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A Mobile Product Image Searching System Integrating Speeded Up Robust Features and Local Binary Pattern

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Abstract

In this paper, we present a novel methodimage retrieval model for mobile product image searching system. For feature extraction, a method integrating Speeded Up Robust Features (SURF) and Local Binary Pattern (LBP) is proposed. SURF is invariant to rotation, scaling, translation and have low calculated cost, so SURF is quite suitable for mobile product image search model. However, SURF is not effective with the noisy images, blur images, illuminated images. Because LBP operator is invariant to changes in illumination and contrast of images, we use LBP to supplement for disadvantages of the SURF features. Our proposed method can improve accuracy and speed of the system. For query, a query model using K-NN Search with vector quantization is used. This model improve performance and reduce the cost of computation of the mobile product image searching system. The experimental results show the feasibility of our proposal model.

Keywords: Content-based Image Retrieval (CBIR), Feature Integration, K-Nearest Neighbor (K-NN), Local Binary Pattern (LBP), Mobile Product Image Search, Speeded Up Robust Features (SURF)

1. Introduction

Content-based image retrieval (CBIR) system is theimage retrieval system that based on automatically extracts some specific information in the image, such as colors, shapes, textures and key points. There are many approaches apply for CBIR. The approach using color features[1,2] hashigh efficiency calculation. This approach is invariable with rotation and scale. However, they do notconsider the content of images and spatial distribution of colors. Also, color features are not effective with imagenoise, blur, and deformed so this approachis not suitable for image retrieval model applies to the product image search system.The approach usingshape features[1] is visual with human perception. But it does not have mathematical basis for the deformed objects. Therefore, this approachis inconsistent to apply for the product image search model. The approach using texture features[1] can describe the spatial variations in the intensity of the pixeland the surface characteristics of the object. But the texture segmentation is still a difficult problem to meet human perception.

The advantages of the methodusing key point in image such as SIFT[3,4,5], SURF[6,7] are in variant to rotation, scaling, translation, distortion. SIFT determinesmore features than SURF, but has computational cost higher than SURF. Because our targetis to build animage retrieval modelfor mobile applications, so the method using SURF is quitesuitable for mobile product image search model. However, SURF is not effective with the noisy images, blur images, illuminated images. LBP[8,9] operator is a best texture descriptor that hasbeen applied to face detection, face recognition, face authentication, image retrieval. LBP operator is in variantto changes in illumination and contrast of images,

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has low calculated cost and supplement for disadvantages of the SIFT or SURF features.

In this paper, we propose the image retrieval models for product image searching system using SURF features and LBP features. This model will improve accurate and speed of the mobile product image search system. By using K-Nearest Neighbor Search with vector quantization, the mobile product image searching system will improve performance and reduce the cost of computation.

The paper is organized as follows. Section 2 presents related work, on which our results are founded. Section 3 presents the proposed image retrieval model. The experimental results are presented in section 4. Finally, section 5 show concludes the paper.

2. Background and Related Works

2.1 LBP Features

The original LBP operator was first introducedas a complementary measure for local image contrast[10]. It labels the pixels of an image by thresholding the 3x3 neighborhood of each pixel with the center value and considering the result as a binary number. Given a location (x, y) in an image, the gray values of neighbor pixels are compared with a threshold, which is the gray value of the pixel (x, y). If the gray value of the neighbor pixel is higher than the threshold, the output will be 1, otherwise the output will be 0. These binary outputs of these neighbor pixels are concatenated to form a binary code, so called Local Binary Pattern (LBP) of the location (x, y).

$$LBP(x_c, y_c) = \sum_{n=0}^{7} s(g_n - g_c)2^n \tag{1}$$

Where g_c is the gray value of the center pixel (x_c, y_c), g_n is the gray value of the neighbor pixel around the center pixel (x_c, y_c) and

$$s(x) = \begin{cases} 1 \; if x \geq 0 \\ 0 \; if x < 0 \end{cases} \tag{2}$$

Then, the operator was extended to have 2 arguments: R and N. R is distance between the pixel and its neighbors. N is the number of neighbor pixels around the centric pixel. The coordinates of p neighbor pixels is:

$$x_p = x_c + Rcos(\frac{2\pi p}{P}) \tag{3}$$

$$y_p = y_c + Rsin\left(\frac{2\pi p}{P}\right), \; p = \{0, 1, \ldots, \; P-1\} \tag{4}$$

