Virtual Recomposition of Frescos: Separating Fragments from the Background

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Abstract

The paper addresses the segmentation of fragments from the background using a clustering approach in the color space. The problem is involved in the on-going development of a digital system for the virtual aided recomposition of fragmented frescos, an innovative approach currently being proved on the S. Matthew’s fresco, made by Cimabue for the Upper Church of S. Francis in Assisi and broken, during the earthquake in 1997, into more than 140,000 pieces. The developed technique has been used to build the fragments’ database. The segmentation process is based on the fast global k-means algorithm. Experiments show that separation of foreground and background on a so large number of images is much more manageable and effective using prototypes built by the clustering algorithm.

1. Introduction

This paper describes the segmentation of fragments from the background [1], a topic involved in the on-going development of a digital system for the virtual aided recomposition of fragmented frescos. This innovative approach to recomposition is being developed on the S. Matthew’s fresco, painted by Cimabue for the Upper Church of S. Francis in Assisi. This fresco, extended over 35 squared meters, broke into more than 140,000 pieces during the earthquake in September 1997.

The particular technique used by Cimabue makes the pictorial film very sensitive to the long physical manipulation required by traditional recomposition. Moreover, the huge number of fragments and their significant differences in size have suggested the application of digital tools to this challenging problem. Fragments do not cover the whole fresco, some of them belong to a neighbor fresco broken during the same event and their contours do not always match exactly.

The developed system is based on a tight cooperation between the automatic algorithms and the operators charged of the recomposition process [2]. It substitutes the physical lab with a geographically distributed digital laboratory: a network of suitably designed stations connected with a server that allow several operators, from different places and at different times, to cooperate in the recomposition using digital images of fragments instead of physical objects. The designed system transposes the traditional recomposition process in a digital way, by offering, to operators the central and critical role of managing and applying new tools and flexible algorithms of image analysis to increase the efficiency and efficacy of their work [3].

Figure 1. The workstation for the virtual aided recomposition. The left-side monitor is the work-area to position the fragments. On the other ones a scaled version of the whole fresco and several logical containers used for organizing the fragments.

The multi-monitor graphical station (Figure 1) allows the selection of part of the image of the whole fresco (visualized in a scaled version on the central monitor) as background for the working area, shown at full resolution on the left-side monitor. The operator find the best place for each fragment by applying simultaneous rotations and translations using a special mouse.

The digital tools expand the capabilities of the human operator that is allowed to create and manage several virtual containers (digital counterpart of the boxes used in the real lab) to collect logically related fragments. The
content of virtual containers can be organized in any way functional to his work. Moreover, he can also duplicate fragments, display them with half-transparency, change color, brightness and contrast, zooming or increasing the field of view: all operations that are impossible on physical fragments and that allow further useful comparisons between the images of fragments. The located fragments can be seen at different scales, offering overviews of the recomposed fresco that are very hard on a physical surface of 35 squared meters. They can also be deformed in order to study the effect of their placement on a curve surface (similar to the one of the vault in the church). Finally, the system manages and synchronizes the cooperation of several operators that, using different graphical workstations connected over a network with a server, can jointly work on the same fresco.

All this advantages compensate the unavoidable loss of information due to the use of two-dimensional images instead of physical fragments, that are observable by several points of view, including their reverse side.

A fundamental improvement to the recomposition process is the support to retrieving fragments of interest from the database (hosting the digital images of every single fragment) using a query-by-example modality that is incremental and iterative. The operator picks-up a set of examples (images of fragments or of details of the reference image) and the system selects in the database the fragments that are more similar to them. If the results are not satisfying, the set can be modified by adding, removing or changing the examples: this process can be repeated until operator's needs are fulfilled. This very simple schema is generally used on text in the web search engines. Color and texture are the most important components of similarity evaluation [4], especially when shapes, due to damages occurred during the fragmentation process, do not necessarily match perfectly.

2. The segmentation approach

The physical fragments have been placed in particular containers, each hosting from few tens to about 300 fragments: they are fitted into foam, a material that keeps them in place and provides an high contrasted background (Figure 2). The input data to the system are the digital images of these containers. Fragments need to be separated from the background in order to create the database of images each containing a single piece. These images have been built by an automatic algorithm based on the analysis of color characteristics: its application on the image of each container produces a set of digital frames where fragments appear separately, surrounded by the foam. In this phase each image receives a unique identifier that combines the references to the physical container holding the corresponding physical fragment and its location inside the box. Using these identifiers the result of the virtual recomposition can immediately be translated in the physical recomposition of real fragments. All these images of the fragments have been stored into a properly designed database.

Figure 2. On the left one of the several hundreds digital images acquired from the physical containers holding the real fragments. They are the input data for the system. During the segmentation phase, images of single fragments are extracted and stored in a suitably designed database. A map of each image (on the right) is created: a unique identifier, assigned to each fragment, can be used in the real restoration for retrieving the real objects corresponding to the components of the virtually recomposed fresco.

