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Extract the Similar Images Using the Grey Level Co-Occurrence Matrix and the Hu Invariants Moments

Beshaier A. Abdulla [a*], Yossra H. Ali [b], Nuha J. Ibrahim [c]

[a] Department of Computers Science, University of Technology, Iraq. beshaierali93@gmail.com

[b] Department of Computers Science, University of Technology, Baghdad, Iraq. 110017@uotechnology.edu.iq

[c] Department of Computers Science, University of Technology, Baghdad, Iraq. 110009@uotechnology.edu.iq

*Corresponding author.

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K E Y W O R D S

Euclidian Distance Measure, Feature Extraction, Grey level co-occurrence Matrix, Hu Invariants Moments, Image Retrieval

A B S T R A C T

In the last years, many types of research have introduced different methods and techniques for a correct and reliable image retrieval system. The goal of this paper is a comparison study between two different methods which are the Grey level co-occurrence matrix and the Hu invariants moments, and this study is done by building up an image retrieval system employing each method separately and comparing between the results. The Euclidian distance measure is used to compute the similarity between the query image and database images. Both systems are evaluated according to the measures that are used in detection, description, and matching fields which are precision, recall, and accuracy, and addition to that mean square error (MSE) and structural similarity index (SSIM) is used. And as it shows from the results the Grey level co-occurrence matrix (GLCM) had outstanding and better results from the Hu invariants moment method.

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1. Introduction

Digital images hold various portions of information named features, a number of those features hold important information, when the features are used to retrieve similar images it will retrieve the images that have similar features to the query image. The chosen methods which were operated on images in the database for feature extraction and later retrieving images from the database by using these features lead to effective retrieval [1]. Image retrieval is the field of study concerned with searching and browsing digital images from database collection. This area of research is very active research since the 1970.Due to more and more images have been generated in digital form around the world, image retrieval attracts interest among researchers in the fields of image processing, multimedia, digital libraries, remote sensing, astronomy, database applications, and other related areas [2]. The Grey level co-occurrence matrix method includes massive computations. Once altogether 256 grey levels are being employed for creating the GLCM's, every GLCM created shall stand (256 × 256) in size. The Grey level co-occurrence matrix is going be performed in the order of the extraction of the textural features which computations for every component in the GLCM are included, thus the bigger the size, the additional computations are executed. [3]. Ever since it has been extensively applied in numerous textures analysis applications besides it continued to be a significant feature extraction method in the field of texture analysis [4].

Moments plus the associated invariants have remained significantly analysed to distinguish the images patterns in different applications. The famous moments contain Zernike moments, geometric moments, rotating moments, and also difficult moments. Moment invariants originally presented through Hu, he originated six pure orthogonal invariants plus single skew orthogonal invariant grounded on algebraic invariants that aren't just independent of size, position, orientation plus parallel projection. Moment invariants are confirmed as suitable measures used to track patterns in the image concerning images, scaling, translation plus rotation below the statement of those images alongside non-stop functions plus noise-free. Moment invariants remain significantly operated towards image registration, image pattern recognition as well as image reconstruction. Though, in practical application digital images are not non-stop plus no noise, since images are quantized via finite-precision pixels within a separate organizes. Adding up, the noise might be presented via several circumstances like a camera. Within this manner, mistakes are certainly presented through the calculation of the moment invariants. In other terms, the moment invariants can differ by the transformation of image geometric. [5].

Salama[6] examined the spatial quantization influence upon the moment invariants. Salama establishes that the error drops once the size of image enlarges plus the reduction of sampling intervals, however, it won't reduce monotonically in overall. They examined three important problems associated with moment invariants, concluding Sensitivity to image noise, Capability for image representation plus Aspects of information redundancy. It's announced that the order moments are more exposed to noise as they get greater. Calculation errors happening in moment invariants may be produced through the quantization plus pollution of noise, and also transformations like scaling as well as rotation. After the dimensions of images are reduced otherwise enlarged, images pixels are going to be inserted otherwise erased. Furthermore, the rotation of the images to effects the alteration of image function, since it includes rounding pixel values plus coordinates. Consequently, moment invariants can alter while images rotate or else scale.

