A PROCEDURE FOR AUTOMATED REGISTRATION OF FINE ART IMAGES IN VISIBLE AND X-RAY SPECTRAL BANDS

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Abstract: This paper presents a two-step procedure for automated registration of photographs and roentgenograms of fine art paintings. Grayscale local maxima in blurred images are used as the control points. The coherent point drift (CPD) point sets matching algorithm is combined with iterative procedure for excluding false correspondences. General projective transformation model is used for image registration. The precise step of the procedure reduces registration error obtained at the coarse step.

1 INTRODUCTION

In this paper, a problem concerned to analysis of multispectral images of fine art paintings is considered. Multispectral images are widely used in the research aimed on restoration and attribution of paintings. One of the aspects of such a research is the analysis of information hidden under the visible paint layer (Kirsh, 2000). The way to analyze the paintings is to combine images of different modalities in order to localize an object in IR, UV, or X-ray image and its corresponding position in the color image.

For the efficient acquisition of information hidden under the visible paint layer, it is necessary to automate operations of image registration, comparison, and analysis of registered images. For this purpose, the computer technologies are widely used (Stork, 2009, Kammerer, 2004, Maitre, 2001, Heitz, 1990, Martinez, 2002).

The majority of the developed systems provides the automated operations for registration and analysis of IR, UV, and visible images. The properties of X-ray images obstruct the automated registration. The main goal of this work is to automate registration of images taken in visible and X-ray spectral bands (see Figure 1).

The images under research are the JPEG images of size 2800x4200 and of 8 or 24 bpp depth. The size and the viewing fields are different and conditioned by the parameters of X-ray unit and the restorer's regions of interest. Visible and X-Ray images differ in size, viewpoint, viewing field, and content. In Figure 2, the same fragment in color photograph and X-ray image is shown.

(a) (b)

Figure 1: Images of the painting obtained in optical (a) and X-ray (b) spectral bands.

The considered problem is identical to the conventional problem of image registration, but the listed above properties of X-ray pictures spoil the solution.

The problem can be formulated as follows. Let $u(x,y): R^2 \to R^1$ be a model image obtained in X-ray spectral band and $v(x',y'): R^2 \to R^1$ be a data image obtained in optical spectral band. It is necessary to find a transform $T: R^2 \to R^2$ minimizing the mean squared error and mapping the data $v(x',y')$ into the model image

$$X = F(X'), \tag{1}$$

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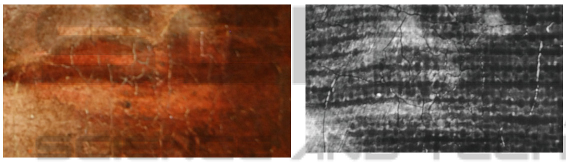
where $X = (x, y)^T \in R^2$ and $X' = (x', y')^T \in R^2$ are the vectors of image coordinates. In the next section conventional approaches to the problem are considered.

2 RELATED WORKS

A problem of multimodal image registration in fine arts is analogous to the problems of multimodal medical or aerial image registration (Maintz, 1998). Solution of the problem includes the following four steps (Zitova, 2003): (a) feature detection; (b) feature matching; (c) transformation model estimating; (d) image resampling and transformation.



(a) (b)

Figure 2: The same image object in color photograph (a) and X-ray (b) spectral bands.

Implementation of each registration step meets its specific problems.

The features extracted at the first step are classified with respect to the types of objects detected in the images: region features, line features, and point features. The features should be associated with distinctive objects and should be invariant with respect to selected transformation model. If the high-contrast details cannot be find in the image one can use features calculated from information characteristics of images. The features are represented by control points (CP), which are used for calculating parameters of image transformation. In (Kammerer, 2004) the control points are selected manually and adjusted by normalized cross-correlation-based algorithm. In automated techniques, Harris corner detector (Harris, 1998) is widely used ((Schmid, 1997, Delponte, 2006), and many others). Additional local feature descriptions such as differential geometry invariants (Schmid, 1997), moment invariants, scale invariant features (SIFT (Lowe, 1999)) can be used (Delponte, 2006). In (Cappellini, 2005) an algorithm for registration of UV and visible images implements the maximization of the mutual information technique based on maximizing measure of statistical dependency of two images. The maximization process implemented as a heuristic iterative search procedure in the space of four parameters.

