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Classification of User Interface Elements by Calculating Variance

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Abstract: ***The image classification has been a difficult problem to deal in the last decades, since it requires in the most of cases the application of complex and sophisticated algorithms as well as large computational resources. In this paper we propose a series of techniques for the classification of different elements used in the creation of user interfaces, which do not require large computational resources so they are quick and can be parallelized. These techniques consist of: a) isolating the image by extracting the area that contains the sketches of user interface elements made by freehand eliminating areas that do not contain information, b) obtaining representative areas from histograms that represent the sketches, c) standardize the information contained in the histograms, d) calculate the variance of the information of the histograms and e) disassociate this information so that finally be used to carry out a classification. The application of this set of techniques gives us a quick result to classify sketches of user interfaces.***

Keywords: Image classification, sketch, histograms, distribution, user interfaces

1. Introduction

In the recent decade, image classification has become a hot research topic in the computer vision field [1].Image recognition and classification has been a popular research subject in the image processing and the application area. With the development of globalization and emergence of various kinds of portals, there is a drastic increase of images. Therefore, it brings great challenges to the image recognition and classification [2].

In image processing histogram is the common way of probability density estimation. It often appears as one of the processing steps in many algorithms such as color correction, binarization, clustering, classification and etc. In classification it usually plays the role of particular object feature (local histogram) or it is used as an empirical estimation of the probability density function (PDF) (global histogram).Existing image classification algorithms exploiting histograms can be divided into several groups. The first group includes the algorithms that produce density estimation for each class separately. Many of them are supervised algorithms which receive the histogram for each class using predefined training sample. Derived probability distribution estimations allow to apply statistical classification algorithms such as Bayesian classifier or maximum likelihood classifier. The second group contains classifiers based on the probability distribution mixture model. This model assumes that entire input dataset probability density function can be presented as the weighted sum of the density functions for each class [3].

In many real-world applications of classification problems, we face the problem that obtaining labels is more difficult than collecting input data: we can easily acquire a large amount of such input data, but labeling these instances is quite burdensome, time- consuming, or expensive. For a large part, this is because of the heavy involvement of human supervision during the labeling process [4].

To solve the problem of image set classification, many researchers have proposed a great deal of methods. According to the type of representations, existing methods can mainly be categorized into two classes, namely parametric-models and non-parametric-models. The parametric-models use a certain statistical distribution model to formulate each image set and then adopt measurements such as KL divergence to measure the similarity between two image sets. Their performance is greatly influenced by the statistical relationship between the query and training sets and a bad result will be produced ifthere does not exist a strong one.The non-parametric models do not rely on the statistical relationshipand represent an image set either by its representative exemplarsor on a geometric surface. For methods which model a complete imageset as a point on a geometric surface, either of the followingforms, namely a subspace, mixture of subspaces or a complex nonlinearmanifold, can be adopted to represent different sets [5].

The research the applications of image segmentation has led to many different techniques, which can be broadly classified into histogram based, edge based, region based, clustering, and combination of these techniques. Large number of segmentation algorithms is present in the literature, but there is no single algorithm that can be considered good for all images. Algorithms developed for a class of images may not always produce good results for other classes of images [6].Set-based visual classification has shown its superior performance relative to traditional single-image-based classification under the same conditions since it can provide considerably more within-set discriminative information [7].

2. Methodology

In this section we are going to explain the methodology to the classification of image: a) isolation of the image, b)obtaining histograms c) standardization d) obtaining variance and e) dissociate points.

2.1 Isolation of the image

Focusing on feature extraction, we listed the following two aspects: the segmentation which is the data extraction phase such that the image is isolated (foreground / background detection) and the types of features used (if they are local, global and what information they model)[8].Feature extraction is one of the most critical steps in image classification,for this reasonit is necessary to know which zone of the image is important.

