Illumination-invariant image mosaic calculation based on logarithmic search

Wolfgang Konen
Institute for Computer Science
Cologne University of Applied Sciences
Steinmüllerallee 1, D-51643 Gummersbach, Germany
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wolfgang.konen@fh-koeln.de

Abstract
This technical report describes an improved image mosaicking algorithm. It is based on Jain’s logarithmic search algorithm [Jain and Jain, 1981] which is coupled to the method of Kourogi et al. [1999] for matching images in a video sequence. Logarithmic search has a better invariance against illumination changes than the original optical-flow-based method of Kourogi.

1 Introduction

1.1 Related work
Many algorithms on image mosaicking are known, however only relatively few of them can work fully automatic, e.g. [Kourogi et al., 1999; Szeliski, 1994; Seshamani et al., 2006; Robinson, 2003] and under real-time conditions [Kourogi et al., 1999; Seshamani et al., 2006; Robinson, 2003]. Except for Seshamani et al. [2006] they have not yet been applied to endoscopic video.

A problem with Kourogi’s method [Kourogi et al., 1999; Konen et al., 2007a,b] is its dependence on illumination conditions. It is a common condition of endoscopic video sequences that the light source moves together with the camera so that the illumination of a certain patch will vary with its location in the field of view. The logarithmic search method [Jain and Jain, 1981; Lundmark, 2001] is a fast search method based on normalized cross-correlation and thus very robust against overall intensity differences or against slowly varying gradients. This report describes a synthesis between logarithmic search and Kourogi’s algorithm.

2 Methods

2.1 Normalized cross correlation
The normalized cross correlation is a robust measure to quantify the similarity between two image patches (or templates) $A$ and $B$. In the most simple form, these patches can be rectangular areas within images, but irregular shapes are possible as well. The normalized cross correlation is defined as

$$C_L(A, B) = \frac{\sum_{m,n}(A_{mn} - \bar{A})(B_{mn} - \bar{B})}{\sqrt{(\sum_{m,n}(A_{mn} - A)^2)(\sum_{m,n}(B_{mn} - B)^2)}}$$

(1)
where $\bar{A}$ and $\bar{B}$ are the average intensities of patch $A$ and $B$, resp. Due to average subtraction and normalization to the variance of both patches, the measure $C_L$ is invariant against global intensity or contrast changes and only weakly affected by a slowly varying intensity gradient. The correlation coefficient $C_L$ is in the range $[-1, 1]$.

### 2.2 Logarithmic search

Logarithmic search [Jain and Jain, 1981] is an improvement over naive template search. If the search area is a square of side length $2w$, then a naive template search requires $4w^2$ cross correlation measurements. The logarithmic search instead forms a cross with cross bar length $w$ and either shifts this cross or halves the cross bar until it reaches $w = 1$. Fig. 1 shows an example where the cross is first shifted to the right, then down, where it finds the best correlation in the center of the cross. Therefore the cross bar length $w$ is halved, and the search continues with the smaller cross. It is easy to see that the complexity of this approach is only $5(ld(w) + S)$ where $S$ is the number of times we have to shift the cross, which is usually a small number.\(^1\) The complexity reduction from $O(w^2)$ to $O(ld(w))$ is the reason for the name „logarithmic search“.

Algorithm 1 describes logarithmic search in detail. Usually template $A$ will be a square, but other shapes are possible as well. Template $B$ has to have the same shape and size as $A$. „Extract template $A$ at location $(x, y)$“ in line 2 means that the center location of the square is at $(x, y)$. Similar for template $B$ in line 6. The initial size $w_{init}$ is usually a power of 2, so that every division by 2 in line 9 yields again an integer value.

If the cross correlation function $C_L(A, B)$ is convex in the search area, logarithmic search is guaranteed to converge to the correct (and more costly to compute) solution of the naive template search.

### 2.3 Kourogí’s pseudo motion method

The pseudo motion algorithm according to Kourogí et al. [1999] – based on the seminal work of Horn and Schunck [1981] on optical flow – is described in more detail in Konen [2009] (in German) and in Konen et al. [2007,a,b]. It estimates a compensated motion vector field $(u_c, v_c)$ for each pixel in the image. Usually it starts with a compensated motion equal to $(0, 0)$ at each pixel and fills in a dense compensated motion field through a loop of iterations.