A variety of feature matching techniques is known. In (Schmid, 1997) an algorithm based on differential invariant description and CPs spatial relations defined as the angles between directions to neighbour points is presented.

Another technique is named the Iteration closest point registration (ICP) (Chen, 1992). The algorithm iteratively assigns correspondences utilizing the nearest neighbour criterion to minimize the sum of squared distances between the points of the two sets. The ICP requires a good initial estimate to converge to a global minimum. The improvements of the ICP technique are described in (Rusinkiewicz, 2001) and (Sharp, 2002).

Another group of feature matching techniques uses the spectral properties of the proximity matrix. The elements of the matrix represent the degree of attraction between image features via a Gaussian-weighted distance metric. In (Scott, 1991) an SVD-based feature matching technique is proposed. The technique can work with point sets of different size but is sensitive to rotation and scaling. In (Shapiro, 1992) an eigenvector approach to the problem of feature matching is presented. Correspondences are established by comparing the ordered eigenvectors of the proximity matrices of different images. This method shows the best results with point sets of the same size. A variety of the spectral-based techniques improving (Scott, 1991) and (Shapiro1992) were developed (Pilu, 1997, Zhao, 2004). In (Myronenko, 2010), a probabilistic technique called the Coherent Point Drift (CPD) algorithm is presented. The alignment of two point sets is considered as a probability density estimation problem. The first point set, represented as the Gaussian mixture model (GMM) centroids, is fitted to the data (the second point set) by maximizing the likelihood. The GMM centroids are moved coherently as a group, which preserves the topological structure of the point sets. The coherence constraint is imposed by regularization of the displacement field. The technique can be used in cases of rigid and non-rigid point set transformations.

The most widely used transformation models describing the geometric deformations specific to image acquisition process are the affine (Kammerer, 2004, Cappellini, 2005) and perspective projection models (Hartley, 2004). In some cases, the other types of models are studied by the authors.

The analysis of publications has shown that: (a) the problem of automated registration of X-ray images of fine art paintings is purely represented in literature; (b) the feature sets commonly used in image registration techniques are ineffective in the current task due to the properties of X-ray images; (c) the Coherent Point Drift point matching technique is attractive in the current research; (d) the model of perspective projection is adequate to the problem under consideration.

Here, we propose a two step procedure, oriented on the specificity of the problem. The main operations of the developed procedure are as follows: (a) image preprocessing (color reduction, correcting X-ray image acquisition deformation, filtering, downsampling, etc.); b) localization of control points; (c) establishing correspondence of the control point sets; (d) calculating transformation matrix and image registration.

To increase the precision of registration, the operations (b) - (d) are running twice at the steps of rough and precise registration.

3 THE PROPOSED SOLUTION

Localization of control points for registration X-ray and visible images is complicated by difference in image content. Characteristic points found in one of the images may not be found in another image of the pair. Also, it is not easy to find geometrical primitives and local features suitable for image registration in the images of fine art paintings. In roentgenograms of paintings, the objects painted using the white lead are strongly discernible and looking bright. The bright regions in X ray images usually correspond to the bright regions in photographs (see Figure 1). This property will be used for selecting the control points. In this work, the local grayscale maxima associated with bright regions of painting will be used as the control points. The local intensity extrema are invariant to translation, rotation, scaling, and global intensity variance. In order to exclude the maxima corresponding to small image details or conditioned by noise, the images should be smoothed. The degree of smoothing should be selected taking into account the value of registration error. We propose a two step registration process. At the coarse step, the strongly smoothed images are used for localizing the control points. In this case, only a few reciprocal points associated with large bright image details will be found. At the precise registration step, the slightly smoothed images are used for the control points detection. This yields that the number of reciprocal points will increase, and the registration error will decrease.

The choice of the best technique for finding correspondences between the control point sets of the images is based on the results of the comparative study of several matching techniques. SVD-, eigenvector-based, structural and Coherent Point Drift algorithms were tested using artificial and real data sets. The CPD algorithm demonstrated the best true/false correspondence ratio for scale factor changes up to 30 percents and rotation angles up to 20 degrees (Murashov, 2010).

