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Research paper

An intelligent system to estimate and classify the agricultural and food products using coloring local features

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Abstract

Color is commonly perceived as an indispensable quality in describing edible nuts, fruits, vegetables and food grains. State-of-the art local feature-based representations are mostly based on shape description, and ignore color information. The measured color values vary significantly due to large amount of variations, which in turn hamper the description of color. The aim of this paper is to extend the description of local features of images of agricultural and food products with color information. To accomplish a wide applicability of the color descriptor, it should be robust to the photometric changes that are commonly encountered in the images of agricultural and food products and also the varying image quality ranging from high quality images to snap-shot photo quality and compressed images. Based on these requirements we derive a set of color descriptors. The set of proposed descriptors are compared by extensive testing on agricultural and food products images, namely, matching, retrieval and classification and on wide variety of image qualities. The results show that the color descriptors remain reli-able under photometric and geometrical changes, and also for poor image quality. For all the experiments carried out, it is observed that a combination of color and shape based–approach outperforms a pure shape-based approach.

Keywords: *Agricultural and Food Products Images; Classification; Matching; Local Features.*

1. Introduction

There exists a broad agreement that local features are an efficient tool for object representation due to their robustness with respect to occlusion and geometrical transformations [1]. A typical application based on local features starts with the detection phase, in which features are localized. If desired the patches can be transformed to be invariant to orientation, scale, and affine transformations. Invariant representations are subsequently extracted by a descriptor. The descriptor should robustly represent both the shape and the color of the features. A considerable amount of research has been dedicated to robust local shape descriptors. An extensive study by Mikolajczyk and Schmid [2] reported the SIFT descriptor [3] to be the best perform. The description of local color has received relatively little attention, and as a result most local feature-based methods [3 - 5] use only luminance and ignore color information.
A lot of work has been dedicated to global color features for color object recognition. Ballard and Swain [6] described objects by their color histograms. Moreover, to obtain invariance with respect to lighting geometry the use of normalized rgb histograms was advocated. This method remained however variant with respect to illuminant changes. To tackle this problem Funt and Finlayson [7] proposed an illuminant invariant indexing method, which was however variant with respect to lighting geometry. Finlayson et al. [8] combined the theories of [6] and [7] and proposed a indexing method which is both invariant to shading and illuminant changes. All methods remained however variant with respect to specularities. Gevers and Smeulders [9] propose invariants for specularity, in combination with illuminant and lighting geometry. The work was later extended to the derivative structure of images in [10], [11], leading to e.g. photometric invariant edge and corner detection. Furthermore, Gevers and Stokman [12] observed that instabilities, caused by the non-linear transformation to compute the photometric invariants, hamper practical use of photometric invariance theory. Based on an error analysis robust photometric invariants are proposed.
Vision-based inspection systems reduce human interaction with the inspected goods, classify generally faster than human beings, and tend to be more consistent in their product classification [15]. Many vision systems have been developed for different food products inspection, such as apples, tomatoes, potatoes, vegetables, eggs, corn, rice, and many other products [16 - 19]. C. Velappan Gnana Arivu et al., (2012) developed an apple grading system using vision box hardware with the advantages of high precision and high automatization [20]. Computer vision systems have been successfully used to recognize or to classify quality parameters like color and size in several agricultural and food commodities including dry beans[21], coffee[22], soya beans seeds[23], peanuts[24] and brazil-nuts[25], [26]. The aim of this article is to enrich local feature-based methods with color information.

2. Materials and methods

The Fig.1 shows the modules of computer vision based intelligent system, to estimate and classify the agricultural and food products using coloring local features. The image acquisition module captures an image and saved it in memory. High resolution images contains product details, but requires maximum time for processing and classification. Low-resolution images are processed very fast, at the cost of accuracy. The suitable resolution should be chosen to give acceptable speed with best accuracy. The first step of pre-processing the image is to reduce the noise and improve the image quality by using median filter in order to determine the location and borders of the food product. After noise removal, the image is segmented into two classes: object and background. This process is dependent on the nature of the food product and the required classification. Features are extracted from food product regions. The final step is training and testing of classifier, which gives the desired decision. The next sections present the data set, feature extraction and classification.

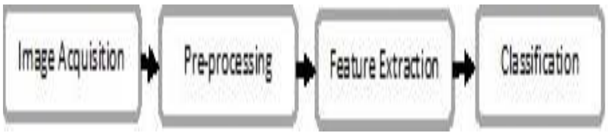

Fig.1: Computer Vision Based Intelligent System.