For our purpose in this work, hand-made sketches of elements that were used for the creation of a user interface were made. In order to apply the proposed techniques to these sketches it is necessary to eliminate the areas that do not contain sketch information to only work with the important area, in Figure 1 examples of this procedure are shown where you have three different figures to which the area without information was eliminated keeping only the part where is the sketch. Absolute location of features is useful for a variety of image parsing problems [9], however, in this work, the location where the sketch is made within the work area is not required, since when isolating the image, the position will be eliminated.

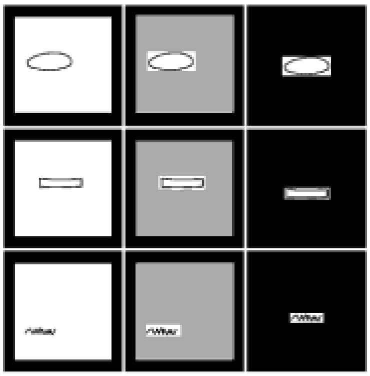


Figure 1: The gray area around the images is deleted.

2.2 Obtaining histograms

A local histogram of an image is a histogram of the values of the pixels that lie in a neighborhood of a given pixel's location. It indicates the particular combination of pixel intensities or colors that appear in that neighborhood. When used as features in an image classification scheme, such histograms can help distinguish one texture from another [10].

Each sketch is represented by two histograms one of the X coordinates and one of the Y coordinates of the sketch image, these histograms are obtained from the following equations. The first histogram is obtained with equation 1, which is the sum of the pixels on the Y axis that lie along the X axis of the image. The second histogram is obtained with equation 2, which is the sum of the pixels of the X axis that lie along the Y axis of the image. Equation 3 and 4 are the vectors that contain the values of the summations of equations 1 and 2.

$$g_{x\{1,2,3...n\}} = \sum_{y=0}^{y=n} Img_{x_{\{1,2,3...n\}}y} \quad (1)$$

$$g_{y\{1,2,3...n\}} = \sum_{y=0}^{y=n} Img_{y_{\{1,2,3...n\}}x} \quad (2)$$

$$\vec{g}_x = [g_{x1}, g_{x2}, g_{x3}, \cdots g_{xn}] \quad (3)$$

$$\vec{g}_y = [g_{y1}, g_{y2}, g_{y3}, \cdots g_{yn}] \quad (4)$$

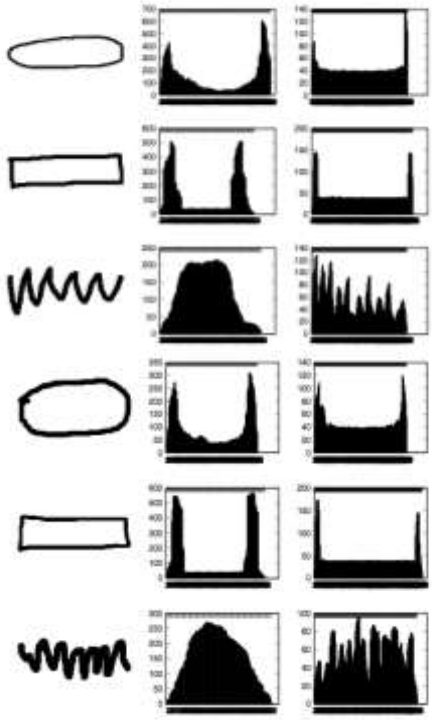


Figure 2: Histograms obtained from different sketches (size and shape)

2.3 Standardization

The hand-made sketches do not have the same dimensions,even though they had already been isolated and had been extracted only the image,not all users will make these sketches of the same size,some will occupy the entire work area and others only one tenth,so some images will be very large and others small,for this it is necessary to standardize its size, that is, the size of $\vec{g}_x$ and $\vec{g}_y$of each sketch must be the same,either the representation of a button, a text or a text entry.

