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Abstract. This paper presents a research on clustering an image collection using multi-visual features. The proposed method extracted a set of visual features from each image and performed multi-dimensional K-Means clustering on the whole collection. Furthermore, this work experiments on different number of visual features combination for clustering. 2, 3, 5 and 7 pair of visual features chosen from a total of 8 visual features used, to measure the impact of using more visual features towards clustering performance. The result show that the accuracy of multi-visual features clustering is promising, but using too many visual features might set a drawback.

Keywords: Image Clustering; Visual Feature; K-Means Clustering;

1 Introduction

There is an enormous growth in image collection all around the world, especially in the past few years with the emerging trend of social media. Many social media such as Facebook, Twittter, Path, and Instagram allow people to publish their own generated image, out to the world. Not to mention images produced from other areas such as from commerce, government, scientific and medical field. It is believed that the collections of data in the form of image contain precious information, as well as textual data does.

However, it is hard to obtain precious information from all of those image collections without an effective and efficient technique for image retrieval. Content-Based Image Retrieval (CBIR) address this issue by using visual contents of an image such as color, shape and texture, to decides the similarity and differences between images. Thus, we can explore and analyze images in collection based on its visual feature.

Furthermore, retrieving, exploring and analyzing from a huge amount of images will be a challenging problem. Thus, we need such method to organize the image in a way that enables efficient image retrieval. One of the proposed technique is clustering [1] [2] [3], which is useful to discover the patterns and characteristics stored in image collection by dividing them into set of clusters. Images in each cluster share similar patterns, but very dissimilar to images in other clusters. In addition, [1] also suggest that clustering could be used for faster image retrieval by minimizing the search area only in cluster which the image belong to, rather than exhaustively searching an entire image collection.

adfa, p. 1, 2011.

Another motivation of this research is the possibility of image-language semantic, which based on the idea of finding semantically related text in visually-similar images. This idea offers alternative way of exploring relationship among term's meaning across languages that could be used to build thesaurus, dictionaries, question answering modules etc. The argument is that similar images might contain text caption that is possibly related. For instance if we can recognize the similarity among images in Figure 1, then we might draw inferences that word 'beach' is related with 'pantai' and 'sanur'. Moreover, with some work on the reasoning part, we also can infer that 'sanur' is a 'beach' and 'pantai' is translation of 'beach' in Indonesian language.

Fig. 1. Image-Language Semantic

Furthermore, this research also wants to address the phenomenon called "curse of dimensionality", in which using more than one visual feature when clustering might improve the performance. This performance improvement will occur until certain number of features, or threshold, when the peak performance of multi-dimensional clustering will be obtained. Any features addition or increase in dimensionality beyond the threshold will suffer the clustering accuracy.

2 Proposed Method

Figure 2 illustrates the overview of proposed method in this research. For the sake of simplicity, the illustration only shows the clustering performed on image collection based on 3 visual features. This research also performed clustering based on 1, 2, 5 and 7 visual features to measure the impact of using more visual features, which follows similar process.

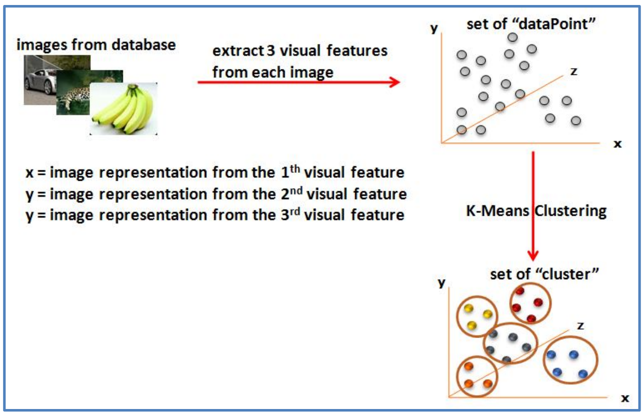

Fig. 2. Proposed Method Overview

Visual feature extraction of each image yields a value to represent an image in the visual feature's context and distinguish one image from another. Then based on visual information, image clustered to organize visually-similar image in the same cluster. K-Means clustering algorithm is used to cluster images based on value from the extraction process of different visual features combination. In other words, the clustering done in high dimensional space (2, 3, 5 and 7) in which each image considered as a point with coordinate of the n-axis (n = {2, 3, 5, 7}). These are the K-Means algorithm used in this research :