2.1. Data set

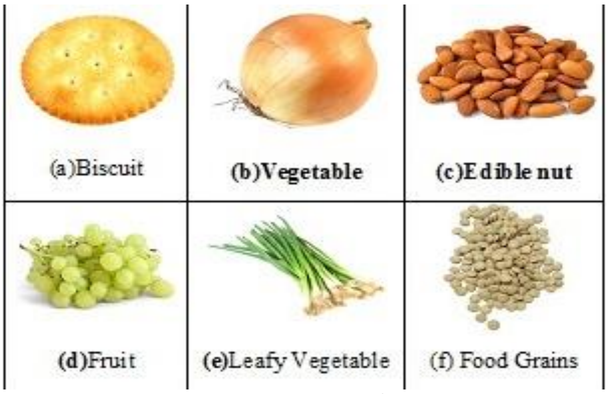

Fig. 2: Sample Dataset of FRID.

The FoodCast Research Image Database (FRID) maintains the standard food related objects (bakery products such as biscuits, fruits, edible nuts, vegetables, leafy vegetables and food grains) dataset. In this dataset, all images of size(530x530 pixels) are standardized and stored as .jpg file format. In this work, total 1800 food related images are considered and categorized into fruits(300 images), biscuits(300 images), edible nuts(300 images), vegetables(300 images), leafy vegetables(300 images) and food grains(300 images). The sample data set is shown in Fig. 2.

2.2. Feature extraction

Feature extraction is a very important phase in this research. We have used the segmented images of different categories from the FRID dataset. These images are considered as input to the developed feature extraction method, so as to extract the features like Color and Shape descriptor, Color histogram, Luminance, Chrominance, Hue angle, Color distance metrics and Scale Invariant Feature Transform [27-29].

2.2.1. Color and shape descriptor

The local feature descriptors with color information, by concatenating a color descriptor, K, to the shape descriptor, S, given by

$$B = \left(\hat{F}, \lambda\hat{K}\right) \tag{1}$$

Where B is the combined color and shape descriptor and λ is a weighting parameter, and ^. indicates that the vector is normalized. For the shape descriptor we rely on the SIFT descriptor [3]. Since the color descriptor is to be used in combination with a shape descriptor it need not contain any spatial information, which leads to the use of local color histograms.

2.2.2. Color histogram

A color histogram is a representation of the distribution of colors in an image. For digital images, a color histogram represents the number of pixels that have colors in each of a fixed list of color ranges that span the image's color space, (i.e. the set of all possible colors). The color histogram can be built for any kind of color space, although the term is more often used for three-dimensional spaces like Red Green Blue as tabulated in Table 1.

Table 1: RGB Color Space

Sl. No.	Feature	Description/Equations
1	*Luminance*	$R = R/255, G = G/255$ and $G = G/255$ $L = 0.2126 * R + 0.7152 * G + 0.0722 * B$
2	*Chrominance*	$C_r = R - L\,;\ C_b = B - L$
3	*Hue angle*	$H^0 = \begin{cases} \frac{1}{360^0}\left[90^0 - tan^{-1} * \frac{F}{\sqrt{3}} + 0^0\right] & G < B \\ \frac{1}{360^0}\left[90^0 - tan^{-1} * \frac{F}{\sqrt{3}} + 180^0\right] & G > B \end{cases}$ where $F = (2 * R - G - B)/(G - B)$
4	*Colour Distance Metric*	$\Delta E_{RGB} = \sqrt{(\mu_R - R_0)^2 + (\mu_G - G_0)^2 + (\mu_B - B_0)^2}$

As a pixel-wise characteristic, the histogram is invariant to rotation, translation, and scaling of an object. A color histogram h(image)= (h_n(image): n=1,...,N) is a N-dimensional vector such that each component h_n(image) represents the relative number of pixels of color C_n in the image, that is, the fraction of pixels that are most similar to the corresponding representative color. To build the color histogram, the image colors should be transformed to an appropriate color space and quantized according to size N. An N-dimensional probability density function (histogram) h(c_1………. c_n) is constructed out of these pixels [13].

