

PH. D. THESIS ABSTRACT

Methodologies for Reducing the Amount of Required Images Used for Articled-Object Recognition

Metodologías para la Reducción del Número de Imágenes Requeridas para el Reconocimiento de Objetos Articulados

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Abstract

The appearance-based approaches are such that any object's model is made through a set of training images describing the object's appearance. In this PhD. thesis, the usage of non-uniform sampling is introduced for building this image set. Non-uniform sampling is held by a linear interpolation technique, which is used to determine the strictly necessary images. Main results are: a significant reduction in the quantity of necessary images for the object's model, as well as more precise models than those obtained by uniform sampling. Non-uniform sampling is used in conjunction with the eigenspaces technique for object recognition, producing a more efficient hybrid technique.

Keywords: non-uniform sampling, object recognition, appearance-based model, interpolation, eigenspaces.

Resumen

Los enfoques basados en apariencia construyen el modelo de un objeto, por medio de un conjunto de imágenes de entrenamiento que describe la apariencia del objeto. En esta tesis doctoral se propone el empleo del muestreo no-uniforme para generar tal conjunto de imágenes. El muestreo no-uniforme es soportado mediante una técnica de interpolación, que determina cuáles son las imágenes estrictamente requeridas para construir el modelo. Los resultados principales obtenidos con esta propuesta son: una reducción significativa de la cantidad de imágenes requeridas para construir el modelo del objeto, además de una mejora en la precisión de los modelos así generados, respecto a los obtenidos con muestreo uniforme. El muestreo no-uniforme es empleado junto con la técnica de espacios fundamentales (*eigenspaces*) para realizar el reconocimiento del objeto, obteniéndose una técnica híbrida más eficiente.

Palabras Clave: non-uniform sampling, object recognition, appearance-based model, interpolation, eigenspaces.

1 Introduction

Geometrical approaches have been widely used in computer vision for object recognition. However, they have two main disadvantages: segmentation errors and loss of information contained in the image caused by the segmentation. Appearance-based approaches were proposed for object recognition, as an alternative for the geometrical approaches, to avoid such disadvantages (Shapiro and Costa, 1994).

Several appearance-based methods have been proposed in the literature. The simplest method is the correlation of an image with an object template. The so-called eigenspace approach was introduced in (Turk, 1991; Murase and Nayar, 1995). Patch detection was employed in (Nelson and Selinger, 1997). Neural nets have also been explored (Pauli *et al.*, 1995; Poggio and Beymer, 1996). Probabilistic techniques were also introduced (Moghaddam and Pentland, 1996; Pope and Lowe, 1996). Several methods have been proposed in the literature for object recognition without previous segmentation (Ohba and Ikeuchi, 1996; Schiele and Crowley, 2000).

Appearance-based techniques use an image set taken from the objects to be processed, and they build the corresponding models using the image set. The acquisition of the image set is usually carried out by means of a discrete and uniform sampling of images (equally spaced), taken around the object, and independent of object's characteristics (Stevens and Beveridge, 2000), so, for any object, the quantity of images is supposed to be an independent constant of the object type.

However, image acquisition could be object-dependent. This can be observed while considering extreme examples of objects that require only one image to build their model, for example, a homogeneously colored sphere. In contrast, there are objects of great complexity in their appearance,

which need a large number of images. Current techniques do not take into account this information and, therefore, such techniques require a constant time to build the model of any object, without depending on the object complexity.

So far in the current literature, efforts towards reduction of the quantity of characteristic views have been made (Epstein *et al.*, 1995; Belhumeur and Kriegman, 1998). However, if viewing position (instead illumination) is changing, no characterization is done. For working on view position changes of the object, diverse techniques on image synthesis have been introduced. However, there are several differences between the appearance-based approach and image synthesis.

Several techniques for modeling objects with less views have been introduced for object recognition (Koenderink and Van Doorn, 1979; Murase and Nayar, 1995), however, they are computationally expensive and hard to use; recently, have been presented some works to determine how many and which images are necessary to model an object. However, their application is restricted to specific objects as faces (Cootes *et al.*, 2000), or they only work with the object's shape (Mokhtarian and Abbasi, 2000).