1. Choose number of cluster output desired, k.
2. Randomly make k clusters and calculate center point of each cluster, or randomly choose k points as initial center point.
3. Assign each point to cluster with nearest center point.
4. Re-calculate the center point of each cluster.
5. Repeat step number 3 and 4 until the convergence criterion achieved (there is no membership change in each cluster or until some number of iteration)

There are 8 descriptors used to extract visual features in this research, this choice based on the all available and usable descriptors in tools used. The tools used for visual extraction is LIRE (Lucene Image Retrieval) java-based API. Here are some overviews of descriptors used:

1. Auto Color Correlogram
   This descriptor extracts the color spatial correlation information in image [5]. It is known for its simple computation and small extraction result size. This descriptor is not affected regardless of changes in background or point of view.
2. CEDD (Color and Edge Directivity Descriptor)
   This descriptor extracts a combination of color and texture from an image into one histogram [6]. The color information extracted based on HSV (Hue, Saturation, Values) color space, whereas texture information extracted by classifying each pixel into one or more texture category. CEDD uses relative modest amount of computing resource in extraction process comparer to MPEG-7 descriptors (Scalable Color, Color Layout, Edge Histogram etc.).
3. Color Layout
   This descriptor extracts information of color spatial-distribution in an image [7]. It divides an image to a 8x8 matrix and applies Discrete Cosine Transform based on YCbCr color space (Yellow, Chromatic blue, Chromatic red). This descriptor is not affected with image dilatation and able to distinguish a sketch image from one another.
4. Edge Histogram
   This descriptor extracts local edge distribution in an image to a histogram [8]. Edge represents frequency and directionality of color changes on image. It divides an image into number of blocks, apply digital filtering and classify each block into one out of five edge categories. This descriptor is not affected with image rotation or translation.
5. FCTH (Fuzzy Color and Texture Histogram)
   This descriptor extracts same information as CEDD does [9], but the difference is the extraction result size of FCTH 30% bigger than CEDD and the texture extraction process. FCTH extracts texture information by applying Haar transform

to each of image blocks and classifying them with a fuzzy texture linking system. This descriptor also persists regardless of images distortion.

6. Gabor
   This descriptor explores texture feature from an image by applying a series of linear filter in edge detection process. An image is processed through a set of Gabor filter which have different scale and orientation, then the average and standard deviation compared to original image is calculated. Gabor descriptor has many similarities with human visual system and proven to be capable of distinguishing image based on texture information [10].
7. Scalable Color
   This descriptor extracts statistical color information of an image in HSV color space into a histogram. Each bin in histogram represents number of pixels containing certain color. The extraction process also involving a Haar transform and a set of low-pass and high-pass filter [7].
8. Tamura
   This descriptor exploits texture feature in an image, such as coarseness, contrast, directionality, line-likeness, regularity and roughness [11]. Now, only the first three characteristics implemented because considered to be the most important part in human vision. Coarseness related to size of texture element, contrast related to image quality and directionality related to orientation of texture.

3 Experiments

For the experiments, an image dataset was obtained from the website wang.ist.psu.edu/iwang/test1.tar. In this scheme, 50 images from 5 categories (each category contain 10 images) are tested against the proposed method. The 5 categories are bus, dinosaur, flower, horse, and mountain. Each image named with its correspondence categories in order to ease the process of accuracy measurement.