Another extension of LBP is Uniform LBP. A LBP is called Uniform LBP if they have at most two bitwise transitions from 0 to 1 or 1 to 0. For example, the patterns 00000011 (1 transitions), 00000110 (2 transitions) and 11000000 (1 transitions) are uniform whereas the patterns 10000101 (4 transitions) are not.

2.2 SURF Features

Speeded Up Robust Features (SURF), proposedby Herbert Bay[11], is thekey points detector and descriptor. The main steps of SURF algorithm is as follows:

Fast Interest Point Detection: The SURF uses the Hessian matrix approximation for interest point detection. The Hessian matrix H(x, σ) in x= *(x,y)* at scale σ is defined as follows

$$H(\mathbf{x}, \sigma) = \begin{bmatrix} L_{xx} & L_{xy} \\ L_{xy} & L_{yy} \end{bmatrix} \tag{5}$$

Where L_{xx} is the convolution of the Gaussian second order derivative with the image I in point x, and similarly for L_{yy}, L_{xy}.

The determinant of the Hessian matrix is used to determine the location and scale of the interest point. The determinant of the Hessian matrix is computed as

$$\det(H_{approx}) = D_{xx}D_{yy} - (0.9.D_{xy})^2 \tag{6}$$

Interest Point Descriptor: The SURF feature descriptor uses Haar wavelet features. The Integral image is used to speed up calculations. Each key point is added an orientation to achieve invariance to image rotation.

2.3 Vector Quantization

A vector quantization is a function q mapped a vector $x \in R^{D \text{ into}}$ $q(x) \in C=\{c_i; \; i \in I\}$, where I ={1, ..., k}, D is the dimension of the vector. The values c_i is called centroid and C={c_1, ..,c_k} is called code book.

In this paper, we use K-Means algorithm to calculate the centroid c_i based on the feature vectors in the data base as follows:

Step 1: Selecting randomly K centroid $c_i(c_i \subseteq RD,\ i = 1..K)$ corresponding to the K clusters. Each cluster is represented by the centroid c_i of the cluster.
Step 2: Computing the distance between the feature vector to K centroids c_i (using Euclidean distance).
Step 3: Clustering feature vectors x_p to the nearest centroid c_i.

$$S_i^{(t)} = \left\{ x_p \,/\, x_p - c_i^t \le x_p - c_j^t \right\} \ (j = 1..K) \qquad (7)$$

Step 4: Identify the new centroid for the cluster.

$$c_i^{(t+1)} = \frac{1}{\left|S_i^t\right|} \sum_{x_j \in S_i^{(t)}} x_j \qquad 8$$

where t is the number of iterations.

Step 5: Repeat step 2 until no change cluster of feature vectors.

3. The Proposed Image Retrieval Model

3.1 SURF_LBP Feature Integration

Our target is to build an image retrieval model for mobile applications. Therefore, the product image search system using SIFT features is not consistent for our model because it has high cost. So it will take more times than the mobile product image searching system using SURF. However, SURF is not effective when the image is noise, blur and illuminated. So we propose a method using SURF and LBP may improve accurate and speed for the system. The main step of our proposed method is as follow:

Step 1, we detect key points of images by using SURF method and present each key point Kp_i as a 64–dimensional vector $SURF_i$.
Step 2, we take the 8x8 region around Kp_i, then we compute the uniform pattern of each pixel from this region and use a 64-dimensional vector to present it:

$$LBP_i = \{LBP_{8,1}^{u_1},\ LBP_{8,1}^{u_2}, \ldots, LBP_{8,1}^{u_{64}}\} \qquad (9)$$

Step 3, we integrate vector $SURF_i$ and vector LBP_i to a 128-dimensional vector.

$$SURF\_LBP_i = \{SURF_i LBP_i\} \qquad (10)$$

Figure 1 shows the process of SURF_LBP feature Integration.