2.4Obtainingvariances

For the representation of each image by means of a point on a graph (See Section 3) the variance of the vector $\vec{g}_x$ and $\vec{g}_y$ of each sketch is obtained.

The variance is calculated as follows:

$$SS_n^2 = \frac{SS_n}{n-1}, n \geq 2 \quad (3)$$

Where $SS_n = \sum_{i=1}^{n}(x_i - \bar{x}_n)^2$, $\bar{x}_n = \frac{1}{2}\sum_{i=1}^{n} x_i$. Equation (3) inquires two passes through the data: first to compute $\bar{x}_n$and then to sum the terms $(x_i - \bar{x}_n)^2$[11].

2.5 Dissociate points

To display a correct classification of coordinates they were labeled by points (show Table 1) where t (text), e (text entry) and b (button) are the results of the variance obtained previously.

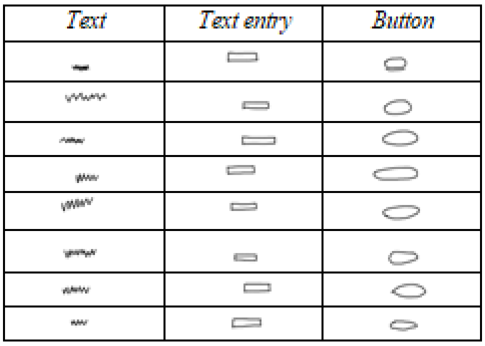
Table 1: Coordinates of each element to be plotted

Text entry	*button*	*text*
(x_{e1},y_{e1})	(x_{b1},y_{b1})	(x_{t1},y_{t1})
(x_{e2},y_{e2})	(x_{b2},y_{b2})	(x_{t2},y_{t2})
. . .	. . .	. . ..
(x_{en},y_{en})	(x_{bn},y_{bn})	(x_{tn},y_{tn})

3. Results

The methodology proposed in this article for the classification of images is tested with eight different figures for each different element of a user interface (show Table 2)

Table2: Set of sketches used



The representation of each sketch is differentiated by colors and letters for the buttons it is represented by a letter b of red color, for the text it is by means of the letter t of blue color and for the text entries it is by means of the letter e of green color (show Figure 4).

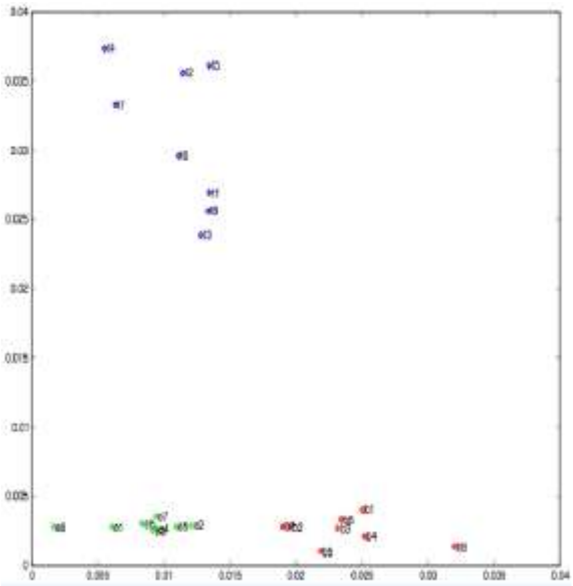


Figure 4: Resultados al clasificar los bocetos

4. Conclusion

The implementation of the techniques proposed in this work, they give us as results an efficient classification of elements for the creation of user interfaces, these techniques were simple as the extraction of sketches by their isolation, the key point for the classification was the calculation of the variance of the vectors that contain the sketches resulting in the coordinates of each sketch which were represented in a dispersion diagram, where it was visualized in a simple way how each element of a user interface is distributed, in the dispersion diagram, the classification of these elements is visually represented, each type of element occupies an area in the separate space, so it is not possible for them to be combined avoiding confusion about what type of element belongs what gives us a good classification.

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