AN INTEGRATED ANALYSIS CONCEPT FOR ERRORS IN IMAGE REGISTRATION

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Image registration is an important ingredient in a wide variety of computer vision applications. Over the years countless algorithms emerged that allow for robust registration of image sequences. Unfortunately, high quality results still cannot be guaranteed in any case. Especially in interactive online systems that strongly rely on results of unsupervised registration algorithms, techniques for automatic quality analysis and failure compensation are indispensable. In this paper we present a new concept for an integrated and fully automatic detection and analysis of errors in registration. Based on a new metric for registration quality assessment, image differences are robustly detected. In addition, a hierarchical analysis scheme is proposed that allows to distinguish between various underlying error sources, all having different impacts on a registration result and requesting for individual compensation strategies.

Introduction

2D geometric image registration often forms a fundamental and constitutional building block in modern computer vision systems. In many applications, like camera motion recovery [1], reconstruction of scene structure [2], or medical and biological image analysis [3, 4], results from registration yield an important basis for higher-level analysis modules and, thus, significantly influence the overall quality of the complete analysis process.

Geometric image registration aims at an identification of corresponding image parts in sets of images, e.g., enabling data compression without loss of information [5] or a reconstruction of camera motion during acquisition. The registration is usually based on a parameterised motion model to describe changes between images of a sequence related to camera motion [6, 7]. In registration parameters for the model are estimated so that corresponding image parts can be aligned by transforming the images into a common coordinate frame.

In general, modern techniques allow for robust image registration and alignment. Nevertheless errors and complete failures may still occur, rendering a fully automatic and unsupervised image registration impossible. Thus, in interactive vision systems that strongly rely on registration results calculated online, it is indispensable to include fully automatic error detection and compensation mechanisms to enable robust self-recovery of the systems from serious registration failures.

Unfortunately, automatic and objective quality assessment of registration results is still an open issue in the computer vision community, and system self-recovery from errors has not yet been addressed at all. Until now only few papers emerged directed at automatic quality analysis (e.g., [8]). Moreover, due to a lack of objective metrics registration quality assessment is mostly left to the human user for manual inspection.

In this paper we present a new approach to overcome this lack of appropriate quality metrics and automatic error detection mechanisms in registration. We propose a new integrated analysis concept that not only allows to automatically *detect* errors in registration, but also enables a more detailed *categorisation* of these errors with regard to underlying *error sources*. Since each error source has an individual impact in registration and requires individual compensation, this is an indispensable prerequisite for fully automatic quality analysis and error correction. Our approach relies on an objective metric for image difference detection, combined with various individual analysis pathways for discriminative error source identification. The concept is outlined in subsequent sections, starting with a general discussion of errors in registration.

Registration Quality

The quality of a registration result is directly related to image differences remaining after an alignment of two registered images. However, image differences are not exclusively related to the registration process, but can also be due to other underlying error sources only loosely linked to it. For example, artefacts due to changes in the scene (e.g., moving objects) or technical properties of the acquisition device (e.g., vignetting) frequently appear and have to be distinguished carefully from effects of geometric registration.

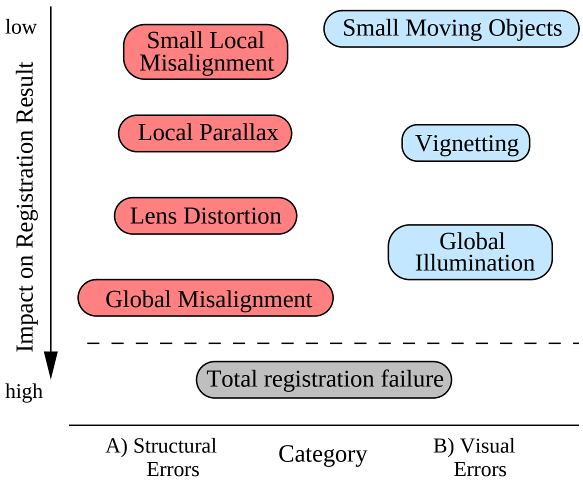

Figure 1: Differences in image registration, grouped into the two main error categories and sorted according to impact on result.

In detail, two main classes of image differences and various underlying error sources have to be separated from each other for objective evaluation: A) *Structural Errors* directly related to the geometric registration process, e.g., caused by an unappropriate motion model, and B) *Visual Errors* originating from image differences between geometrically correctly aligned image pixels. Vignetting, global illumination changes or moving objects cause errors of this class (see also Fig. 1).

Unfortunately, quality criteria commonly used in registration, like the well-known Mean Squared Error (MSE) or reprojection errors [9], that in principal also should allow for quality assessment, usually are not capable of performing such a discriminative analysis. They often show a lack of local sensitivity, most of the time either relying on unspecific averaging schemes [10] or considering only subsets of all relevant image pixels [9].

Integrated Analysis Concept

Our approach aims at a robust and distinctive analysis of image differences and underlying error sources in geometric registration. It overcomes the abovementioned problems of existing metrics by focusing on high local sensitivity, putting strong emphasis on pixel-wise calculations. In addition, the two main types of errors as well as different underlying error sources are thoroughly distinguished applying an integrated analysis scheme.