We propose the use of non-uniform sampling to reduce the quantity of necessary images for object modeling and recognition. Non-uniform sampling is supported by a simple proposed technique, which determines the required images to approximate the object's appearance within a given error (ϵ). A linear interpolation and SSD-distance criterion guides the images election.

Non-uniform sampling has been widely used in diverse areas, as approximation theory or image processing and image synthesis, but not in the context of appearance-based object recognition. Although interpolation has been widely used in digital image interpolation techniques, we propose the usage of interpolation as criterion of selection, instead of using it only as a technique to obtain interpolated images. Object recognition is made by using the eigenspaces technique to show the usage of the proposed technique. Experimental results show that reduction in the quantity of required views can be possible, if the behavior of the object's appearance is taken into count, and no pose estimation is necessary.

2 Preliminaries

2.1 Interpolation

Definition 1: A trajectory in \mathbf{R}^n is a function $\sigma: [a, b] \rightarrow \mathbf{R}^n$. The points $\sigma(a)$ and $\sigma(b)$ are trajectory's extremes.

Definition 2: Let $\sigma_1: [a, b] \rightarrow \mathbf{R}^n$ be a trajectory. Let $C = \{(x_1, y_1), (x_2, y_2), \dots, (x_m, y_m)\}$ be such that $\sigma_1(x_i) = y_i$, for $i=1, \dots, m$, with $x_1 \leq x_2 \leq \dots \leq x_m$. We say that a trajectory $\sigma_2: [a, b] \rightarrow \mathbf{R}^n$, interpolates $\sigma_1(x)$ inside the

interval $[x_1, x_m]$, if $\sigma_2(x_i) = y_i$, for $i=1, \dots, m$.

Notice that $\sigma_2(x)$ is not uniquely determined. For this reason, for an ϵ given, $\sigma_2(x)$ is selected such that $|\sigma_1(x) - \sigma_2(x)| < \epsilon$, for all x in $[x_1, x_m]$. Such ϵ is named the associated interpolation error. If the trajectory $\sigma_2(x)$ that interpolates $\sigma_1(x)$ is a straight line, interpolation is linear; otherwise, it is non-linear.

Sometimes, it is impossible to find a trajectory $\sigma_2(x)$ that meets the error criterion given inside the interval. In this case, the interpolation problem of $\sigma_1(x)$ is changed for the $\sigma_1(x)$ *piecewise interpolation problem*: it is necessary to find a set of $m-1$ trajectories $\sigma_2(x), \sigma_3(x), \dots, \sigma_m(x)$, that interpolate $\sigma_1(x)$, respectively, in the intervals $[x_1, x_2], [x_2, x_3], \dots, [x_{m-1}, x_m]$, within the tolerance ϵ .

Definition 3: Let $\mathbf{X} = (x_1, x_2, \dots, x_n)$ and $\mathbf{Y} = (y_1, y_2, \dots, y_n)$ be two vectors in \mathbf{R}^n . The SSD distance (sum-of-squared-difference) between \mathbf{X} and \mathbf{Y} is defined by:

$$\|\mathbf{X} - \mathbf{Y}\|^2 = \sum_{i=1}^n (x_i - y_i)^2$$

2.2 Eigenspaces Overview

The eigenspaces technique (Murase and Nayar, 1995) comprises a set \mathbf{I} of training images into a compact representation that captures the key appearance characteristics of the object. Although uniform sampling was used in (Murase and Nayar, 1995), the set \mathbf{I} can be a uniform or non-uniform sampling of the visual workspace. This compression process is computationally intensive, and its complexity depends on the size of \mathbf{I} (if the size of \mathbf{I} is smaller than the number of pixels that constitutes the images, otherwise, depends upon the number of pixels). For this reason, reducing the size of \mathbf{I} is desired, as it was proposed in (Altamirano *et al.*, 2003) by means of non-uniform sampling.

3 Image Acquisition

In order to generate appearance-based models of an object, we begin with the object image acquisition. By taking images around the object, the acquisition is carried out. The object rotates in front of the camera (or the camera rotates around the object) for an angle θ_i , respect to a fixed initial position to take the i^{th} -image \mathbf{I}_i , with $i=1, \dots, r$ and $\theta_{i-1} < \theta_i$. The camera and the illumination source can be moved around the object, before object modeling. However, when the image acquisition process begins, both positions must stay fixed in the rest of image acquisition process and in the recognition phase. In addition, the background of images acquired to model the object is usually controlled.