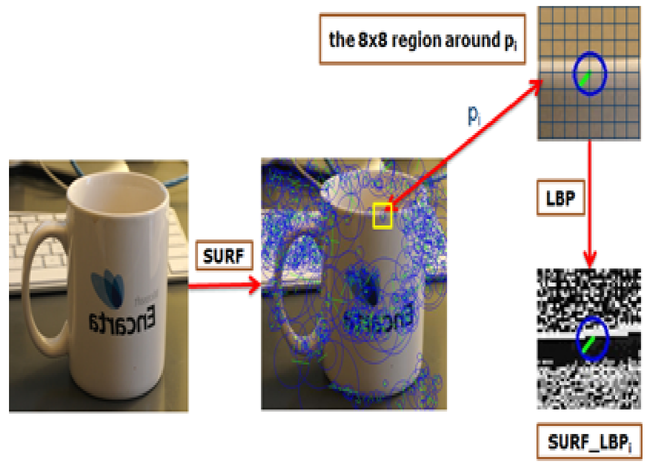

Figure 1. The process of SURF_LBP Feature Integration.

3.2 K-Nearest Neighbor Search using Vector Quantization

After extracting features of images, we use K-Nearest Neighbor (K-NN) search using vector quantization to query product images. The querying process includes two phases as follows:

Phase offline - Feature extraction and feature vector quantization for the image in the database: First, we extract feature vectors of the images in the database (the feature vector SURF_LBP). Then, we use K-Means algorithm to quantize feature vectors into centroid $c_i = q(x)$ in the Codebook.

Phase Online - K-Nearest Neighbor Search using Vector Quantization: First, we extract feature vector of the query image. Next, we calculate the measure of similarity between the query feature vector and the centroid c_i in the Codebook based on the formula (11). Then, we get the Top-N centroids c_i closet the query feature vector. Then, we choose the images in a data set that corresponds to those centroids. Next, we calculate the measure of similarity between the query feature vector and the feature vector of those images based on the following formula:

$$d(x, y) = \sqrt{\sum_{i=1}^{n} |x_i - y_i|^2} \qquad (11)$$

where d (x, y) is the Euclidean distance between two vectors x and y.

Finally, we get the Top-K images closest the query image.