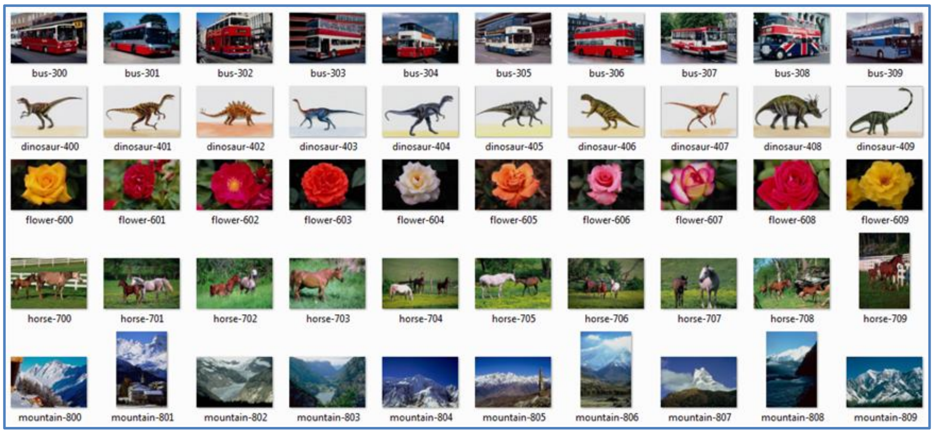

Fig. 3. Image Dataset

The accuracy measurement based on the number of images that is properly clustered. An image said to be in proper cluster if its category is the dominant category belong to the cluster. For example, cluster 1 occupied by 10 images that is 8 bus images, 1 flower image and 1 horse image, then it can be said that the cluster is a bus' cluster and there is 8 images properly clustered into this cluster.

If somehow there are two dominant categories, only one of them will be regarded as dominant category in a cluster by alphabetical order. For example in cluster 2 occupied by 5 horse images, 5 flower images and 1 mountain image, then flower will be picked as dominant category by alphabetical order. It should also be noted that either if we chose horse as dominant category, there still be a total of 5 images properly clustered.

Each experiment's run tested a combination of visual feature for clustering purpose. To simplify the scope of research and as there is prior information of the number of categories existed in dataset, the k parameter in K –Means clustering is set to 5. So, each run will always resulting 5 clusters and the accuracy of it can be calculated as:

$$accuracy = \frac{total\ of\ properly\ clustered\ images}{total\ of\ all\ images\ clustered}$$

The total of all images clustered is the size of dataset, which are 50.

4 Results

Table 1 shows the overall results of experiments per clustering type, which this research used combination of 2, 3, 5 and 7 pair out of 8 visual features. In addition, clustering with only 1 feature also performed to have a thorough comparison of the advantage of high dimensionality clustering. The experiments take on all possible combination of visual features in each clustering type, which are 8 for 1D clustering, 28 for 2D clustering, 56 for 3D clustering, 56 for 5D clustering and 8 for 7D clustering.

The highest accuracy obtained by 3D clustering type, which uses CEDD-EdgeHistogram-ColorLayout as the visual feature combination. These three visual features evidently the best combination to distinguish visually similar images from another images. The lowest accuracy occurred in 3D clustering that uses visual feature combination of CEDD-EdgeHistogram-ScalableColor (see appendix).

Based on Table 1, the average accuracy of all runs in each clustering dimension generally decreasing when the number of visual feature used for clustering is increasing, except for 2D clustering. This fact shows the "curse of dimensionality" existence, which the threshold or number of features combination to get the best average accuracy would be 2.

If we look at other perspective, highest accuracy obtained, it would be fair to say that the "curse of dimensionality" also exist with the threshold would be 3. This means that using multi visual features would improve clustering performance until certain number of dimension. Nevertheless, employing too many visual features beyond the dimension's threshold might raise some confusion instead of clarity when distinguishing and classifying an image.

Table 1. Experiment Results per Clustering Type

Type	Total Combination	Highest Accuracy	Lowest Accuracy	Average Accuracy
1D	8	0.88	0.54	0.688
2D	28	0.94	0.52	0.691

3D	56	0.98	0.5	0.670
5D	56	0.96	0.52	0.610
7D	8	0.66	0.52	0.570

There are 18 runs with accuracy equal or more than 0.9 as shown in Table 2. Most of them obtained with 3D clustering (9 out of 18), 5 of them used 2D clustering and 4 used 5D clustering. This shows that 3D clustering give most of the best clustering performance in this research.