The images acquired in the upper half sphere $\mathbf{I}_1, \dots, \mathbf{I}_r$ are represented as $n \times m$ matrixes, and matrix's columns are stacked to form vectors $\mathbf{v}_1, \dots, \mathbf{v}_r \in \mathbf{R}^{nm}$. Looking at the

Definition 1, we can see that such vectors belong to a trajectory $\sigma: [0, 2\pi] \rightarrow \mathbb{R}^m$ parameterized for the angle θ of the object rotation in front of the sensor, regarding a fixed initial position. This trajectory is called in the literature **the trajectory determined by object's appearance**, or simply, **object's appearance**.

Usually, proposed techniques for object recognition assume for simplicity, that $\theta_i - \theta_{i-1} = k$, with k a constant, which means that the object always rotates to the same angle (with respect to the current position), in order to capture the next image. Typical values found in the literature for k oscillate between 5° and 12° . These values are based on empiric observations, and therefore do not present any formality to set them. Moreover, this value is fixed and independent of the object class (texture, shape, color, etc.).

Acquiring images in a uniform way supposes a large storage capacity and required time for model calculation.

4 Non-Uniform Image Acquisition

To overcome the previously commented limitations, we propose to use non-uniform sampling for modeling the object's appearance (Altamirano *et al.*, 2003). Non-uniform sampling is supported through of a simple proposed technique that adapts the value of the angles θ_i according to the object's appearance and precision requirements.

This technique is based on the observation that object's appearance can be approximated by means of piecewise linear interpolation (see Definition 2), within an error ε . Of course, it is possible to create another techniques to support non-uniform sampling, probably, using non-linear interpolation, but we propose this technique as an easy way of exploring non-uniform sampling.

The technique starts with the acquisition of a couple of images denoted by \mathbf{X} , \mathbf{Y} , taken at 0° and 180° , respectively. Next, the technique interpolates linearly between \mathbf{X} and \mathbf{Y} using the function:

$$g(\lambda) = \lambda\mathbf{X} + (1-\lambda)\mathbf{Y}; \quad 0 \leq \lambda \leq 1.$$

Later, we take another image \mathbf{Z} in the middle point (90°), and compare \mathbf{Z} to the image \mathbf{Z}' obtained by linear interpolation at the same point, which corresponds to $g(0.5)$. If SSD (see Definition 3), between \mathbf{Z} and \mathbf{Z}' is smaller than ε , the algorithm determines that only a couple of images are required to approximate object's appearance between 0° and 180° . If this condition is not fulfilled, the interval is divided into 2 parts: the first one contains the images between 0° and 90° whereas another part includes the images between 90° and 180° . In a similar way an analysis is made for the images included between 180° and 360° . The process is iterative analyzing each new interval generated. The algorithm finishes when it is possible to approximate the object's appearance within an error ε . A complete description of the algorithm can be found in (Altamirano *et al.*, 2003).

4.1 Automatic Determination of Precision

The proposed technique requires a precision value ε , to start, but the precision that should be used for each particular object cannot be known *a priori*. So, in order to the system automatically suggests a precision value, some strategy is claimed. In (Altamirano *et al.*, 2003), we introduce two statistical strategies for the system that automatically determines one value for this precision. These strategies will work alongside as the proposed technique does. Both strategies are based on the observation that the k first images acquired by the proposed technique can be used to obtain information, about local variations in object's appearance. Such information can be used to estimate a precision value. The first one approximates the average of k samples, and the second one approximates the maximum precision using the physical limit of the rotation system. In both cases, estimation will be best if k is bigger.

4.2 Generalized Non-Uniform Sampling

In previous Sections, we supposed that the object is in the turntable center, and the object rotates in front of the camera. Moreover, we supposed that camera was in a fixed position with respect to turntable, and stays static. Finally, we supposed that the illumination source was fixed with respect to the camera and the turntable. However, we can notice that if are removed any or all of these suppositions, the object's appearance would be defined for several parameters, and the exposed technique in Section 3 cannot applicable anymore. Some parameters could be considered (but not restricted to) include: Turntable angle, Camera elevation angle (relative to turntable plane), Position of illumination source, Position of any part of an articulated object, etc. We proposed the generalization for working on N parameters of the basic technique exposed in Section 3. Of course, because we are considering N parameters, several changes are claimed. A complete description of this generalized case can be found in (Altamirano *et al.*, 2002).