At the first step of the procedure the Coherent Point Drift algorithm (Myronenko, 2010) seems to be the most appropriate for finding correspondences between the control points of the two images. At the second step the control point correspondences are found directly from the analysis of coordinate-based proximity matrix. For eliminating the false correspondences, the special iterative procedure is proposed. The task of obtaining the optimal transform between two images is solved using conventional technique (Hartley, 2004). The next sections are devoted to the main operations of the proposed procedure.

4 IMAGE PREPROCESSING

For simplification, all of the image processing operations deal with grayscale images. Hence, the first operation is the color reduction. The second operation is aimed on correcting distortions in X-ray images conditioned by the construction of used X-ray unit. For this purpose the following transformation is used:

$$r = r' L / (L + \Delta L),$$

where r and r' are the lengths of the position vectors of the same point in the corrected and original images, L is the distance from the X-ray emitter to the painting, ΔL is the painting thickness.

The canvas texture of X-ray image (see Figures 1, 2) obstructs control points detection. To suppress the periodical intensity oscillations, the image filtering is applied:

$$v_f = \Phi^{-1}(\Phi(v) \cdot I_m),$$

where v and v_f are the initial and the filtered images, Φ and Φ^{-1} are the operations of forward and backward Fourier transform, I_m is the filter mask, $(\cdot)$ denotes the operation of elementwise multiplication. The filter mask is obtained from the inverted Fourier spectrum image after thresholding and removing the low pass component.

In order to reduce the computational expenses at the main stages of the procedure, image processing algorithms operates with images of size equal to 1/4 or 1/8 of the initial size. At the final stages, the full-size images are utilized. As soon as the control points are associated with the bright image areas, it is reasonable to segment the regions of interest in order to exclude the waste of points. For this purpose the algorithm of adaptive thresholding is used (Niblack, 1986).

5 IMAGE REGISTRATION AT THE COARSE STEP

Both at the coarse and the precise steps, the local intensity maxima associated with the bright details existing in X-ray and visible images are used as the control points candidates. For reducing the noise remained after filtering and suppressing the influence of small objects and details, the images are blurred by convolution with Gaussian kernel:

$$G(x,y,\sigma)=\frac{1}{2\pi\sigma^2}e^{-(x^2+y^2)/2\sigma^2},$$

where x, y are the spacial coordinates, σ is the parameter. Chosen σ value should provide only a few local maxima in one region of interest.

For detection local intensity maxima, an algorithm proposed in (Kuijper, 2002) is used. Local intensity maxima detected in the images presented in Figure 1 at σ = 6 are shown in Figure 3.

The next operation to be done is to find correspondences between two point sets detected in X-ray and visible images.

For this purpose the Coherent Point Drift method (Myronenko, 2010) is applied. The result of the algorithm is the correspondence probability matrix. Maximal element in row *i* and column *j* shows the correspondence of point *i* in the first image to point *j* in the second one. The CPD method is efficient, but it can establish false correspondences working with real images. In order to decrease the number of false associations additional local feature descriptions are usually used (Pilu, 1997, Zhao, 2004).

In case of significant differences in image modalities (see Figure 2) the local feature descriptions cannot improve the result. For eliminating false correspondences the following iterative procedure is proposed. The correspondence is considered as false if the registration error for this control point couple gives maximal contribution to an error functional.

(a) (b)

Figure 3: Local intensity extrema in visual and in X-ray images.

Let the quality of control point registration at iteration *i* is defined as

$$I_i=\sum_{j=0}^{p-i}d_{ij}^2$$

$$d_{ij}^2=(x_{ij}-x_{ij}^{Ti})^2+(y_{ij}-y_{ij}^{Ti})^2,$$

where *i* is an iteration number, *j* is a point couple number, *p* is an initial number of control point couples, x_j^{Ti} and y_j^{Ti} are the coordinates of *j* point couple in the data image transformed by a transformation *T* calculated at step *i*. The control point couple number *k* is excluded if the following condition is held:

$$\Delta I_{ik}=d_{ij}^2=\max_j(d_{ij}^2),\ 0\le k\le p-i$$

The process is terminated when $\max_j|d_{ij}|<d_{\max}$, where $d_{\max}$ is the absolute error bound, or if $I_i<I_{\max}$, $I_{\max}$ is depending on the mean squared error bound. The registration quality is evaluated by the absolute error value, mean squared error, and visually.