Moreover, by taking a close look into images in each cluster result, it was found that the dinosaur category is the easiest category to cluster. Table 3 shows result of the proposed method which able to cluster the dinosaur images perfectly in 20 runs out of 56 - 3D clustering runs done. Another category that ever been clustered perfectly in the experiments are horse and mountain category.

Table 2. Run Result with Accuracy >= 0.9

Type	Features	Accuracy
3D	CEDD-EdgeHistogram-ColorLayout	0.98
5D	AutoColorCorrelogram-CEDD-Gabor-EdgeHistogram-ColorLayout	0.96
5D	CEDD-FCTH-Gabor-EdgeHistogram-ColorLayout	0.96
3D	FCTH-EdgeHistogram-ColorLayout	0.96
3D	AutoColorCorrelogram-EdgeHistogram-ColorLayout	0.94
5D	AutoColorCorrelogram-FCTH-Gabor-EdgeHistogram-ColorLayout	0.94
3D	AutoColorCorrelogram-Gabor-ColorLayout	0.94
2D	EdgeHistogram-ColorLayout	0.94
2D	Gabor-ColorLayout	0.94
3D	Gabor-EdgeHistogram-ColorLayout	0.94
3D	AutoColorCorrelogram-CEDD-EdgeHistogram	0.92
2D	CEDD-EdgeHistogram	0.92
3D	CEDD-FCTH-ColorLayout	0.92
2D	FCTH-EdgeHistogram	0.92
5D	AutoColorCorrelogram-CEDD-FCTH-Gabor-ColorLayout	0.9
2D	AutoColorCorrelogram-FCTH	0.9
3D	CEDD-Gabor-ColorLayout	0.9
3D	FCTH-Gabor-ColorLayout	0.9

Table 3. Perfectly Clustered Categories per Clustering Type

Type	Perfectly Clustered
1D	dinosaur (2x), horse (1x)
2D	dinosaur (12x), horse(2x)
3D	dinosaur (20x), horse(7x), mountain (1x)
5D	dinosaur (15x), horse(5x)
7D	dinosaur (1x)

5 Conclusions and Future Possibilities

Based on the experiment results, clustering with multi visual features could improve clustering performance compared to using only one visual feature. Nevertheless, using too many visual features in combination might lower the accuracy of the result. In this research scope, combination of CEDD, Edge Histogram and Color Layout proven to be the most promising set of visual feature to cluster the image collection.

Different visual extraction tools and another type of visual features might be worth to try in the future. Finding the right combination of type and number of visual feature for clustering might increase the chance to distinguish one image from another in more precise manner. Furthermore, finding the right number of clusters for K-Means clustering initialization is also a problem when dealing with real-world image collection which prior knowledge of clusters existed is unknown.

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7 Appendix

Type	Features	Accuracy	Perfectly Clustered Category
1D	-AutoColorCorrelogram-	0.64	horse;
1D	-CEDD-	0.84	
1D	-ColorLayout-	0.88	horse; dinosaur;
1D	-EdgeHistogram-	0.76	