Within this paper there is a comparison study between the two previously mentioned algorithms which is done by building up an image retrieved system using both algorithms separately, evaluating the performance of the system, and comparing the results.

2. Literature Survey

Several researched focus on the field of image retrieval systems, and the several different types of techniques used, some of these researches include:

In [7] Ruliang Zhang and Lin Wang, 2011, they introduced a new algorithm that is used for image matching that is under the name of the IMEA algorithm, which is based on the Hu invariants moments. The first stage in it is the population initialization. Then a subgraph set is created. Now, planning the based on Hu invariants moments fitness function, the seven Hu invariants moments of the template image plus the searched subgraph are computed. In order to measure the similarity between the subgraph plus template image, the Euclidean distance measure is applied. Lastly, the different subgraph is built through different evolutionary policy. The different subgraph is replaced with the extreme value of fitness function subgraph. The outcomes from the experiments show the IMEA algorithm's huge sturdiness and effectiveness.

In [8] Ricardus Anggi and Catur Supriyanto et al., the Coconut tree grows rapidly in the tropical region such as Indonesia. Coconut wood is used as an alternative or complementary raw material for housing or making furniture. Abundant coconut trees are planted, however, the utilization of coconut wood as raw material for furniture is still very rare in Indonesia. This is caused by the low quality of coconut wood since it has not found adequate technology for the processing of coconut wood. This paper presents our experimental work on coconut wood quality classification using a self-tuning MLP classifier (AutoMLP) and Support Vector Machine (SVM). For the SVM classifier, we used the LibSVM library, available in RapidMiner. The Grey-Level Co-occurrence Matrix (GLCM) is used to extract the texture features of coconut wood images. The experiment result shows that AutoMLP gives the best accuracy rate at 78.82%, which is slightly better than 77.06% of SVM.

In [9] Ying-Jun Guo and Zi-Jun Sun et al, in their paper they extracted the texture features of forehead wrinkles, edge crack, and other different kinds of defects of steel strip, they proposed a feature extraction technique which is based on GLCM. They achieved Matlab simulation using four-dimensional parameters characteristics to describe the texture features of steel strip defects. Their results showed that the feature parameters of GLCM are able to describe the strip image texture effectively and also classify the different types of defects.
In [10] Shao Jie, Pang Xinyu et al., 2017, their paper introduces a technique of joining moment invariants with fractal dimension. Plus in order to distinguish the images axis orbit edge, a Canny operator is applied.
These two techniques are utilized as the BP neural networks feature vectors. Forty samples sets are trained and sampled of the usual fault axis in order to examine. Different eight sets of axis orbit recognition rates reached 100% also the recognition result is acceptable. Test outcomes showed that the applied technique has great both recognition speed plus accuracy, also ensures great practical value for the rotor system intelligent fault diagnosis.

3. Research Methodology

The aim of this research is to show the difference in performance between two different algorithms which are the grey level co-occurrence matrix (GLCM) and the Hu invariants moments. In this research, a comparison is performed as shown in Figure 1.