Obviously, in the case of the RGB color space, N equals to three. Let us denote the N marginal distributions (channel wise histograms) of this pdf by h_n (c); n∈ [1; N]. When a quantization to M levels is needed, M + 1 pieces of histogram bin boundaries b_m; m∈ [0; M] are derived from h_n(c) so that, in the case of a discrete color distribution, each bin contains an equal number of entries [13].

$$\sum_{c=b_i}^{b_{i+1}-1} h_n(c) = \sum_{c=b_j}^{b_{j+1}-1} h_n(c), \forall i,j \in \{0 \ldots \ldots M-1\} \tag{2}$$

where b_0 =0 and b_M is one larger than the original number of quantization levels. Later on, the derived bin boundaries are used in quantizing both sample and model distributions. Each color channel is quantized separately, and a number of distributions are created. An N-dimensional quantized histogram for each color space was created with 8, 16, 24, and 32 levels per channel. The histograms are denoted by $RGB8^3$, $RGB16^3$, $RGB24^3$ and $RGB32^3$; [13]. These histograms are used in demonstrating the effect of change in illumination on chrominance and luminance. Among these color histograms, the $RGB16^3$ and $RGB32^3$ give, distinctive difference among the food products.

2.2.3. Scale invariant feature transform (SIFT)

The Scale Invariant Feature Transform (SIFT) developed by Lowe is the most well-known method for finding interest points and feature descriptors, providing invariance to scale, rotation, illumination, affine distortion, perspective and similarity transforms, and noise. Lowe demonstrates these by using several SIFT descriptors together to describe an object. There is additional invariance to occlusion and clutter. Since a few descriptors are occluded, others will be found. We provide some detail here on SIFT since it is well designed and well known. SIFT is commonly used as a benchmark against which other vision methods are compared.

SIFT is a complete algorithm and processing pipeline, including both an interest point and a feature descriptor method. It includes stages for selecting center-surrounding circular weighted Difference of Gaussian (DoG) maxima interest points in scale space to create scale-invariant keypoints (a major innovation). Feature descriptors are computed surrounding the scale-invariant keypoints. The feature extraction step involves calculating a binned Histogram of Gradients (HOG) structure from local gradient magnitudes into Cartesian rectangular bins, at selected locations centered around the maximal response interest points derived over several scales.

2.3. Classification

In this research work, we have used the support vector machine(SVM) to classify the agricultural and food products using coloring local features

2.3.1. Support vector machine

The SVM is a maximal margin classifier. Instead of modeling probability distribution of the training vectors, SVM tries to separate the different classes by directly searching for adequate boundaries between them [14]. For this purpose, it constructs hyper-planes with maximum margin in the feature space between the classes. In this work, for classifying samples, the SVM is constructed using the training set. SVM is used for discrimination of six data sets of the agricultural and food products, and the ‘‘one-against-one’’ approach is utilized to convert binary classification into multiclass learning. To find an effective classifier for classification, the parameters of SVM shown in Table 2 are tuned in this work.

Table 2: Tuned Parameters of the SVM Used in This Study

Parameter	Possible entries
Regularization parameter C	1, 10
Kernel function type	Linear

3. Results and discussion

An affine invariant Harris-Laplace detector has been used for all the experiments[2]. In the shape normalization step the images are reduced to 20 by 20 neighborhoods. The SIFT is computed from this shape normalized patch. In the case color descriptors first color normalization is applied, and then the color descriptors, being the histograms of RGB (see Table 1), hue angle (see Table 1), Luminance(see Table 1), chrominance(see Table 1) and color distance metric(see Table 1), are computed. Furthermore, $\lambda = 0.6$ (see Eq.1) is experimentally found to give good results, and the descriptor lengths are 128 bins for SIFT. The average estimated values are illustrated in Table 3.

Table 3: The Average Estimated Values of Data Set

classification	Shape and Color					
	SIFT	RGB	Hue	Luminance	Chrominance	Color Distance Metric
Fruits	57	89	90	85	17	81
Vegetables	50	67	69	65	10	70
Leafy Vegetables	55	70	73	68	15	67
Biscuits	43	91	92	89	07	89
Edibl Nuts	47	45	49	56	12	51
Food Grains	53	55	59	60	19	62

This experiment tests the descriptors on an image classification task. Based on the descriptors in the image, a decision is made on whether the image is a member of the class or not. The multi-class classification is performed on six data sets. They are Fruits, Vegetables, Leafy Vegetables, Biscuits, Edible nuts, and Food grains of each 300 images. The classes are divided in 150 training and 150 testing images. The descriptors are clustered by a K-means algorithm, which forms a set of visual words. Subsequently, each image is represented by a frequency histogram of the visual words. Based on these histograms, one-against-all classifiers are trained with a linear SVM. A test image is subsequently classified with all classifiers, and is assigned to the class for which it obtains the highest score.