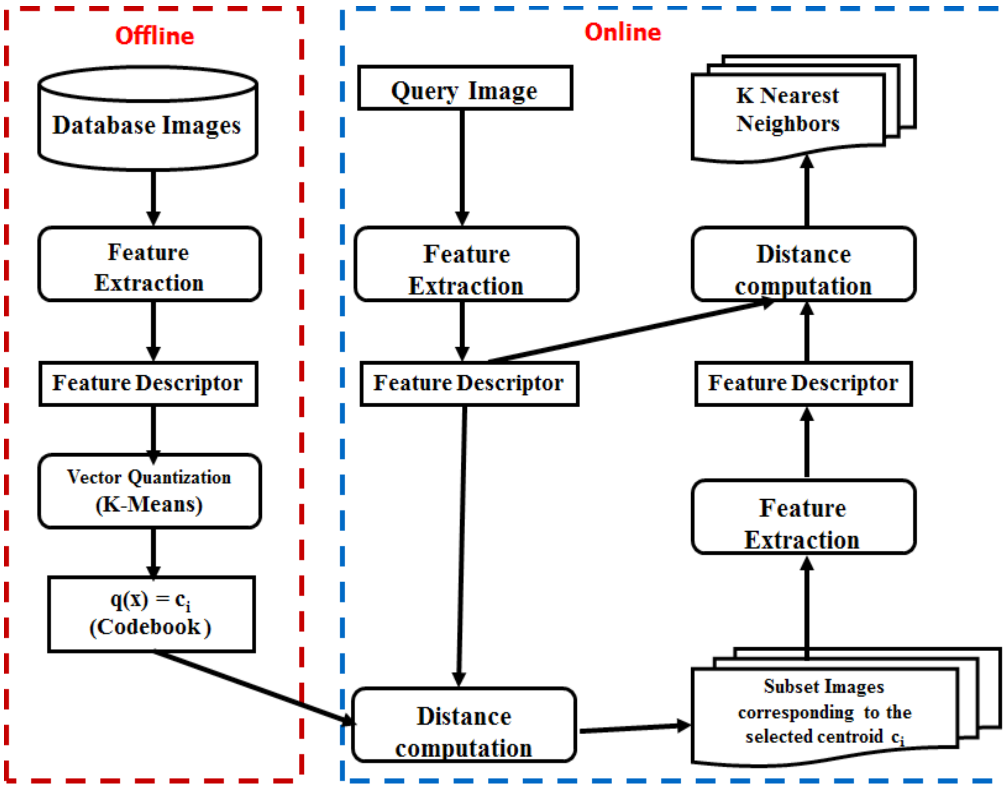

Figure 2. below shows the proposed image retrieval model.

The proposed image retrieval model based on K-NN search with product quantization using *SURF_LBP* integrations.

Our proposed model will greatly reduce the computational cost that increases the speed of mobile product image searching system because the calculation of similar measurements are only performed between the query feature vector and the centroid c_i instead with all feature vectors of the image in data set. So the scope of the search on the data set will be narrowed to a sub set corresponding to the selected centroids.

4. Experimental Results

In our research, we use the dataset is described in section 4.1. The proposed method and other methods are implemented on Samsung Note 5 with CPU Exynos 7420 Octa-Core 2.1 GHz, Ram 4GB and OS Android 5.1.1 (Lollipop).

4.1 Dataset

We choose 868 product images from Caltech256 dataset[12]. Each product image has clean background and the objects positioned at the image center. The Figure 3 shows some examples of dataset.

Figure 3. Some example of dataset

We use precision (P), average precision (AP), mean average precision (MAP) and searching times to evaluate the performance of our proposed models.

$$P = \frac{|\{relevant\ images\} \cap \{retrieved\ images\}|}{|\{retrieved\ images\}|} \quad (12)$$

$$AP = \frac{\sum_{k=1}^{n} P@kxI(k)}{\sum_{j=1}^{n} I(j)} \quad (13)$$

Where P@k is the precision at rank k, I(k) is an indicator function equaling 1 if the item at rank k is a relevant object, zero otherwise.

$$MAP = \frac{\sum_{q=1}^{Q} AP_i}{Q} \quad (14)$$

where Q is the number of queries.

4.2 Experiments of Proposed Model using SURF_LBP Features

We used our proposed model to make10 queries for each specific product category. Then, we compared our method with the method using SIFT feature, the method using SURF feature. Table I show the mean average precision and searching times at rank 5, rank 10, rank 15 of other methods and our method. The proposed model using SURF_LBP features have mean average precision higher than other methods and have searching times better than SIFT method.

The average precision of other methods and our methods Figure 4 shows the mean average precision of our method and other methods.

		SIFT + KNN		SURF + KNN		SURF_LBP + KNN	
		MAP	Times (s)	MAP	Times (s)	MAP	Times (s)
Mug	Top-5	**0.707**	**0.335**	**0.467**	**0.130**	**0.703**	**0.260**
	Top-10	0.607	0.289	0.524	0.135	0.623	0.254
	Top-15	0.579	0.334	0.505	0.141	0.593	0.256
Teddy bear	Top-5	0.635	0.288	0.598	0.157	0.696	0.195
	Top-10	0.624	0.294	0.585	0.194	0.684	0.191
	Top-15	0.597	0.297	0.558	0.201	0.647	0.192
T-Shirt	Top-5	0.857	0.405	0.717	0.190	0.830	0.316
	Top-10	0.741	0.408	0.701	0.194	0.799	0.318
	Top-15	0.698	0.408	0.675	0.203	0.737	0.327
Back – pack	Top-5	0.754	0.400	0.545	0.284	0.961	0.370
	Top-10	0.762	0.395	0.562	0.263	0.869	0.384
	Top-15	0.758	0.404	0.527	0.279	0.822	0.397
Head - phone	Top-5	0.830	0.395	0.689	0.229	0.928	0.399
	Top-10	0.785	0.394	0.694	0.241	0.891	0.379
	Top-15	0.766	0.401	0.688	0.244	0.869	0.393