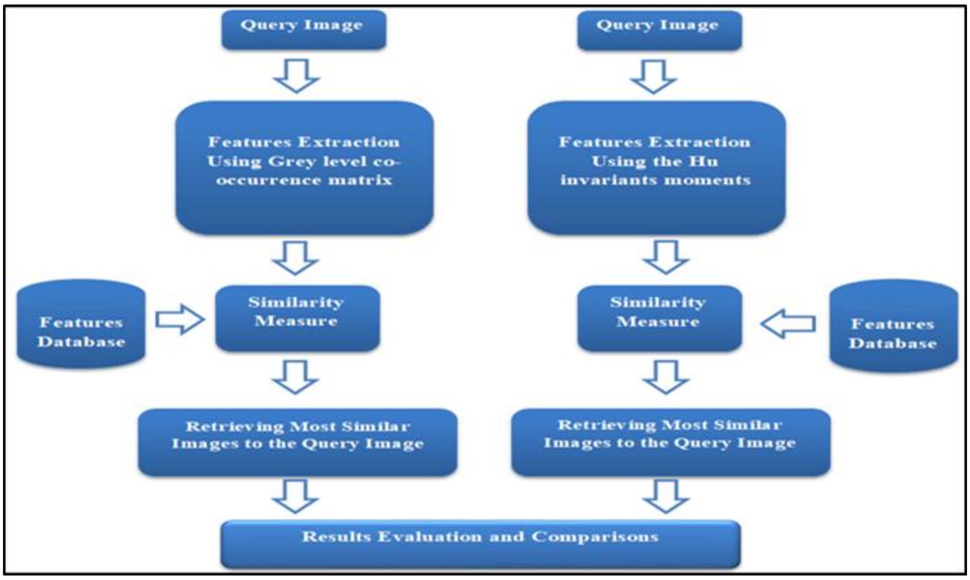

Figure 1: The proposed comparison study diagram

The proposed comparison methodology is proceeded by building up an image retrieval system using the two different methods separately, The aim of this system is to show which algorithm provides better-extracted features that describe the images and as a result will provide a better similar images results. This image retrieval system includes image features extraction, similarity measure employing Euclidian distance, retrieving the most similar images to the query image, and lastly system evaluation using several evaluation measures.
Used database in this research is local the reason behind using such a kind database is because of the lack of availability of a particular image database that is needed in this research. So, as a result, used database is created, the used database consists of several images with different image sets. Figure 2 shows a sample of used databases.

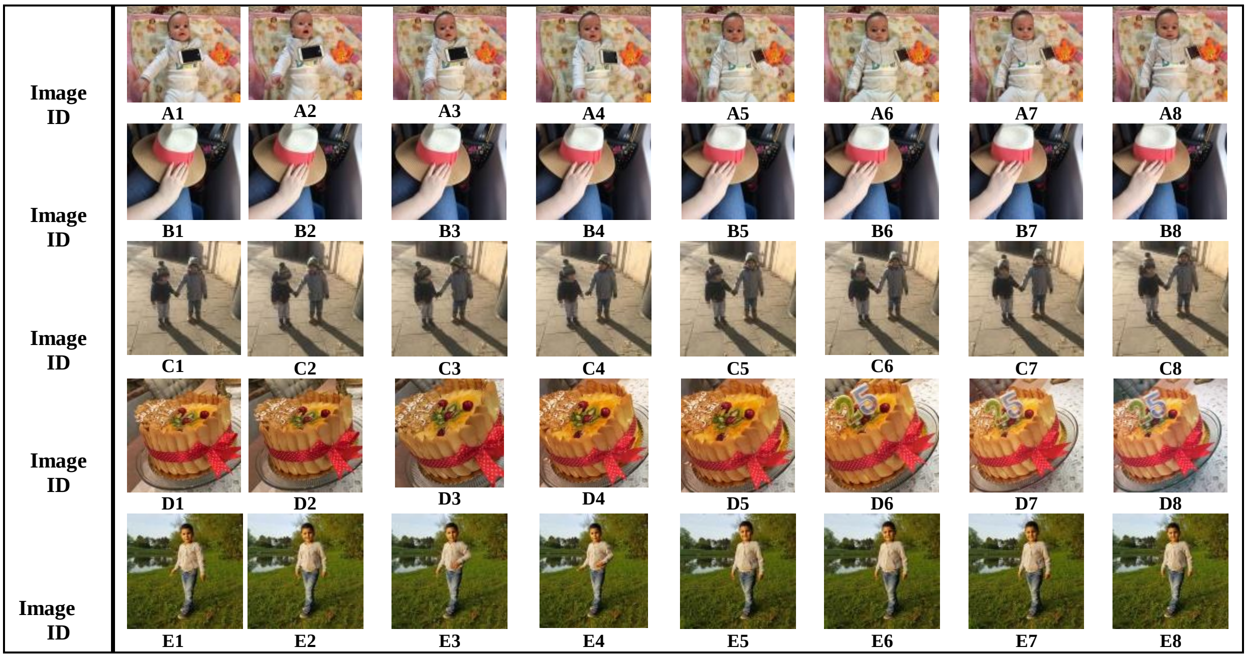

Figure 2: A Sample of the Database Image

Algorithm (1): The proposed comparison system

Input: Query Image

Output: The then most similar images to the query image

Begin:
Step 1: Create the two separate GLCM features database and the Hu moments features database.
Step 2: the Query image features extraction phase begins by using each of the two algorithms apart
Step 3: the similarity phase begins by using the Euclidian distance measure in two parts:

- GLCM: computing the similarity between the query image features and the stored features in the GLCM features database.
- Hu moments: computing the similarity between the query image features and the stored features in the Hu moments features database.

Step 4: Each algorithm will retrieve the most ten similar images to the query image.
Step 5: Evaluate the algorithm results and perform some comparisons
End

Stage 1: Implementing the Grey Level Co-Occurrence Matrix

First, the grey level co-occurrence matrix is performed to extract the database images features and create the GLCM features database; features will be extracted using the GLCM method as results each image in the database will be represented by an array of eight features in the features database. Later the query image features are also extracted in order to measure the similarity using Euclidean distance between the query image features and features stored in the database. Table 1 summarizes the extracted features from the database images.

Table 1: Results of implementing the GLCM algorithm

	Extracted Features Using GLCM Algorithm							
Image ID	Mean	Variance	ASM	Entropy	IDM	HOM	CON	COR
A1	0.980	0.961	0.974	0.959	0.948	0.961	0.928	0.959
B1	0.981	0.959	0.976	0.965	0.948	0.959	0.934	0.965
C1	0.981	0.962	0.974	0.960	0.949	0.962	0.932	0.960
D1	0.977	0.952	0.967	0.950	0.939	0.952	0.914	0.950
E1	0.937	0.951	0.965	0.965	0.949	0.939	0.951	0.949
F1	0.780	0.941	0.914	0.993	0.921	0.678	0.911	0.921
G1	0.932	0.976	0.998	0.934	0.923	0.987	0.934	0.986
H1	0.954	0.989	0.921	0.987	0.932	0.956	0.943	0.989
I1	0.945	0.921	0.990	0.956	0.936	0.987	0.933	0.978
J1	0.943	0.928	0.944	0.890	0.234	0.945	0.934	0.918

Stage 2: Implementing the Hu invariants moments

Now the Hu invariants moments will be implemented in order to extract the database images features and create the Hu moments features database, seven features will be extracted from each image in the database using the Hu moments and as a result, each image will be presented by a seven features array in the Hu moments features database. Later the Hu moments will be used to extract the query image features in order to compute the similarities between the query image features and the stored features in the database using Euclidian distance. Table 2 summarizes the extracted features from the database images.

Table 2: Results of implementing the Hu moments algorithm

	Extracted Features Using Hu Moments Algorithm						
Image ID	M1	M2	M3	M4	M5	M6	M7
A1	0.101	9.155	1.130	2.630	3.741	4.616	3.952
B1	0.441	9.658	1.458	3.309	1.624	4.362	3.633
C1	0.322	9.568	1.380	3.314	4.511	4.371	3.849
D1	0.890	9.352	1.406	2.879	5.019	5.327	5.655
E1	0.765	8.768	1.464	3.272	1.320	3.866	3.142
F1	0.410	9.123	1.132	2.622	3.123	4.324	3.912
G1	0.729	9.634	1.457	3.467	1.731	4.984	3.734
H1	0.009	9.589	1.373	3.327	4.593	4.749	3.163
I1	0.342	9.326	1.478	2.828	5.045	5.374	5.495
J1	0.712	9.344	1.876	2.874	5.419	5.322	5.555

