Joint Optimization of Image Registration and Comparametric Exposure Compensation Based on the Lucas-Kanade Algorithm*

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Abstract

An iterative registration algorithm, the Lucas-Kanade algorithm, is combined with an exposure compensation algorithm to jointly optimize the spatial registration and the exposure compensation. The coordinate descent method is employed to minimize a mean squared error between image pairs. Based on a simple regression model, a nonparametric estimator, the empirical conditional mean and its polynomial fitting are used as histogram transformation functions for the exposure compensation. The proposed algorithm performs a good registration for real perspective and microscopic images, and can easily adopt other exposure compensation approaches and variations of the Lucas-Kanade algorithms due to its implicit flexibility.

1. Introduction

Research on the registration of images has been significantly conducted in various fields, such as computer vision and medical imaging. Superposing the multiple captured images into a single image can increase the dynamic range of the pixel levels and improve the signal-to-noise ratio if all images are properly aligned and exposed. When we align differently exposed images, we may use a feature-based registration technique, of which performance is less sensitive to the exposure difference. However, to reduce the effect of the different exposure on the registration, we should account or compensate the exposure difference during registration. To perform the comparametric exposure compensation [8], two images should contain the same scene and be aligned with respect to the overlapped scene. For an accurate registration, contradictively, the images should have the same exposure or illumination conditions. Therefore, devising a joint optimization technique for the spatial registration and exposure compensation is required.

Mann [7] conducted a joint registration based on the comparametric exposure compensation with the affine model [8]. He used the perspective warp for the registration, and derived a combined linear equation of the affine function and the warp for a joint optimization. Candocia [2] performed a continuous piecewise-linear (PWL) fitting to obtain a preferred comparametric function [8]. He also derived a combined equation to find the parameters for the PWL and the warp.

In this paper, an iterative registration algorithm, the Lucas-Kanade algorithm [5], is combined with an exposure compensation algorithm for a joint optimization. The proposed algorithm has separable optimization phases of registration and compensation based on the *coordinate descent method* [6, p. 227]. Hence, in terms of the flexibility in implementation, the proposed algorithm is more advantageous than the joint approaches of Mann and Candocia. In the proposed algorithm, the exposure compensation is conducted by using the histogram transformation function (HTF). Based on the *simple regression model*, a nonparametric estimator, the empirical conditional mean (ECM), and its polynomial (POL) fitting are used for HTF. Since POL can provide a good performance even when the fitting order is quite low, POL is more efficient in the aspect of the computational complexity compared to the PWL case.

2. Exposure Compensation

In this section, we introduce an exposure compensation scheme that is based on HTF. Let $\mathbf{x} = (x, y) \in \mathbb{R}^2$ denote vectors containing the pixel coordinates. For the exposure compensation, let $U(\mathbf{x})$ and $V(\mathbf{x})$ denote a pair of images, which have the same scene. Suppose that each image has m pixels and the images take values from a finite set $\mathcal{V} := \{v_i\} \subset \mathbb{R}$, of which size is n. Thus, n could be 256 as an example. Based on a simple regression model, consider a

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map η as $v \mapsto \eta(v)$, where $v \in \mathcal{V}$ and $\eta(v) \in \mathbb{R}$. We now define the *compensation error*:

$$\delta(\eta) := \frac{1}{m} \sum_{\mathbf{x}} [U(\mathbf{x}) - \eta(V(\mathbf{x}))]^2,$$

where U and $\eta(V)$ are the reference and the compensated images, respectively. Note that η is an HTF for the exposure compensation. An optimal η is given by the regression function of U on V. An inductive method to obtain the regression function is searching for a map that achieves the empirical minimum, $\min_\eta \delta(\eta)$. Define a nonparametric estimator η^o as

$$\eta^o(v) := \sum_{\mathbf{x}} I_{\{V(\mathbf{x})\}}(v) \cdot U(\mathbf{x}) / \sum_{\mathbf{x}} I_{\{V(\mathbf{x})\}}(v), \qquad (1)$$

if $\sum_{\mathbf{x}} I_{\{V(\mathbf{x})\}}(v) \neq 0$, and $\eta^o(v) := 0$ otherwise, for $v \in \mathcal{V}$. Here, for a set $S \subset \mathbb{R}$, $I_S(v) = 1$ if $v \in S$, and $I_S(v) = 0$ otherwise. The estimator η^o is then an empirical optimum that achieves $\delta(\eta^o) = \min_\eta \delta(\eta)$. We call this estimator ECM, and can derive a convergence rate of m^{-1} on η^o [4].