1D	-FCTH-	0.68	dinosaur;
1D	-Gabor-	0.54	dinosaur;
1D	-ScalableColor-	0.62	
1D	-Tamura-	0.54	
2D	-AutoColorCorrelogram-CEDD-	0.64	
2D	-AutoColorCorrelogram-ColorLayout-	0.8	dinosaur;
2D	-AutoColorCorrelogram-EdgeHistogram-	0.82	
2D	-AutoColorCorrelogram-FCTH-	0.9	dinosaur;
2D	-AutoColorCorrelogram-Gabor-	0.56	dinosaur;
2D	-AutoColorCorrelogram-ScalableColor-	0.62	
2D	-AutoColorCorrelogram-Tamura-	0.54	
2D	-CEDD-ColorLayout-	0.84	horse; dinosaur;
2D	-CEDD-EdgeHistogram-	0.92	
2D	-CEDD-FCTH-	0.78	dinosaur;
2D	-CEDD-Gabor-	0.66	dinosaur;
2D	-CEDD-ScalableColor-	0.56	
2D	-CEDD-Tamura-	0.54	
2D	-EdgeHistogram-ColorLayout-	0.94	dinosaur;
2D	-EdgeHistogram-ScalableColor-	0.7	
2D	-FCTH-ColorLayout-	0.78	dinosaur;
2D	-FCTH-EdgeHistogram-	0.92	
2D	-FCTH-Gabor-	0.62	dinosaur;
2D	-FCTH-ScalableColor-	0.6	
2D	-FCTH-Tamura-	0.54	
2D	-Gabor-ColorLayout-	0.94	horse; dinosaur;
2D	-Gabor-EdgeHistogram-	0.68	dinosaur;
2D	-Gabor-ScalableColor-	0.6	
2D	-Gabor-Tamura-	0.54	
2D	-ScalableColor-ColorLayout-	0.72	
2D	-Tamura-ColorLayout-	0.52	
2D	-Tamura-EdgeHistogram-	0.54	
2D	-Tamura-ScalableColor-	0.54	
3D	-AutoColorCorrelogram-CEDD-ColorLayout-	0.84	horse; dinosaur;
3D	-AutoColorCorrelogram-CEDD-EdgeHistogram-	0.92	
3D	-AutoColorCorrelogram-CEDD-FCTH-	0.78	dinosaur; horse;
3D	-AutoColorCorrelogram-CEDD-Gabor-	0.66	dinosaur;
3D	-AutoColorCorrelogram-CEDD-ScalableColor-	0.58	
3D	-AutoColorCorrelogram-CEDD-Tamura-	0.54	
3D	-AutoColorCorrelogram-EdgeHistogram-ColorLayout-	0.94	dinosaur;
3D	-AutoColorCorrelogram-EdgeHistogram-ScalableColor-	0.7	
3D	-AutoColorCorrelogram-FCTH-ColorLayout-	0.78	dinosaur;
3D	-AutoColorCorrelogram-FCTH-EdgeHistogram-	0.74	dinosaur;
3D	-AutoColorCorrelogram-FCTH-Gabor-	0.62	dinosaur;
3D	-AutoColorCorrelogram-FCTH-ScalableColor-	0.6	
3D	-AutoColorCorrelogram-FCTH-Tamura-	0.54	
3D	-AutoColorCorrelogram-Gabor-ColorLayout-	0.94	horse; dinosaur;
3D	-AutoColorCorrelogram-Gabor-EdgeHistogram-	0.64	dinosaur;
3D	-AutoColorCorrelogram-Gabor-ScalableColor-	0.64	
3D	-AutoColorCorrelogram-Gabor-Tamura-	0.54	
3D	-AutoColorCorrelogram-ScalableColor-ColorLayout-	0.72	
3D	-AutoColorCorrelogram-Tamura-ColorLayout-	0.52	
3D	-AutoColorCorrelogram-Tamura-EdgeHistogram-	0.54	
3D	-AutoColorCorrelogram-Tamura-ScalableColor-	0.54	
3D	-CEDD-EdgeHistogram-ColorLayout-	0.98	horse; mountain; dinosaur;
3D	-CEDD-EdgeHistogram-ScalableColor-	0.5	
3D	-CEDD-FCTH-ColorLayout-	0.92	horse; dinosaur;
3D	-CEDD-FCTH-EdgeHistogram-	0.88	dinosaur;
3D	-CEDD-FCTH-Gabor-	0.7	dinosaur;
3D	-CEDD-FCTH-ScalableColor-	0.6	
3D	-CEDD-FCTH-Tamura-	0.54	
3D	-CEDD-Gabor-ColorLayout-	0.9	horse; dinosaur;
3D	-CEDD-Gabor-EdgeHistogram-	0.74	dinosaur;
3D	-CEDD-Gabor-ScalableColor-	0.6	
3D	-CEDD-Gabor-Tamura-	0.54	
3D	-CEDD-ScalableColor-ColorLayout-	0.74	