Watch	Top-5	0.792	0.347	0.778	0.238	0.955	0.219
	Top-10	0.785	0.362	0.774	0.243	0.922	0.228
	Top-15	0.750	0.363	0.743	0.248	0.904	0.246
DVD Player	Top-5	0.916	0.299	0.157	0.201	0.868	0.288
	Top-10	0.834	0.300	0.291	0.195	0.843	0.291
	Top-15	0.813	0.290	0.334	0.207	0.811	0.300
Total ARP		0.742	0.349	0.572	0.208	0.811	0.294

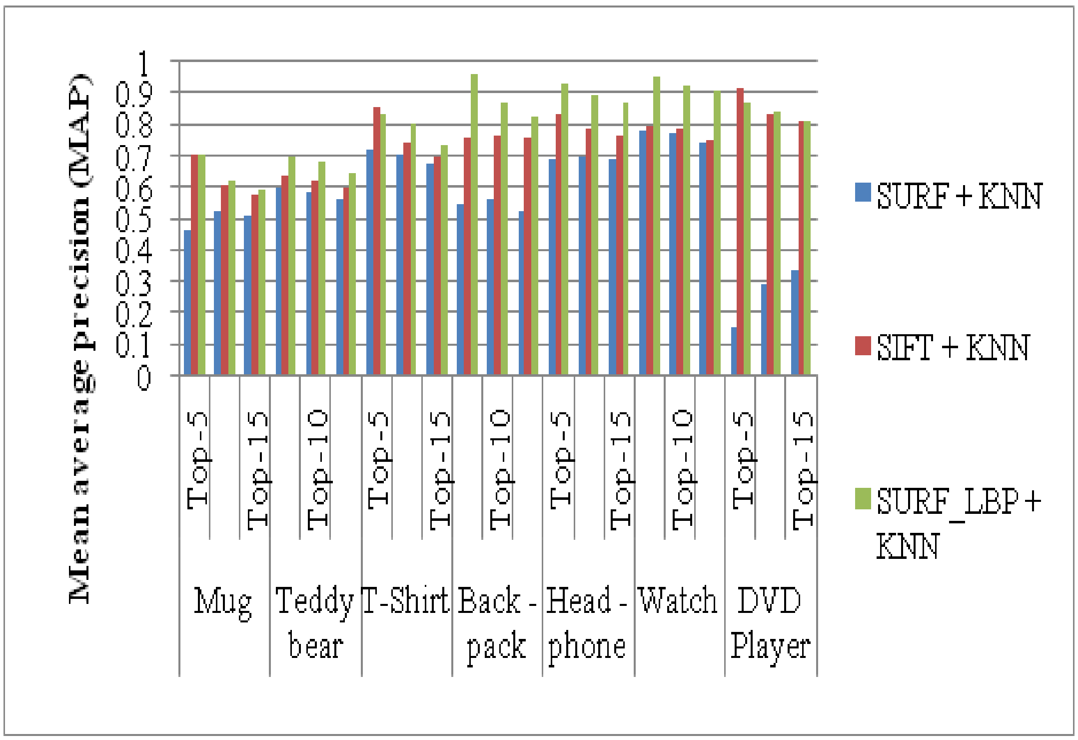

Figure 4. Performance evaluation of other methods and our method: Mean average precision.

We continue to experiment with 10 random queries and compared our method with the method using SIFT feature, the method using SURF feature. Table II show the precision and searching times at rank 5, rank 10, rank 15 of our proposed method and other methods. The proposed method has highest precision and the good searching times. Figure 5 shows the precision of our method and other methods.