4. Conclusion

In this paper, a principled approach has been adopted to extend the SIFT shape descriptor with a color descriptor. A color descriptor is obtained using a set of photometric invariant color histograms derived from the four criteria namely photometric robustness, geometric robustness, photometric stability and generality. We propose a solution to dependence of derivative-based invariants to the edge-sharpness. The descriptors are tested on a matching, retrieval, and a classifier. It is observed that a pure color-based approach outperforms a shape-based approach for colorful objects, and for all reported data the combination of shape and color outperforms a pure shape-based approach, with gain going up as much as 70 percent. This work yielded better results depending on the data set for different color descriptors.

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References

[1] Schmid, C., Mohr, R., “Local gray value invariants for image retrieval”, *IEEE Trans. on Pattern Analysis and Machine Intelligence,* Vol. 19, pp. 530-534, 1997. https://doi.org/10.1109/34.589215.

[2] Mikolajczyk, K., Tuytelaars, T., Schmid, C., Zisserman, A., Matas, J., Schaffalitzky, F., Kadir, T., Van Gool, L., “A comparison of affine region detectors”, *Inter-national Journal of Computer Vision,* Vol. 65, pp. 43-72, 2005. https://doi.org/10.1007/s11263-005-3848-x.

[3] Lowe, D., “Distinctive image features from scale-invariant key points”, *International Journal Computer Vision* Vol. 60, pp. 91-110, 2004. https://doi.org/10.1023/B:VISI.0000029664.99615.94.

[4] Lazebnik, S., Schmid, C., “A maximum entropy framework for part-based texture and object recognition”, *In: Proc. IEEE Int'l Conf. Comp. Vision*, pp. 832-838, 2005.

[5] Fergus, R., Perona, P., Zisserman, A., “ Object class recognition by unsupervised scale-invariant learning”, *In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition,* Vol. 2, pp. 264-271, 2003.

[6] Ballard, D.H., “Generalizing the Hough transform to detect arbitrary shapes”, *Pattern Recognition,* Vol. 12, pp.111-122, 1981. https://doi.org/10.1016/0031-3203(81)90009-1.

[7] Funt, B., Finlayson, G., “Color constant color indexing”, *IEEE Trans. on Pattern Analysis and Machine Intelligence,* Vol. 17, pp. 522-529, 1995. https://doi.org/10.1109/34.391390.

[8] Finlayson, G.D., Schiele, B., Crowley, J.L., “Comprehensive color image normalization’, *In: ECCV '98: Proceedings of the 5th European Conference on Computer Vision,* Vol. I, Springer-Verlag, pp. 475-490, 1998. https://doi.org/10.1007/BFb0055685.

[9] Gevers, T., Smeulders, A., “Color based object recognition”, *Pattern Recognition*, Vol. 32, pp. 453-464, 1999. https://doi.org/10.1016/S0031-3203(98)00036-3.

[10] Geusebroek, J., van den Boomgaard, R., Smeulders, A., Geerts, H., “Color invariance”, *IEEE Trans. Pattern Analysis Machine Intelligence*, Vol. 23, pp. 1338-1350, 2001. https://doi.org/10.1109/34.977559.

[11] Van de Weijer, J., Gevers, T., Geusebroek, J., “Edge and corner detection by photometric quasi-invariants”, *IEEE Trans. Pattern Analysis and Machine Intelligence,* Vol. 27, pp. 625-630, 2005. https://doi.org/10.1109/TPAMI.2005.75 .