3D	-CEDD-Tamura-ColorLayout-	0.52	
3D	-CEDD-Tamura-EdgeHistogram-	0.54	
3D	-CEDD-Tamura-ScalableColor-	0.54	
3D	-EdgeHistogram-ScalableColor-ColorLayout-	0.68	
3D	-FCTH-EdgeHistogram-ColorLayout-	0.96	dinosaur;
3D	-FCTH-EdgeHistogram-ScalableColor-	0.74	
3D	-FCTH-Gabor-ColorLayout-	0.9	horse; dinosaur;
3D	-FCTH-Gabor-EdgeHistogram-	0.8	dinosaur;
3D	-FCTH-Gabor-ScalableColor-	0.64	
3D	-FCTH-Gabor-Tamura-	0.54	
3D	-FCTH-ScalableColor-ColorLayout-	0.74	
3D	-FCTH-Tamura-ColorLayout-	0.52	
3D	-FCTH-Tamura-EdgeHistogram-	0.54	
3D	-FCTH-Tamura-ScalableColor-	0.54	
3D	-Gabor-EdgeHistogram-ColorLayout-	0.94	dinosaur;
3D	-Gabor-EdgeHistogram-ScalableColor-	0.62	dinosaur;
3D	-Gabor-ScalableColor-ColorLayout-	0.6	
3D	-Gabor-Tamura-ColorLayout-	0.52	
3D	-Gabor-Tamura-EdgeHistogram-	0.54	
3D	-Gabor-Tamura-ScalableColor-	0.52	
3D	-Tamura-EdgeHistogram-ColorLayout-	0.52	
3D	-Tamura-EdgeHistogram-ScalableColor-	0.54	
3D	-Tamura-ScalableColor-ColorLayout-	0.56	
5D	-AutoColorCorrelogram-CEDD-EdgeHistogram-ScalableColor-ColorLayout-	0.68	dinosaur;
5D	-AutoColorCorrelogram-CEDD-FCTH-EdgeHistogram-ColorLayout-	0.8	horse; dinosaur;
5D	-AutoColorCorrelogram-CEDD-FCTH-EdgeHistogram-ScalableColor-	0.7	
5D	-AutoColorCorrelogram-CEDD-FCTH-Gabor-ColorLayout-	0.9	horse; dinosaur;
5D	-AutoColorCorrelogram-CEDD-FCTH-Gabor-EdgeHistogram-	0.74	dinosaur;
5D	-AutoColorCorrelogram-CEDD-FCTH-Gabor-ScalableColor-	0.66	dinosaur;
5D	-AutoColorCorrelogram-CEDD-FCTH-Gabor-Tamura-	0.54	
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5D	-AutoColorCorrelogram-CEDD-FCTH-Tamura-ColorLayout-	0.52	
5D	-AutoColorCorrelogram-CEDD-FCTH-Tamura-EdgeHistogram-	0.54	
5D	-AutoColorCorrelogram-CEDD-FCTH-Tamura-ScalableColor-	0.54	
5D	-AutoColorCorrelogram-CEDD-Gabor-EdgeHistogram-ColorLayout-	0.96	horse; dinosaur;
5D	-AutoColorCorrelogram-CEDD-Gabor-EdgeHistogram-ScalableColor-	0.64	dinosaur;
5D	-AutoColorCorrelogram-CEDD-Gabor-ScalableColor-ColorLayout-	0.6	
5D	-AutoColorCorrelogram-CEDD-Gabor-Tamura-ColorLayout-	0.52	
5D	-AutoColorCorrelogram-CEDD-Gabor-Tamura-EdgeHistogram-	0.54	
5D	-AutoColorCorrelogram-CEDD-Gabor-Tamura-ScalableColor-	0.52	
5D	-AutoColorCorrelogram-CEDD-Tamura-EdgeHistogram-ColorLayout-	0.52	
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5D	-AutoColorCorrelogram-FCTH-EdgeHistogram-ScalableColor-ColorLayout-	0.76	
5D	-AutoColorCorrelogram-FCTH-Gabor-EdgeHistogram-ColorLayout-	0.94	horse; dinosaur;
5D	-AutoColorCorrelogram-FCTH-Gabor-EdgeHistogram-ScalableColor-	0.6	dinosaur;
5D	-AutoColorCorrelogram-FCTH-Gabor-ScalableColor-ColorLayout-	0.6	
5D	-AutoColorCorrelogram-FCTH-Gabor-Tamura-ColorLayout-	0.52	
5D	-AutoColorCorrelogram-FCTH-Gabor-Tamura-EdgeHistogram-	0.54	
5D	-AutoColorCorrelogram-FCTH-Gabor-Tamura-ScalableColor-	0.52	
5D	-AutoColorCorrelogram-FCTH-Tamura-EdgeHistogram-ColorLayout-	0.52	
5D	-AutoColorCorrelogram-FCTH-Tamura-EdgeHistogram-ScalableColor-	0.54	
5D	-AutoColorCorrelogram-FCTH-Tamura-ScalableColor-ColorLayout-	0.56	
5D	-AutoColorCorrelogram-Gabor-EdgeHistogram-ScalableColor-ColorLayout-	0.7	dinosaur;