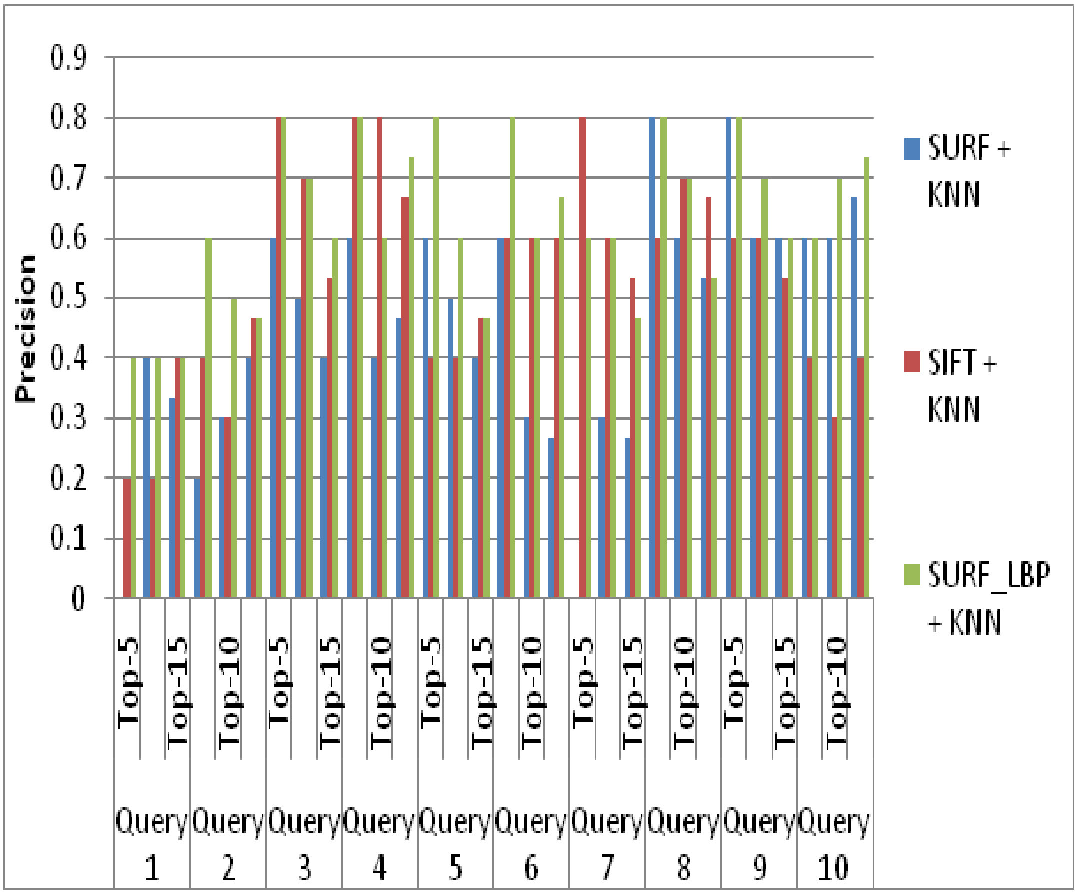

Figure 5. Performance evaluation of other methods and our method: Average precision.

The average precision of other methods and our methods

		SIFT + KNN		SURF + KNN		SURF_LBP + KNN	
		Precision	Times (s)	Precision	Times (s)	Precision	Times (s)
Query 1	Top-5	0.200	0.366	0.000	0.154	0.400	0.254
	Top-10	0.200	0.370	0.400	0.146	0.400	0.285
	Top-15	0.400	0.402	0.333	0.151	0.400	0.399
Query 2	Top-5	0.400	0.309	0.200	0.134	0.600	0.268
	Top-10	0.300	0.339	0.300	0.127	0.500	0.348
	Top-15	0.467	0.368	0.400	0.136	0.467	0.305