To be effective, the aided retrieval of fragments using a query-by-example modality requires a reliable separation of fragments from the background: in this way the analysis of color and texture can operate only on the useful pictorial content of each fragment. Moreover, each fragment can be further divided into homogeneous regions: this allows a stronger and more precise characterization that improves the performance of the retrieval phase. This second segmentation can separate the pictorial film from regions belonging to the brick or to the plaster and, equally important, can identify regions with homogeneous contents in terms of color and texture. This paper deals with the segmentation process needed to separate the fragments from the background. Specifically it deals with the fine determination of fragment masks, separating the pixels belonging to fragments from the ones related to background.

To reach this result an approach based on the fast global k-means algorithm has been applied [5]. This is a deterministic effective global clustering algorithm that minimizes the clustering error employing the k-means algorithm as a local search procedure. It adds a cluster...
center at a time using a deterministic global search procedure based on the execution of the k-means algorithm on the already found clusters centers augmented with a new element picked up from the available data set. The original code, written for the Matlab environment, has been ported to C languages to allow the processing of the huge number of images (more than 140,000) in an acceptable time.

In our problem, the data set fed to the clustering algorithm is composed by all the colors present in the image to be analyzed, each described by its three coordinates in the CIE-Lab color space. The global k-means algorithm aims to partition the data set in M disjoint subsets such that a suitably defined clustering criterion is optimized: in this case it minimizes the clustering error, that is the sum of the Euclidean distances between data points and corresponding cluster prototypes.

The algorithm, to solve the search for M clusters (this number depends on the application), sequentially solves all the problems with 1, 2, ..., M-1 clusters. The basic idea is that the optimal solution for M clusters can derive from several local searches, each made using the k-means algorithm on the optimal M-1 cluster centers augmented by a new center initialized at different positions in the data space. The method is effective and avoids the strong dependence of other methods on the initialization or on empirically adjustable parameters [6].

The global k-means would require, at each step, the k-means algorithm to be executed using as new center each element of the data set that need to be clustered. This computational load can be reduced, without significant loss in quality of the solution, using the fast global k-means. This latter method computes an upper bound of the expected error for each possible initialization: \( E_0 \leq E - b_n \) where \( E \) is the error in the M-1 clustering problem and \( b_n \) measures the guaranteed reduction in the error measure obtained by inserting a new cluster center at position \( x_n \). The k-means is executed only for the initial value associated with the lower upper bound.

The fast global k-means algorithm has been used to divide the whole image into \( M=10 \) clusters, a number that offers enough representatives to both foreground and background colors. Finding a threshold value on the CIE-Lab colors to separate foreground and background on such a huge number of images has been impossible. Instead it is has been easier to fix a threshold on the prototypes, separating clusters related to background from clusters associated to fragments: the same threshold has worked on quite all the images allowing fully satisfactory binary masks to be obtained. As shown in figure 3 (second row), this segmentation is effective but still originates a significant number of artifacts: regions with different size (from small dots to significant blobs) that are misclassified due to their color values. To correct this problem a filtering step, based on the recursive application of a median filter (size 3), removes spots assigning them to the correct class (figure 3, third row).

Figure 3. Two fragments: the second row shows the results of thresholding on clustering results with some misclassifications (spots and larger regions). The median filtering removes small spots (third row). The blobs removal algorithm corrects larger regions still sensibly smaller than fragments. The final result is shown in the fourth row.

It corrects most of the misclassified regions without affecting the fine details of the fragment shape. Larger
regions (sensibly smaller than the fragments) assigned to the wrong class are coped with by a blob detection algorithm based on a region growing schema. Their value is switched (from foreground to background or vice versa) producing the result shown in figure 3 (fourth row).

These three steps have been applied to the whole collection of images without any further human intervention. The resulting masks select, for each image of the fragments, the pixels that must be considered by the image processing and analysis tools.

3. Conclusions

The paper describes a part of an on-going project, done in close cooperation with the Central Institute for Restoration that is in charge of the whole restoration of the S. Francis church in Assisi: the virtual recomposition of the S. Mathew’s fresco, painted by Cimabue.

The presented approach has been used to segment fragments from the background. It has built the masks that identify the pixels that must be processed by the automatic algorithms that extract the visual characteristics used for querying-by-example the database.

The segmentation has been done by clustering the colors and by using a threshold on the obtained prototypes: this has proved to be much more effective and general, on the whole huge set of images (more than 140,000), than any threshold policy applied directly on the colors present in the images.

The project is very challenging: the available data do not provide the best base for this kind of work. The available images of the whole fresco are quite different from the digital images of fragments in both geometrical resolution and colorimetric characteristics. Large effort is being made to reduce this gap that strongly decreases the expected performance of the system. The restorers, working in Rome using a station connected to our server in Bari, are anyway very interested in this strongly innovative approach and have already pointed out several improvements that the system brings into their work.

They provide new stimuli about further functionalities and visual characteristics that can be fruitfully introduced in the system as well as support to its fine tuning and to the evaluation of its performance. Up to now restorers have correctly identified several fragments. Figure 4 reports some of them on a working-area (a small region of the fresco that can be completely displayed at full resolution on a single monitor). The identified fragments have confirmed the expected differences in colors between the acquired fragments and the best color image available of the whole fresco. The on-going work is expected to provide other very interesting hints arising from the extensive application of the system to a real challenging recomposition such as the S. Matthew fresco.

Figure 4. Some early results obtained by applying the system to the virtual recomposition of the S. Matthew fresco.

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5. References