5D	-AutoColorCorrelogram-Gabor-Tamura-EdgeHistogram-ColorLayout-	0.56	
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5D	-CEDD-FCTH-Gabor-EdgeHistogram-ColorLayout-	0.96	horse; dinosaur;
5D	-CEDD-FCTH-Gabor-EdgeHistogram-ScalableColor-	0.7	dinosaur;
5D	-CEDD-FCTH-Gabor-ScalableColor-ColorLayout-	0.6	
5D	-CEDD-FCTH-Gabor-Tamura-ColorLayout-	0.56	
5D	-CEDD-FCTH-Gabor-Tamura-EdgeHistogram-	0.54	
5D	-CEDD-FCTH-Gabor-Tamura-ScalableColor-	0.52	
5D	-CEDD-FCTH-Tamura-EdgeHistogram-ColorLayout-	0.52	
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5D	-CEDD-FCTH-Tamura-ScalableColor-ColorLayout-	0.56	
5D	-CEDD-Gabor-EdgeHistogram-ScalableColor-ColorLayout-	0.72	dinosaur;
5D	-CEDD-Gabor-Tamura-EdgeHistogram-ColorLayout-	0.56	
5D	-CEDD-Gabor-Tamura-EdgeHistogram-ScalableColor-	0.52	
5D	-CEDD-Gabor-Tamura-ScalableColor-ColorLayout-	0.56	
5D	-CEDD-Tamura-EdgeHistogram-ScalableColor-ColorLayout-	0.56	
5D	-FCTH-Gabor-EdgeHistogram-ScalableColor-ColorLayout-	0.7	dinosaur;
5D	-FCTH-Gabor-Tamura-EdgeHistogram-ColorLayout-	0.56	
5D	-FCTH-Gabor-Tamura-EdgeHistogram-ScalableColor-	0.52	
5D	-FCTH-Gabor-Tamura-ScalableColor-ColorLayout-	0.56	
5D	-FCTH-Tamura-EdgeHistogram-ScalableColor-ColorLayout-	0.56	
5D	-Gabor-Tamura-EdgeHistogram-ScalableColor-ColorLayout-	0.56	
7D	-AutoColorCorrelogram-CEDD-FCTH-Gabor-EdgeHistogram-ScalableColor-ColorLayout-	0.66	dinosaur;
7D	-AutoColorCorrelogram-CEDD-FCTH-Gabor-Tamura-EdgeHistogram-ColorLayout-	0.56	
7D	-AutoColorCorrelogram-CEDD-FCTH-Gabor-Tamura-EdgeHistogram-ScalableColor-	0.52	
7D	-AutoColorCorrelogram-CEDD-FCTH-Gabor-Tamura-ScalableColor-ColorLayout-	0.56	
7D	-AutoColorCorrelogram-CEDD-FCTH-Tamura-EdgeHistogram-ScalableColor-ColorLayout-	0.56	
7D	-AutoColorCorrelogram-CEDD-Gabor-Tamura-EdgeHistogram-ScalableColor-ColorLayout-	0.56	
7D	-AutoColorCorrelogram-FCTH-Gabor-Tamura-EdgeHistogram-ScalableColor-ColorLayout-	0.56	
7D	-CEDD-FCTH-Gabor-Tamura-EdgeHistogram-ScalableColor-ColorLayout-	0.56	