As it was mentioned above, the suitable transformation for solving the considered problem is the general projective transformation. The problem for calculating transformation matrix is formulated as follows (Hartley, 2004). Let $u(x,y):R^2\rightarrow R^1$ be a model image obtained in X-ray spectral band and $v(x',y'):R^2\rightarrow R^1$ be a data image obtained in optical spectral band. It is necessary to find a transformation matrix H

$$\tilde{X} = H\tilde{X}' \tag{2}$$

minimizing the mean squared error and mapping $v(x',y')$ into $u(x,y)$. In (2) $\tilde{X} = (x,y,1)^T$ and $\tilde{X}' = (x',y',1)^T$ are the homogeneous coordinates of the model and the data images, H is a homogeneous 3x3 matrix. For calculating H, it is necessary to solve $2n$ algebraic equations for n associated control points. We use Levenberg-Marquardt algorithm providing good convergence (Madsen, 2004). Computational complexity of the procedure is comprised of the complexity of the CPD algorithm (linear) and Levenberg-Marquardt algorithm applied n times, where n is the number of iterations depending on the number of control point pairs. For image registration task, computational cost of Levenberg-Marquardt technique is comparable to that of the gradient descent method.

6 IMAGE REGISTRATION AT THE PRECISE STEP

At the precise registration step in order to provide suitable precision, the control points are detected in slightly blurred images ($\sigma \leq 3$). At this step for control points association we analyze directly the proximity matrix of two point sets because corresponding maxima in the images registered at the previous step are closely spaced. For association of found intensity maxima points the following operations are needed: (a) coordinates of the newly detected data image maxima are transformed using the matrix H obtained at the coarse step; (b) the proximity matrix of two maxima sets is calculated; (c) maximal elements in rows and columns of the proximity matrix are found. Indices of the found matrix element define the correspondence of an element i of the first point set to an element j of the second set; (d) a new transformation matrix H is calculated, and the data image of the original size is transformed.

The result of registration of images shown in Figure 1 is shown in Figure 4.

7 EXPERIMENTAL RESULTS

The developed procedure was tested on six real image pairs. At the first step, from 8 to 30 corresponding pairs of control points were detected for different images. At the second step, up to the several hundreds of points are detected in photograph and roentgenogram and up to 100 control points couples selected by the point set matching algorithm.

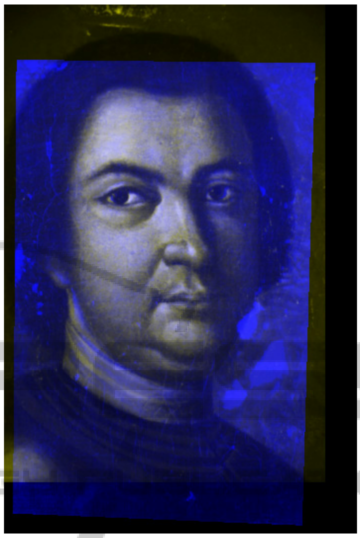


Figure 4: Registered images from Figure 1.

The registration precision needed for fine art paintings restoration can be achieved by the proper localization of control points. For this purpose it is necessary to detect control points in different regions of the images. However, this cannot be done in some cases due to the properties of the roentgenograms depending on the amount of the white lead used by the painter. The registration quality is evaluated by the mean squared error $\overline{e}$ computed at the control points. The suitable precision of registration of images of paintings at the precise step $\overline{e}_2 \leq 2$ is obtained when the error value $\overline{e}_1 \leq 4$ pixels. This result is in accordance with the results presented in (Kammerer, 2004) for infrared and visible images of paintings.

8 CONCLUSIONS

The two-step procedure of the automated registration of multimodal images of fine art paintings is developed. Local intensity extrema detected in blurred images are used as the control points. The control points are associated with bright regions in the painting visible in X-ray and optical spectral bands. At the coarse step the Coherent Point Drift algorithm is applied for establishing correspondences between the characteristic point sets. The control point coordinates are used as the features for constructing proximity matrix. The algorithm is combined with iterative procedure for excluding false correspondences. The general projective transformation model is used for image registration. The registration precision is in accordance with the existing method. The future research will be aimed on improving the control point set matching technique and application of alternative transformation models.

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