Query 3	Top-5	0.800	0.322	0.600	0.173	0.800	0.173
	Top-10	0.700	0.349	0.500	0.165	0.700	0.243
	Top-15	0.533	0.327	0.400	0.201	0.600	0.207
Query 4	Top-5	0.800	0.446	0.600	0.238	0.800	0.175
	Top-10	0.800	0.378	0.400	0.224	0.600	0.387
	Top-15	0.667	0.384	0.467	0.276	0.733	0.213
Query 5	Top-5	0.400	0.391	0.600	0.209	0.800	0.222
	Top-10	0.400	0.429	0.500	0.217	0.600	0.301
	Top-15	0.467	0.376	0.400	0.215	0.467	0.333
Query 6	Top-5	0.600	0.398	0.600	0.245	0.800	0.212
	Top-10	0.600	0.425	0.300	0.242	0.600	0.422
	Top-15	0.600	0.499	0.267	0.188	0.667	0.260
Query 7	Top-5	0.800	0.344	0.000	0.236	0.600	0.232
	Top-10	0.600	0.327	0.300	0.238	0.600	0.345
	Top-15	0.533	0.423	0.267	0.186	0.467	0.327
Query 8	Top-5	0.600	0.368	0.800	0.270	0.800	0.281
	Top-10	0.700	0.397	0.600	0.273	0.700	0.349
	Top-15	0.667	0.385	0.533	0.264	0.533	0.490
Query 9	Top-5	0.600	0.367	0.800	0.262	0.800	0.363
	Top-10	0.600	0.412	0.600	0.279	0.700	0.313
	Top-15	0.533	0.361	0.600	0.208	0.600	0.296
Query 10	Top-5	0.400	0.455	0.600	0.235	0.600	0.386
	Top-10	0.300	0.492	0.600	0.221	0.700	0.233
	Top-15	0.400	0.404	0.667	0.187	0.733	0.283
Total ARP		**0.536**	**0.387**	**0.454**	**0.210**	**0.626**	**0.297**

We also compared our method with the object extraction method[13], and the spatially-constrained method[14]. Table III show the precision of our proposed method and other methods.

The average precision of other methods and our methods

Method	AP
Object Extraction[13]	0.491
Spatially-constrained model [14]	0.277
SIFT + K-NN	0.536
SURF+K-NN	0.454
SURF_LBP + K-NN (Our proposed method)	0.626

Figure 6 shows the average precision of our method and other methods.

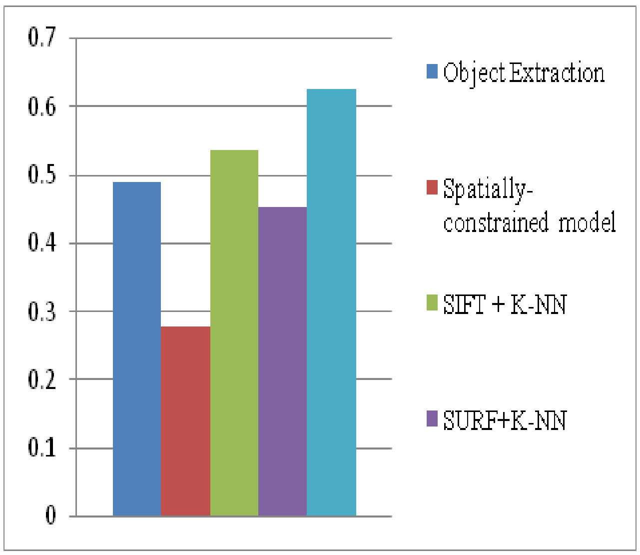

Figure 6. Compare proposed method with other methods..

5. Conclusions

In this paper, we have proposed an image retrieval model for mobile product image searching system integrating SURF feature and LBP feature. This model will improve accuracy and speed of the mobile product image searching system. Beside, by using K-NN Search with vector quantization, the mobile product image searching system will improve performance and reduce the cost of computation. The experimental results showed the feasibility of our proposal model.

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