K}{2} \tag{6}$$

The attributes of the located sources, such as coordinates, gray level values, failure counters, probability and fitness values are kept in the memory. The fitness value for the source pixel is the value of the gray level value getting from the fitness function. Searching and using resources is still allowed to continue. If directed source is permitted source, the source's neighbor data is held as the directed source. If there is no better source adjacent to the located source, failure counter is increased. Banned resource is the source whose failure counter becomes equal to limit. The probability value of all sources is calculated by the fitness values.

In this study, fitness function is calculated by on grayscale value of each pixel. First, fitness and then likelihood values are computed according to these values. Located source's probability and one of its neighbor's are selected randomly before the probability values are compared. Failure values of current resources are controlled whatif it is equal or not to limit value in each comparison steps. If a failure value is the same with limit value, the current source is banned and the number of scout individual count is increased. None of the bees position on these banned sources again. In this study, our limit criteria is set as 5.

There are three cases about the comparison steps:

1. If current source's probability value is worse than probability boundary value, current source's failure counter increased by 1 (Figure 2.a).
2. If current source's probability value is better than probability boundary value, a random neighbor is selected from current source's neighborhood. If neighbor's value is worse than probability boundary value or current source's probability value, current source's failure counter increased by 1 (Figure 2.b).
3. If current source's probability value is better than probability boundary value, a random neighbor is selected from current source's neighborhood. If neighbor's value is better than probability boundary value and current source's probability value, and neighbor becomes new (current) source and old source's failure counter value is set as 0 (Figure 2.c).

(a)
(b)
(c)

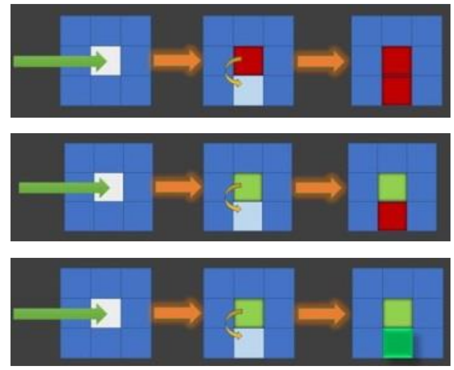


Figure 2. *Cases of comparison steps for neighbor pixels*

Then, located sources are controlled for belonging to any edge line or not by the examining pixels in directional aspects (Figure 3).

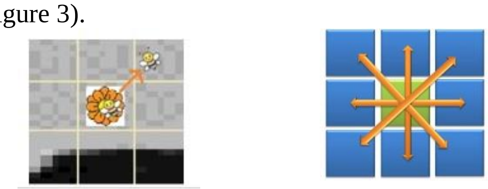


Figure 3. *Examining the neighbor pixels*

The threshold value for each image is specified by using the standard deviation of the image gray levels as given Eq. (7).

$$threshold\ value = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2} \tag{7}$$

If the grayscale color difference is higher than the specified threshold value, this pixel can be belong to an edge line. If the current source is determined as an edge pixel and that pixel's value is set as 1 on the result image (Figure 4).

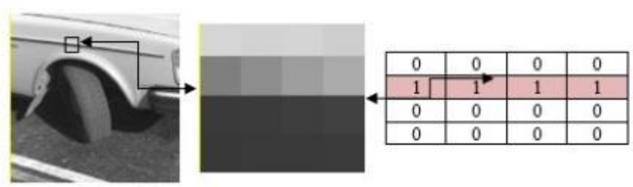


Figure 4. Labeling the edge boundary

3. Experimental results

In [36], algorithm was tested for gray scale images and compared with the Canny, Sobel and Roberts edge detection methods using Hamming Distance (HD).