Stage 3: Matching using Euclidian distance

After completing the feature extraction procedures the next step begins with inputting a query image and also extracting its features, next the matching phase begins by matching the input image features with each feature in the database. Since the database images include different sets of images, all the database images were used to evaluate the performance of the two algorithms. In total more than 100 images tests were performed in order to evaluate the performance of the two methods separately, only a sample of the tests is showed in this paper. The similarity measure considered for comparison of images is Euclidean distance. The formula for Euclidean distance is shown as follows:

$$D(x, y) = \sum_{t=1}^{n} |xi - yi| \quad (1)$$

4. Experiment Results

The proposed database used in the experimental tests consists of different images. The evaluation comparisons between the Grey level co-occurrence matrix and the Hu moments algorithms are applied using the known measurements that involve the recall, precision plus accuracy. Those measurements contain quantities that are: true positive (TP), false positive (FP), true negative (TN), and false-negative (FN) [11]:

1. True positive (TP):- it's the amount of the images that were retrieved which are alike to the input image.
2. False-positive (FP):- it's the amount of the images that were retrieved which are not similar to the input image.
3. True negative (TN):- it's the amount of the not retrieved images that are dissimilar to the input image.
4. False-negative (FN):- it's the amount of not retrieved images but is similar to the input image.

$$\text{Accuracy} = \frac{(TP+TN)}{Total\ number\ of\ the\ database\ images} \quad (2)$$

$$\text{Precision} = \frac{TP}{(TP+FP)} \quad (3)$$

$$\text{Recall} = \frac{TP}{(TP+FN)} \quad (4)$$

In addition, MSE and SSIM measurements are applied for evaluating the system
SSIM (Structural Similarity Index) is computed using the below equation [12]:

$$\text{SSIM(x,y)}=\frac{(2\mu_x\mu_y+c_1)(2\sigma_{xy}+c_2)}{(\mu_x^2+\mu_y^2+c_1)(\sigma_x^2+\sigma_y^2+c_2)} \quad (5)$$

Whereas the MSE (Mean Squared Error) is calculated using the following equation [13]:

$$\text{MSE}=\frac{1}{m*n}\sum_0^{m-1}\sum_0^{n-1}\|f(x,y)-g(x,y)\|^2 \quad (6)$$

Where
f is the original image data matrix, **g** is the degraded image data matrix, **m** signifies the rows of the image of pixels and I signifies the row index, **n** signifies the image columns number of pixels and j signifies the column index
The experiment results will be shown in three stages, the first stage will show the GLCM results evaluation, the second stage will show the Hu invariant's moment results evaluation and the third stage will consist of the evaluations comparisons.

Stage 1: The Grey level co-occurrence matrix tests evaluation

The accuracy, precision, and recall in all the performed different images tests using the GLCM indicate and prove the ability of the GLCM to provide the correct retrieved images. The higher accuracy, precision, and recall values of the GLCM method prove the more proper performances. Table 3 illustrates a sample of the evaluation results on the grey level co-occurrence matrix performance. Figure 3 shows a chart of the GLCM results evaluation.

Table 3: GLCM Evaluation Results

Test number	Accuracy	Precision	Recall	TP	FP	TN	FN
1	0.94	0.7	0.7	7	3	87	3
2	0.90	0.5	0.5	5	5	85	5
3	0.94	0.7	0.7	7	3	87	3
4	0.94	0.7	0.7	7	3	87	3
5	0.92	0.6	0.6	6	4	86	4

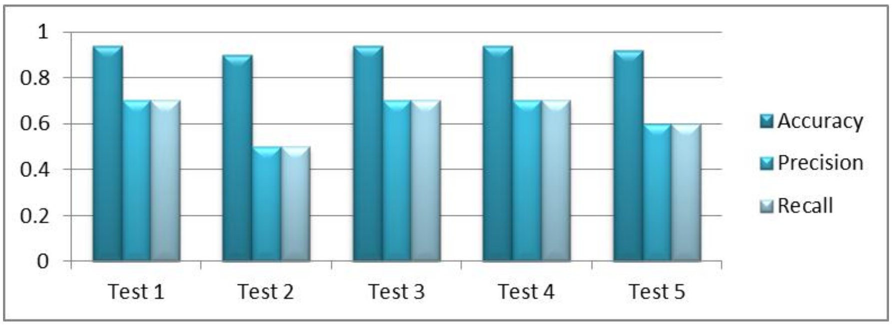

Figure 3: Chart describe the GLCM results evaluation

Stage 2: The Hu Invariants moments tests evaluations

The accuracy, precision, and recall in all the performed different tests using the Hu invariant's moment indicate the quite good performance and the ability of the Hu moments to provide the correct retrieved images. The lower accuracy, precision, and recall values of the Hu moments method prove the poor performance. Table 4 illustrates a sample of the evaluation results on the Hu moments performance. Figure 4 shows a chart of the Hu moments results evaluation.