[12] Gevers, T., Stokman, H., "Robust histogram construction from color invariants for object recognition", *IEEE Trans. Pattern Analysis and Machine Intelligence,* Vol. 26, pp. 113-118, 2004. https://doi.org/10.1109/TPAMI.2004.1261083.
[13] Topi Maenpaa, Matti Pietikainen, "Classification with color and texture: jointly or separately", *Pattern Recognition,* Vol. 37, pp. 1629 – 1640, 2004. https://doi.org/10.1016/j.patcog.2003.11.011.
[14] Keuchel, J., Naumann, S., Heiler, M., & Siegmund, A., "Automatic land cover analysis for Tenerife by supervised classification using remotely sensed data", *Remote Sensing of Environment*, Vol. 86, No. 4, pp. 530–541, 2003. https://doi.org/10.1016/S0034-4257(03)00130-5.
[15] Chetima, M. M., & Payeur, P., "Automated tuning of a vision-based inspection system for industrial food manufacturing", *In: Instrumentation and Measurement Technology Conference (I2MTC)*, 2012 IEEE International. IEEE, pp. 210-215, 2012.
[16] Jin, J., Li, J., Liao, G., Yu, X., & Viray, L. C. C., "Methodology for potatoes defects detection with computer vision", *In: International symposium on information processing*, pp. 346-351, 2009.
[17] VG, Narendra. & Hareesh, K. S., "Quality inspection and grading of agricultural and food products by computer vision-A Review", *International Journal of Computer Applications* (0975–8887), 2(1), 2010.
[18] Arivu, C. V. G., Prakash, G., & Sarma, A. S. S., "Online image capturing and processing using vision box hardware: Apple grading", *International Journal of Modern Engineering Research*, Vol.2, No. 3, pp. 639-643, 2012.
[19] Brosnan, T., & Sun, D. W., "Improving quality inspection of food products by computer vision—a review", *Journal of food engineering*, Vol. 61, No.1, pp. 3-16, 2014. https://doi.org/10.1016/S0260-8774(03)00183-3.
[20] Du, C. J., & Sun, D. W., "Recent developments in the applications of image processing techniques for food quality evaluation", *Trends in food science & technology*, Vol. 15, No. 5, pp. 230-249, 2004. https://doi.org/10.1016/j.tifs.2003.10.006.
[21] Kumar, M., Bora, G., & Lin, D., "Image processing technique to estimate geometric parameters and volume of selected dry beans", *Journal of Food Measurement and Characterization,* Vol. 7, No. 2, pp. 81-89, 2013. https://doi.org/10.1007/s11694-013-9142-7.
[22] Deddy Wirawan Soedibyo, Usman Ahmad, Kudang Boro Seminar, Dewa Made Subrata I., "The Development of Automatic Coffee sorting system based on image processing and artificial neural network", *The International Conference on the quality information for competitive agricultural based production system and commerce*, pp. 272-275, 2010.
[23] Rafael Namias, Carina Gallo, Roque M Craviotto, Miriam R Arango, Pablo M Granitto, "Automatic Grading of Green Intensity in Soybean Seeds", *13th Argentine Symposium on Artificial Intelligence*, ASAI, pp. 96-104, 2012.
[24] Hong Chen, Jing Wang, Qiaoxia Yuan, Peng Wan, "Quality classification of peanuts based on image processing", *Journal of Food, Agriculture and Environment,* Vol. 9, No. 3&4, pp. 205-209, 2011.
[25] Castelo-Quispe, S., Banda-Tapia, J. D., López-Paredes, M. N., Barrios-Aranibar, D., & Patino-Escarcina, R. , "Optimization of brazil-nuts classification process through automation using colour spaces in computer vision", *International Journal of Computer Information Systems and Industrial Management Applications,* Vol. 5, pp. 623-630, 2013.
[26] Sun Da Wen, *Computer Vision Technology for Food Quality Evaluation*, Food Science and Technology, International series, Elsevier Inc. (2008).
[27] Shearer, S. A., & Holmes, R. G., "Plant identification using color co-occurrence matrices", *Transactions of the American Society of Agricultural Engineers*, Vol. 33, No. 6, pp. 2037–2044, 1990. https://doi.org/10.13031/2013.31574.
[28] Burks, T. F., Shearer, S. A., & Payne, F. A., " Classification of weed species using color texture features and discriminant analysis", *Transactions of the American Society of Agricultural Engineers*, Vol. 43, No. 2, pp. 441–448, 2000. https://doi.org/10.13031/2013.2723.
[29] Pydipati, R., Burks, T. F., & Lee, W. S., "Identification of citrus disease using color texture features and discriminant analysis", *Computers and Electronics in Agriculture*, Vol. 52, No. 1&2, pp. 49–59, 2006. https://doi.org/10.1016/j.compag.2006.01.004.