To generalize the ECM curve for relatively small sample size cases, we used the Nadaraya-Watson estimator with the *Epanechnikov* kernel [4]. In the aspect of the generalization, designing parametric estimators is sometimes advantageous than the nonparametric case. To design a parametric estimator for relatively small sample size cases, we can use the fitting of the ECM with global or piecewise polynomials [3, p. 117] for HTF. PWL in [2] can also be used as HTF. Using POL, we can smooth the ECM curve and obtain good compensated images for relatively low-orders of p without worry about the problem of placing knots, which is crucial in the PWL fitting. We may use a global p-th order POL:

$$\eta_{\mathrm{POL}}(v) := a_0 + \cdots + a_{p-1} v^{p-1} + a_p v^p,$$

where $p = 1, 2, \ldots$, and $a_0, \ldots, a_p \in \mathbb{R}$ are the polynomial coefficients. A special case of polynomials for $p = 1$ is the affine function, which is used in the well known *affine correction* [8, Proposition III.3].

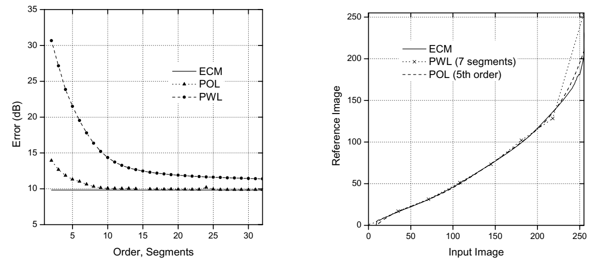
A polynomial minimizing $\delta(\eta_{\mathrm{POL}})$ is obtained by solving a linear equation $\mathbf{A}\mathbf{a} = \mathbf{b}$, where the $(p+1) \times (p+1)$ matrix $\mathbf{A} = [\alpha_{jk}]_{j,k=1,\ldots,p+1}$ is

$$\alpha_{jk} := \sum_{i=1}^{n} m_i v_i^{(j+k)-2}, \text{ for } j, k = 1, \ldots, p+1,$$

and the vector $\mathbf{b} = [b_j]_{j=1,\ldots,p+1}$ is

$$b_j := \sum_{i=1}^{n} m_i \eta^o(v_i) v_i^{j-1}, \text{ for } j = 1, \ldots, p+1,$$

with the unknown vector $\mathbf{a} = [a_{j-1}]_{j=1,\ldots,p+1}$. Here, $m_i := \sum_{\mathbf{x}} I_{\{V(\mathbf{x})\}}(v_i)$. Note that we use the ECM η^o and m_is for calculating $\mathbf{A}$ and $\mathbf{b}$. Similarly, we can construct a $(N-1) \times (N-1)$ matrix to find parameters for a PWL fitting, which has N linear segments. However, since POL can yield smaller error than the PWL case for relatively small p compared to N as shown in Figure 1(a), we can significantly reduce the computational complexity by using POL. As an example, the estimators of ECM, POL, and PWL for a differently exposed image pair are illustrated in Figure 1(b). The POL and PWL have similar designing complexity, where $p + 1 = N - 1$ with $p = 5$. The shape of POL is very similar to that of ECM. However, the PWL curve shows a knot-placing problem at the right part of the curve.



(a) (b)

Figure 1. Image exposure compensation. (a) Compensation error with respect to p and N. (b) Estimators for the histogram transformation functions.

3. Joint Optimization Algorithm

In this section, an iterative image registration is conducted in conjunction with the exposure compensation. For registering images, we employ the Lucas-Kanade optic flow algorithm [5], which is a Gauss-Newton gradient descent optimization scheme.