The concept comprises three layered detection and analysis stages, as depicted in Figure 2. In the first stage various pixel-wise difference criteria for error detection are calculated, motivated by metrics from the field of *image quality* assessment [10, 11, 12]. Images of these criteria then form the base for further analysis steps in the second and third stage, aiming at a thorough detection of visual and structural errors as well as different error sources. The latter two stages include different analysis pathways individually adjusted to the various error sources that might affect a registration result and need to be distinguished. These pathways are sketched out in Fig. 3. Below, all three stages are briefly outlined. Further information can also be found in [13, 14].

Stage 1: Pixel-wise Differences

Initially three pixel-wise difference measures are calculated within the overlapping area of two aligned images. In detail, these are the pixel-wise image intensity difference, an *edge map* quantifying differences in local gradient orientation (cf. [11]), and a *risk map* characterising local structural image properties (cf. [12]). These measures, stored as gray-scale images, yield the input for the next stage, directed to a distinction of visual and structural errors.

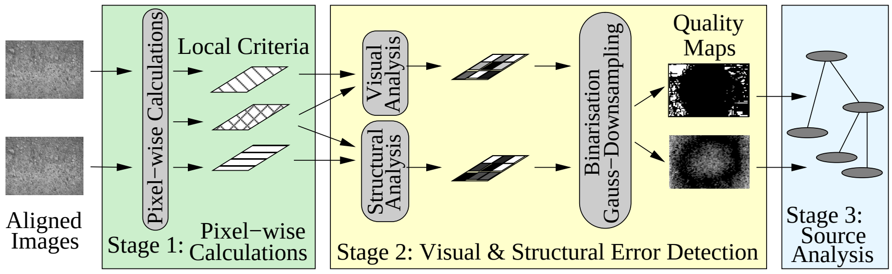

Figure 2: Overview of the three-layered concept for quality assessment and distinctive error analysis in geometric image registration.

Stage 2: Structural vs. Visual Errors

As outlined above, structural errors are defined as image differences due to incorrectly aligned pixels, being directly related to structural mismatches between images. Thus, structural errors can only be detected in image sections with sufficient structure. Vice versa visual errors can best be identified in homogeneous regions. Accordingly, the set of all image pixels is divided into two groups, either lying in structured or homogeneous neighbourhoods, based on the formerly calculated risk map. Subsequently structural errors are identified by big differences in local gradient orientation, and visual errors by significant intensity differences. The result of these calculations is given by so called *quality maps* that specify existence and location of structural and visual errors between both images (Fig. 4). Depending on subsequent analysis pathways these maps can either be binarised or represented by gray-scale images (see below).

Stage 3: Error Source Identification

Visual errors most of the time occur either due to changes within the scene, e.g., local moving objects and changes in illumination, or due to specific properties of the acquisition device. In particular, often vignetting, i.e., a darkening of images in corners, needs to be distinguished from global changes. The latter ones can usually be corrected by global normalisation while vignetting requires model-based compensation strategies.

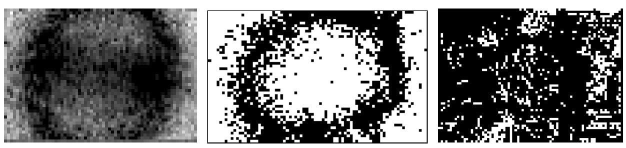

Figure 4: Example quality maps, here for structural errors. Left, gray-scale image, middle and right, maps binarised by thresholding.

Structural errors originate from geometric misalignment of corresponding pixels. This may happen according to the choice of an unappropriate model, not matching the requirements of camera motion and scene structure, and resulting in parallax or local mismatches. Also problems within the optimisation embedded in the registration stage, e.g., convergence to local minima, may cause such errors. Anyway, one of the most important practical problems are *non-linear lens distortions* [15].

To distinguish between different error sources the quality maps undergo specific analysis processes (Fig. 3). The energy of the maps correlates well with the overall registration quality and visual appearance of registered images. Even so, for source identification mainly the spatial distributions of errors are exploited as most of the error sources are related to specific residual patterns. Below two example analysis pathways are outlined in detail.

Example 1 - Vignetting Analysis

To detect vignetting in registered images, we define the *Border-Center-Ratio* R_{BC} of visual errors. Given the intensity differences of image pixels lying in homogeneous neighbourhoods, at first a suitable threshold is applied to detect visual errors as pixels with big difference. Subsequently the resulting binarised quality map is downsampled by dividing it into blocks of size 8×8 pixels. For each block the percentage P_{ve} of pixels with visual errors is determined. Afterwards a new quality map is generated where each block is represented by a single pixel, being either white (if $P_{ve} > \theta_{ve}$, with θ_{ve} a suitable threshold) or black. Finally, the set of blocks is divided into center and border blocks, whereas the latter ones cover approximately the outer third of the image area.