(a1) Airfield (b1) ABC result of a1 (a2) Baseball (b2) ABC result of a2

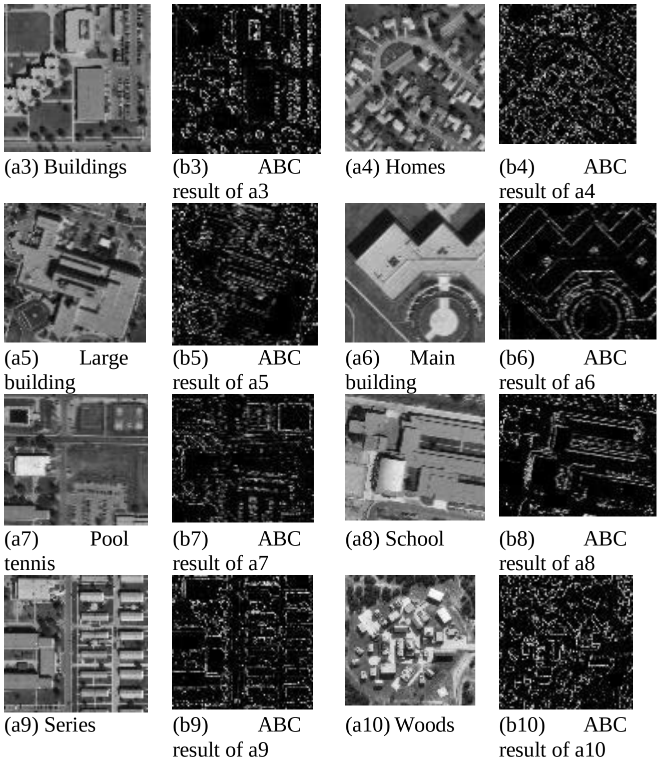


Figure 5. *Edge detection results of ABC*

The sizes of populations was specified according to images' width and height values by using Eq.6 and the maximum number of iterations criteria was set as 50000. Some iteration numbers such as 1000, 2000, 5000 and 50000 were compared to find the optimum iteration number and the best edge result was achieved with 50000 iteration. The limit parameter was set as 5 because a pixel has maximum 8 neighbors. Threshold and boundary probability values were computed for all tested images. RADIUS/DARPA-IU Fort Hood gray level object images and their ABC method's results are given in Figure 5. ABC method can be used as an alternative method for edge detection according to obtained experimental results.

Figure 6 shows operating times of test images which are given in Figure 4. Run time is increasing according to increasing the number of iteration.

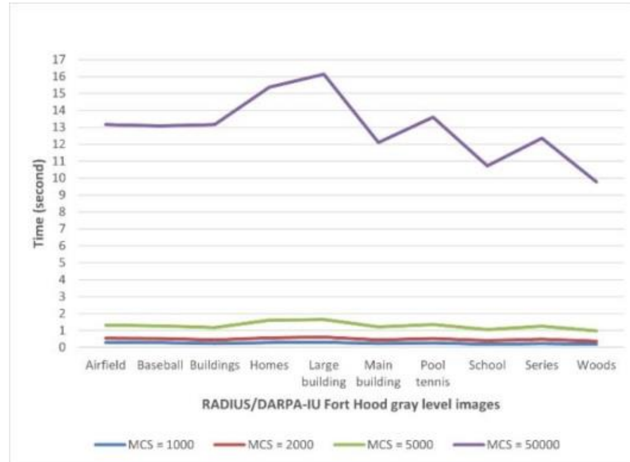


Figure 6. *Operating times for RADIUS/DARPA-IU Fort Hood aerial images*

Detection Error (DE) and Similarity (S) rates are used to compare results with the literature (Eq. 8-9). DE rate is computed according to result of values that are obtained from Specificity-Sensitivity analysis.

$$\mathrm{DE} = \sqrt{(1-TP)^2 + (FP)^2} \tag{8}$$

$$S = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{1+d_i^2} \tag{9}$$

Table 1 shows Sensitivity-Specificity analysis values for edge detection. Eq. (8) gives Detection Error rates.

Table 1. *Sensitivity-Specificity Analysis Values for Edge Detection*

	Edge (+)	**Edge (-)**
Test (+)	True Positive (TP)	False Positive (FP)
Test (-)	False Negative (FN)	True Negative (TN)

Our results obtained from ABC which are applied on 10 aerial gray scale images are compared with the ground truth images. The HD, DE and S results of these comparisons are given in Table 2 [37].

ABC method's DE results and S results (in Table 2) of RADIUS/DARPA-IU Fort Hood aerial images were compared with previous experimental research in the literature [15].

DE rates comparison shows that 6 of our results are worst findings and the others are acceptable values. The reason for such high rates of the developed algorithm, which environmental factors' edge information is not mentioned in the ground truth images. Our method's sensitivity is high for environmental factor's edge information on test images.

S rates comparison shows that one of our rates is the best result which is obtained from Airfield test image, the other results are acceptable values.