Let $\mathcal{W}_t(\mathbf{x}; \mathbf{p}) \in \mathbb{R}^2$ denote the warp for given $\mathbf{x}$, where $\mathbf{p} = (p_1, \ldots, p_t) \in \mathbb{R}^t$ is a vector of t parameters. The warp $\mathcal{W}_t$ takes the pixel $\mathbf{x}$ in the coordinate frame of the template image $T(\mathbf{x})$ and maps it to the sub-pixel location $\mathcal{W}_t$ in the coordinate frame of the input image $U(\mathbf{x})$ [1]. Here, the template image T is a part of the input image V. We suppose that, within the relationship of a warp, T and a part of U have the same scene. In order to jointly optimize the spatial registration and the exposure compensation, we now propose a exposure-compensating Lucas-Kanade algorithm, which iteratively decreases the following overall *compensation-registration error*:

$$\delta(\eta; \mathbf{p}) := \frac{1}{m_0} \sum_{\mathbf{x}} \left[U(\mathcal{W}_t(\mathbf{x}; \mathbf{p})) - \eta(T(\mathbf{x})) \right]^2. \qquad (2)$$

Here, the sum is performed over all of the pixels $\mathbf{x}$ in the template $T(\mathbf{x})$, of which size is m_0 ($< m$). Each iteration

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of the proposed algorithm is composed of the following two separable optimization phases:

- Exposure compensation: $\min_\eta \delta(\eta; \mathbf{p})$
- Spatial registration: $\min_{\Delta\mathbf{p}} \delta(\eta; \mathbf{p} + \Delta\mathbf{p})$

The first phase is searching an optimal map, e.g., the ECM η^o of (1) as shown in Section 2, for the exposure compensation. The second phase is then searching an optimal increment of $\Delta\mathbf{p}$ for the registration. Consequently the compensation-registration error of (2) decreases to a limit based on the coordinate descent method.

Before entering the main optimization phases, a template T should be extracted from V with an initial warp. To set a template, a center part of U is first selected and then find the corresponding part of V using a coarse translation-based alignment. We use these corresponding part and the translation parameters for setting a template and an initial warp. The proposed algorithm is now summarized as follows:

Proposed Algorithm

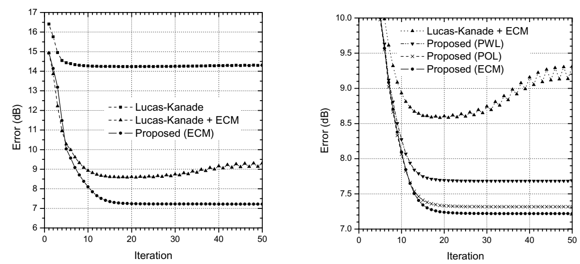
0) Set a template T with an initial warp $\mathcal{W}_t$.
1) Warp U with $\mathcal{W}_t(\mathbf{x}; \mathbf{p})$ to compute $U(\mathcal{W}_t(\mathbf{x}; \mathbf{p}))$.
2) Compute η^o from (1) using T and U as the input and reference images, respectively. Compute $\eta^o(T(\mathbf{x}))$.
3) Compute an optimal increment $\Delta\mathbf{p}$ [1, (10)],[5].
4) If $\|\Delta\mathbf{p}\| < \epsilon$, then stop with η^o and $\mathcal{W}_t(\mathbf{x}; \mathbf{p})$. Otherwise, $\mathbf{p} \leftarrow \mathbf{p} + \Delta\mathbf{p}$ and goto Step 1).

We can then mosaic the images, $U(\mathcal{W}_t(\mathbf{x}; \mathbf{p}))$ and $\eta^o(V(\mathbf{x}))$. Otherwise, regarding V as a reference image for the exposure compensation, we can mosaic $\eta^o_{\text{inv}}[U(\mathcal{W}_t(\mathbf{x}; \mathbf{p}))]$ and $V(\mathbf{x})$, by deriving an ECM η^o_{inv} similarly to (1). Here, since the estimators are designed using only the template T, which is a part of the whole image V, techniques of generalization for the whole image should be considered as discussed in Section 2.