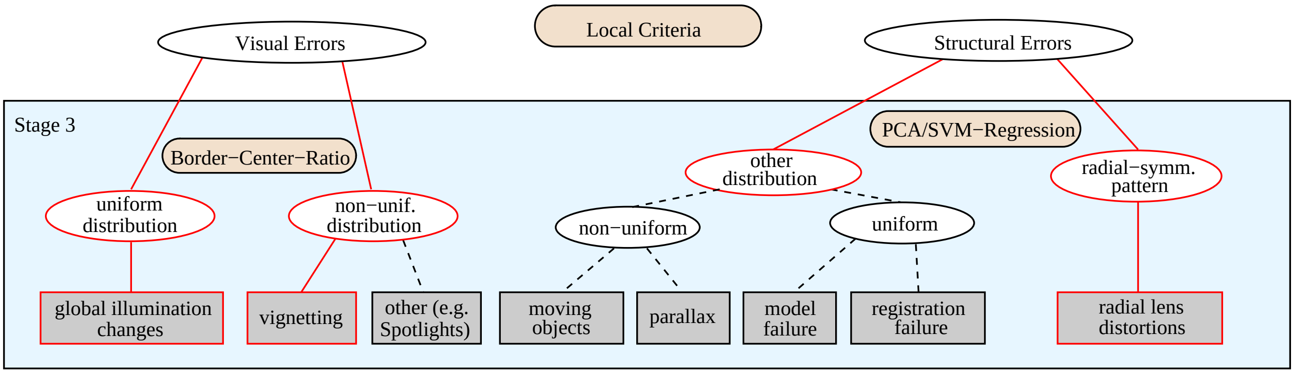

Figure 3: Overview of the third stage of the integrated concept for detailed error and quality analysis in image registration. Already implemented and tested pathways are marked with solid red lines, while black dashed lines indicate pathways that will complete the scheme in near future.

Then the ratio R_{BC} of relative amounts of blocks with errors in border and center part is calculated. In case of vignetting significantly more border than center blocks will show errors ($R_{BC} \gg 1$), while in case of global illumination changes R_{BC} should be ≈ 1.

Example 2 - Lens Distortion Identification
Radial lens distortions in registered images have shown to cause striking radial symmetric patterns in calculated gray-scale quality maps of structural errors (cf. Fig. 4). They are the more pronounced the larger the amount of distortions is. Here the quality map is given by a downsampled version of the edge map, considering only pixels in structured neighbourhoods. To automatically analyse the patterns we adopt a machine learning approach based on PCA and SVM regression [14]. The quality map as a whole is interpreted as a feature vector. In the first step, principal component analysis is applied to a given set of training samples with known distortions to reduce the dimensionality of the input data. Subsequently, given a subset of 50 eigenvectors as basis, the low-dimensional feature vectors are used to train a support vector machine in ε-regression mode [16] using RBF kernels. The trained SVM can then be used to detect distortions in unknown data, and also to predict their amount.

Experiments

To demonstrate the practical functionality of our concept, tests were carried out on various image pairs. Here two examples are discussed, showing the detection of vignetting and lens distortions.

For detecting vignetting the Border-Center-Ratio R_{BC} is calculated as outlined in the previous section. In Figure 5 two binary example quality maps are depicted, showing visual errors detected between registered images suffering from vignetting (left) and global illumination changes (right). As expected, on the left $R_{BC} = 14$ holds, while for the right example in this case $R_{BC} = 1$. Accordingly, in both cases the underlying error source can uniquely be determined.

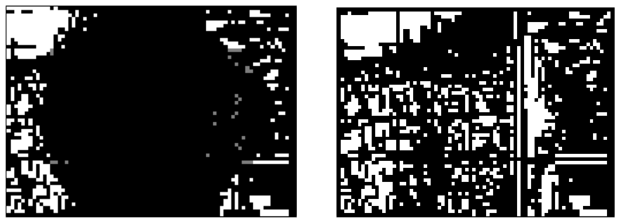

Figure 5: Binarised quality maps. On the left vignetting occurred in the images while on the right global illumination changed.

The pathway for lens distortion detection was tested on a set of artificially distorted images to have ground-truth. The distortions in each image pair were quantified using a model-independent distortion measure Δ_{avg}, defined as the average offset of a subset of image pixels given a certain amount of distortion. In our experiments Δ_{avg} varied between 0 and ≈ 30. PCA and SVM training was performed on 6000 training image pairs. For testing, the distortion of 400 test image pairs was predicted, yielding a minimal Root Mean Squared Error of 3.8. This shows the potential of our approach to reliably identify and predict the amount of distortions in image pairs, based on distributions of structural residuals in local quality maps.

Conclusion

In this paper a new concept for an integrated analysis of errors in image registration was discussed, marking a first step towards fully automatic registration quality assessment and failure recovery. Initial tests on real data underline the potential of the approach that in contrast to existing quality metrics allows to distinguish between various error types and sources. Current work now focuses on the completion of the hierarchical analysis scheme, especially aiming to identify local parallax and other motion model related errors. In addition, a more detailed analysis of non-uniform illumination changes will be integrated, e.g., to distinguish between vignetting and local spot lights.

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