4. Conclusion

Most of the edge detection methods such as Sobel, Canny, etc. require a predefined mask. When masks are used, corner pixels of the image and pixels of the frame around the image are often either ignored or assumed to be zero. The edge extraction was done using the ABC without this kind of data loss and the dependency on the mask was removed. Its major components; i.e. graph representation, initial bee distribution, fitness function and likelihood values based on gray values of image were investigated and adapted to the underlying problem. The control of whether neighboring pixels belong to the edge was also compared with the proposed algorithm in three different stages, and the best result was tried to be obtained. Suitable values of the algorithm parameters were determined through empirical studies.

In this work, the positioning of the ABC optimization algorithm's swarm individuals was carried out on a random pixel in the input image. In the basic ABC, first resource is specified by the formula, but in the study 8 adjacent pixels of the first resource are defined as new resources. Gray scale values of an image are used as knowledge about the quality. The numbers of populations vary according to the image size so it makes the algorithm adaptive. For maximum number of cycles, different iteration numbers between 1000 and 50000 was used and the best of them selected. Also, the limit parameter is equal to 5 after the experiments. The threshold value is computed based on the standard deviation of each image by using a formula.
In the study, run times for each number of iterations were tested and these times showed us that if maximum iteration number was increased, run time became longer. But on the other hand, if maximum iteration number was increased, result image showed us more edge information for related image.
Also improved method's results are compared with Ground Truth (GT) images according to Detection Error (DE) and Similarity (S) calculations' results. The obtained results show that the proposed method can be used for edge detection implementation as an alternative method.

Our goal for the future is to include the surrounding pixels of the image in the identification of the edges to achieve better results. For this aim, we are working on the modified ABC algorithm

Table 2. *Comparisons of Edge Detection Algorithms on Aerial Images*

		Airfield	Baseball	Buildings	Homes	Large building	Main building	Pool tennis	School	Series	Woods
Rothwell	***DE***	0.4707	0.5710	0.5506	0.5991	0.5292	0.5608	0.5273	0.5638	0.4321	0.5634
	S	0.7692	0.6815	0.6886	0.6332	0.6844	0.6967	0.6722	0.6495	0.7577	0.6581
Bergholm	***DE***	0.4643	0.5968	0.6047**	0.5703	0.5970**	0.5651	0.5639	0.5844	0.5297	0.5846
	S	0.7651	0.6359	0.5895**	0.5978**	0.5401**	0.6191	0.5923**	0.5846**	0.6084**	0.5912
Canny	***DE***	0.5057	0.5668	0.5593	0.5712	0.5328	0.6180	0.5086	0.5571	0.4143	0.5526
	S	0.7593	0.6961	0.6892	0.6851	0.6976	0.6612	0.7208	0.6743	0.7682	0.6849
Schunck	***DE***	0.5147	0.5689	0.5640	0.5743	0.5459	0.6130	0.5367	0.5647	0.4276	0.5695
	S	0.7382	0.6848	0.6804	0.6762	0.6730	0.6499	0.6596	0.6474	0.7656	0.6748
Lacroix	***DE***	0.5340	0.5865	0.5736	0.4851	0.5180	0.5193	0.5396	0.5701	0.4522	0.5274
	S	0.7162	0.6579	0.6570	0.7143	0.6823	0.6988	0.6527	0.6419	0.7259	0.6760
Deriche	***DE***	0.5276	0.5726	0.5500	0.6302	0.5194	0.6677**	0.4852	0.5928	0.5303	0.6856**
	S	0.7516	0.6934	0.6871	0.6169	0.7082	0.6088**	0.7100	0.6458	0.6810	0.5667**
ROC	***DE***	0.4634	0.5505	0.5425	0.5177	0.5084	0.5439	0.5029	0.5444	0.4139	0.5241
	S	0.7760	0.6995	0.6946	0.7064	0.7014	0.6998	0.7046	0.6669	0.7767	0.6922
Kappa	***DE***	**0.4126***	**0.5183***	**0.4885***	**0.4402***	**0.4440***	**0.4561***	**0.4343***	**0.5001***	**0.3619***	**0.4602***
(r = 0.7)	***S***	0.8492	**0.7249***	**0.7355***	**0.7599***	**0.7506***	**0.8357***	**0.7639***	**0.7835***	**0.8090***	**0.7448***
	DE	0.86**	0.76**	0.59	0.64**	0.59	0.54	0.63**	0.66**	0.63**	0.68
ABC	***S***	**0.85***	0.63**	0.69	0.68	0.73	0.73	0.66	0.74	0.70	0.64
	HD	0.0656	0.1406	0.1506	0.1988	0.1547	0.1086	0.1365	0.1335	0.1605	0.1561

**: Best for column **: Worst for column*

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