4.3 Non-Uniform Sampling and Eigenspaces

We mentioned that the technique of eigenspaces is computationally intensive, and thereby, the proposed technique can be used to reduce the required time for the model calculation, improving also its precision. The technique of eigenspaces can use the determined images by the proposed algorithm as its training set of images, instead of the larger number used currently. Notice that it is only true, if pose estimation doesn't matter, but the proposed technique can be easily modified, to verify good approximation in both parameter and appearance spaces. Of course, in this case, image quantity reduction may be not significant. However, in several applications where pose estimation no matters, the computation of eigenspaces will be faster using a non-uniform sampling.

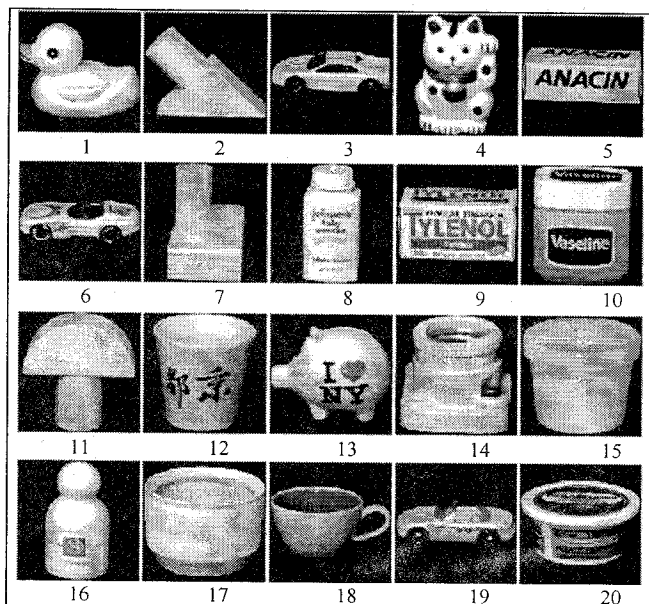


Figure 1: Some objects taken from Columbia Object Image Library (Nayar *et al.*, 1996) used to study non-uniform sampling

5 Experimental Results

A software system that acquires the necessary images for modeling the appearance of objects was developed. The software was coupled to a motorized turntable that rotates the object. The rotation system received the commands of the software in order to acquire images in the positions determined by the algorithm. The software system determines how many and which images are required to satisfy the precision criterion ϵ , for each object studied. The number of images founded by the proposed technique represents a significant reduction with respect to traditional approaches. Of course, this number will correspond to required precision for the object model. In addition to the number of images, the algorithm determines *which* images are required for each particular object, and for each value of the error ϵ . To experiment the proposed technique, only two parameters were used: turntable angle and camera elevation angle.

The proposed technique was applied to a large image base (about 50 objects); 20 objects of it are shown in Figure 1. In Table 1 are shown experimental results for objects in Figure 1 (only one parameter: turntable rotation). Notice the significant reduction achieved with non-uniform sampling respect to uniform sampling.

Object number	Maximum precision (36 images)	Number of necessary images	
		Uniform sampling	Non-Uniform sampling
1	2073	36	32
2	3514	36	27
3	5103	36	18
4	2945	36	26
5	5252	36	23
6	7282	36	18

7	2360	36	31
8	2152	36	25
9	5817	36	26
10	3287	36	22
11	2509	36	29
12	2319	36	11
13	4164	36	22
14	3448	36	26
15	1445	36	6
16	1267	36	13
17	2733	36	6
18	2545	36	26
19	4655	36	18
20	3647	36	9

Table 1: Comparison between uniform and non-uniform sampling.

6 Conclusions

Non-uniform sampling was introduced as a fast way for building appearance-based models when pose estimation doesn't matter. A simple technique has been presented for non-uniform image acquisition of an object; the technique is based upon linear interpolation and is used to determine the strictly necessary images to capture object's appearance, within a defined error ϵ , and to diminish the buffered images. Also it was shown how the technique can be used together with the eigenspaces technique, for reduction of computational time used in model construction.

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