The proposed algorithm has an advantage over the joint approaches of Mann [7] and Candocia [2] especially in its flexibility thanks to the separable optimization phases. For example as in Step 2), we can employ nonparametric estimators, which shows better compensation results than the comparametric function case. Furthermore, we can easily adopt other sophisticated parametric estimators, such as POL and PWL, and even the comparametric functions. We can also use different warps, and can employ several different updating rules for Step 3) [1].

(a) (b)

Figure 2. Images for registration (Pair A). (a) Whole image V (1/640sec, f5) and Template T. (b) Image U (1/640sec, f4).



(a) (b)

Figure 3. Compensation-registration errors. (a) Comparison 1. (b) Comparison 2.

4. Numerical Results

We now show numerical results on the proposed exposure-compensating Lucas-Kanade algorithm. In Figure 2, an image pair for registration are shown, where the size of the image is given by 320×240 pixels with 8 b/pixel, taken by Canon PowerShot G2. These two images have different exposure settings and are related by the perspective warp $\mathcal{W}_8$, which is composed of 8 parameters as $\mathcal{W}_8(\mathbf{x}; \mathbf{p}) = \big((p_1x + p_2y + p_3)/(p_4x + p_5y + 1), (p_6x + p_7y + p_8)/(p_4x + p_5y + 1) \big)$. The compensation-registration error with respect to the iteration in the proposed algorithm is shown in Figure 3. The registration without exposure compensation ('Lucas-Kanade') shows a high error as 14.31dB. Each error of 'Lucas-Kanade + ECM' is obtained by compensating exposure using ECM after the Lucas-Kanade iteration. In other words, the exposure compensation is separately conducted from the registration. Even though the errors are significantly reduced to 9.31dB compared to the 'Lucas-Kanade' case, the errors are not monotonically decreased. The proposed algorithm with ECM shows a decreasing error curve and further reduces the error to 7.22dB. The improvement due to using the proposed algorithm is more evident if we observe the mosaicked images as follows. In Figure 4, the mosaicked images are illustrated. Here, the overlapped parts are obtained by averaging the two images. Figure 4(a) is obtained

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(a)

(b)

(c)

Figure 4. Mosaicked images of Pair A. (a) Lucas-Kanade (b) Lucas-Kanade + ECM. (c) Proposed algorithm using ECM.

from the Lucas-Kanade algorithm, where the exposure difference is observed. Figure 4(b) is obtained from 'Lucas-Kanade + ECM' in Figure 3. Even the exposure difference is compensated, some misregistrations, which are visible as a loss of detail or ghosting, still remain. However, in the proposed algorithm, we can notice that the joint optimization significantly alleviates the misregistrations as shown in Figure 4(c). Similarly, different image pairs as shown in Figure 5 are tested for the proposed algorithm. The numerical results are summarized in Table 1.

We can use a second-order polynomial warp $\mathcal{W}_{12}$ or a third-order polynomial warp $\mathcal{W}_{20}$ for the joint registration. However, as shown in Table 1, it seems that $\mathcal{W}_{12}$ and $\mathcal{W}_{20}$ are not appropriate for the image pairs that have the perspective relationship. If the warp contains more free parameters than necessary, then it sometimes get stuck into local minima [9]. Note that for microscopic images, $\mathcal{W}_{20}$ shows an excellent joint registration result, since $\mathcal{W}_{20}$ includes a second-order polynomial radial distortion model.

(a)

(b)

Figure 5. Image pairs for registration. (a) Pair B. (b) Pair C.

Table 1. Numerical Results (dB)

Image Pairs	Warps	Lucas-Kanade	Lucas-Kanade + ECM	Proposed (ECM)
A	$\mathcal{W}_8$	14.31	9.31	7.22
	$\mathcal{W}_{12}$	12.17	7.63	7.25
	$\mathcal{W}_{20}$	12.27	8.60	7.84
B	$\mathcal{W}_8$	14.82	9.57	8.56
C	$\mathcal{W}_8$	17.48	9.71	7.70

5. Conclusion

In this paper, we conducted joint optimization of the spatial registration and the exposure compensation based on an iterative scheme, the Lucas-Kanade algorithm. The proposed algorithm shows a better registration result compared to a separated registration and compensation scheme for various real images that have different exposure properties.

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