Table 4: Hu Moments Test evaluations

Test number	Accuracy	Precision	Recall	TP	FP	TN	FN
1	0.84	0.2	0.2	2	8	82	8
2	0.86	0.3	0.3	3	7	83	8
3	0.84	0.2	0.2	2	8	82	8
4	0.84	0.2	0.2	2	8	82	8
5	0.84	0.2	0.2	2	8	82	8

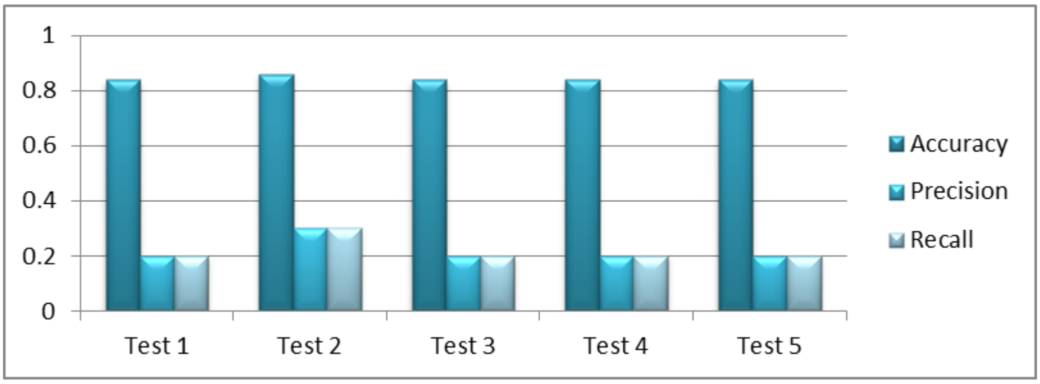

Figure 4: Chart describes the Hu moment's results evaluation

Stage 3: Comparison of the results evaluations

The results in Table 5 shows only a sample of the performed image tests, in these shown image tests the grey level co-occurrence matrix outperform the Hu invariants moments method in the entire tests that were performed using different query image in each imaging test. Note that the GLCM outperforms the Hu moments in the entire tests. The bold numbers indicate better values.

The comparison study also adopted the error metric MSE and SSIM similarity measure metric to evaluate the performance of the two applied algorithms separately. These two measures were used to reflect the system quality and its ability to retrieve similar images to the query image. Table 6 shows a comparison of the overall performance average of the five conducted tests that were performed using the grey level co-occurrence matrix and the Hu invariants moment separately.

Table 5: Result evaluation comparison between GLCM and the HU invariants moment

Test number	Used method	Accuracy	Precision	Recall
1	GLCM	**0.94**	**0.7**	**0.7**
	Hu Moments	0.84	0.2	0.2
2	GLCM	**0.90**	**0.5**	**0.5**
	Hu Moments	0.86	0.3	0.3
3	GLCM	**0.94**	**0.7**	**0.7**
	Hu Moments	0.84	0.2	0.2
4	GLCM	**0.94**	**0.7**	**0.7**
	Hu Moments	0.84	0.2	0.2
5	GLCM	**0.92**	**0.6**	**0.6**
	Hu Moments	0.84	0.2	0.2

Table 6: Comparison of the overall performance average between GLCM and Hu moments

Test Number	GLCM		Hu invariant moments	
	MSE	SSIM	MSE	SSIM
1	1051.9	0.32	1543.7	0.28
2	813.876	0.408	1667.178	0.322
3	1057.61	0.363	1071.571	0.336
4	701.576	0.477	1322.79	0.316
5	785.134	0.463	1040.622	0.417

5. Conclusion

This paper presented a comparison study between two different methods by performing two different algorithms the grey level co-occurrence matrix and the Hu invariants moments which is done by building up an image retrieval system using these two algorithms separately for features extraction using Euclidian distance measure to compute the similarities between the images extracted features. These two algorithms were applied separately on the database images in order to create the features database and on the query image to extract its features. Later Euclidian distance was used to measure the similarities between the query image extracted features and the stored features database. After that, an evaluation comparison was performed using accuracy, precision, recall, MSE, and SSIM on the GLCM and Hu invariant moment. The experiment results showed that the GLCM outperformed the Hu invariant's moment in all different images tests. The high accuracy, precision, recall, and the SSIM measures and the low value of the MSE measure of the GLCM prove the better ability of the GLCM algorithm to retrieve similar images to the query image. This proves that the GLCM features are more able than the Hu invariants moment to describe the image in order to get the correct similar image retrieval.

References

[1] A. Abu Mezied and A. Alattar, “Medical image retrieval based on gray cluster co-occurrence matrix and edge strength,” The IEEE Transactions on Promising Electronic Technologies, pp.71-76, 2017.

[2] H. H Wang, D. Mohamed, N.A Ismail “Approaches, challenges and future direction of image retrieval,” the Journal of Computing, Vol. 2, pp.193-199, 2010

[3] J. Y. Tou, Y.H. Tay and P.Y. Lau, “One-dimensional grey-level co-occurrence matrices for texture classification,” in IEEE International Symposium on Information Technology, Vol.3, pp.1-6, 2008.

[4] J. C. Kavitha and A. Suruliandi, “Texture and color feature extraction for classification of melanoma using SVM,” The IEEE International Conference on Computing Technologies and Intelligent Data Engineering (ICCTIDE'16), pp.1-6, 2016.

[5] Z. Huang and J. Leng, “Analysis of Hu’s moment invariants on image scaling and rotation,” The IEEE 2nd International Conference on Computer Engineering and Technology, Vol.7, pp.V7-476 - V7-480, 2010.

[6] G. I. Salarna and A. L. Abbott, “Moment invariants and quantization effects,” in IEEE Computer Society Conference, pp. 157-163, 1998.

[7] R. Zhang and L. Wang “An image matching evolutionary algorithm based on hu invariant moments,” The IEEE International Conference on Image Analysis and Signal Processing, pp. 113 – 117, 2011.

[8] R. A. Pramunendar, C. Supriyanto, D. H. Novianto, I. N Yuwono, G. F. Shidik and P. N. Andono “A classification method of coconut wood quality based on gray level co-occurrence matrices,” The 2013 International Conference on Robotics, Biomimetic, Intelligent Computational Systems (ROBIONETICS) Yogyakarta, Indonesia, pp. 254-257, 2013.

[9] Y. Guo, Z. Sun, H. Sun and X. Song, “Texture features extraction of steel strip surface defect based on gray level co-occurrence matrix,” The IEEE 2015 International Conference on Machine Learning and Cybernetics, Guangzhou, pp.217-221, 2015.

[10] S. Jie, P. Xinyu, Y. Zhaojian and L. Juanli, "Research on intelligent recognition of axis orbit based on hu moment invariants and fractal box dimension," The IEEE 14th International Conference on Ubiquitous Robots and Ambient Intelligence (URAI), pp. 794 – 799, 2017.

[11] R. Zhang and L. Wang "An image matching evolutionary algorithm based on hu invariant moments," The IEEE International Conference on Image Analysis and Signal Processing, pp. 113 – 117, 2011.

[12] S. S. Cheung and C. Kamath "Robust background subtraction with foreground validation for urban traffic video," The EURASIP Journal on Applied Signal Processing, Vol. 14, pp. 2330–2340, 2005.

[13] Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli, "Image quality assessment: from error visibility to structural similarity," The IEEE transactions on image processing, Vol. 13, pp. 600-612, 2004.