For reference, we describe this algorithm in a nutshell as follows: The goal of the improved optical flow algorithm according to Kourogí et al. [1999] is to estimate the motion field between successive

\(^1\) Instead of a 5-point cross it is equally well possible to use a 9-point neighborhood (including self).
frames \( I(t - 1) \) and \( I(t) \) of a video sequence. It calculates at each pixel \((x, y)\) the so-called pseudo motion
\[
\begin{bmatrix}
u_p \\ v_p
\end{bmatrix} = \begin{bmatrix}
-I_x^{(c)}/I_x \\ -I_y^{(c)}/I_y
\end{bmatrix} + \begin{bmatrix}
u_c \\ v_c
\end{bmatrix}
\]
with \( I_x^{(c)} = I(x + u_c, y + v_c, t) - I(x, y, t - 1) \) (2)
where \( I_x \) and \( I_y \) denote the spatial gradient and \((u_c, v_c)\) is the so-called compensated motion at this pixel location, \( I(x, y, t) \) is the luminance signal at pixel \((x, y)\) in frame \( t \). Our algorithm proceeds as follows: Initially we start with \((u_c, v_c) = 0\) or with an estimate from the previous frame. Then the following steps are carried out in a loop:

(A) Calculate the pseudo motion \((u_p, v_p)\) according to Eq. (2) for each pixel inside the endoscopic mask.

(B) Accept only those pixel which fulfill the following criteria: (a) \( I_x \) and \( I_y \) are not 0, (b) \((x + u_p, y + v_p)\) is inside the endoscopic mask and (c) \(|I(x + u_p, y + v_p, t) - I(x, y, t - 1)| < T\). Here, \( T \) is a suitable gray level threshold, e.g. \( T = 5 \).

(C) Find the affine parameters \( \vec{a} = \{a_1, \ldots, a_6\} \) for a global motion field best-fitting the pseudo motion at all accepted pixel locations \( i \), i.e. solve the overdetermined system of equations
\[
\begin{align*}
& a_1 x_i + a_2 y_i + a_3 = u_{p,i} \\
& a_4 x_i + a_5 y_i + a_6 = v_{p,i}
\end{align*}
\]
in a least-squares sense.\(^2\) The solution \( \vec{a} \) from Eq. (3) gives a new estimate for \((u_c, v_c)\)
\[
\begin{align*}
& u_c(x_i, y_i) = a_1 x_i + a_2 y_i + a_3 \\
& v_c(x_i, y_i) = a_4 x_i + a_5 y_i + a_6
\end{align*}
\]
(4)

(D) Continue with step (A) using the new compensated motion vector field \((u_c, v_c)\).

The loop is terminated either after a fixed number of iterations or when the change in the global motion field drops below a certain threshold.

In contrast to that, the pseudo motion method based on logarithmic search, which will be described next, is a single-pass algorithm (no iterations). It calculates the precise pseudo motion vectors only for a set of landmarks, not for all pixel.

\(^2\)It is also possible to use instead of the 6-parameter affine transformation the 8-parameter projective transformation, if the image material requires this wider class of transformations.
2.4 Pseudo motion based on logarithmic search

Algorithm 2 Pseudo motion with logarithmic search. Input: Reference image \( I_r \), object image \( I_o \), threshold \( c_{min} \) for cross correlation coefficient, minimum acceptance rate \( a_{min} \), maximum distance \( e_{max} \). Output: The best transformation \( \tilde{a} \) and the set of accepted matches \( M'' \).

1: function \( PMOTIONLog(I_r, I_o, c_{min}, a_{min}, e_{max}, N) \)
2: \( M = \{ \} \) \hspace{1cm} \( \triangleright \) LogSearch part
3: for (each landmark \( L = (x, y) \)) do
4: \( M \leftarrow M \cup \{(L, u_p, v_p, C_L)\} \)
5: end for
6: \( M' = \{m \in M \mid m \) is among the first \( a_{min}N \) elements of the sorted list OR \( C_L \geq c_{min} \} \)
7: \( M'' = \{m \in M' \mid m \) is among the first \( a_{min}N \) elements of the sorted list OR \( e_m < e_{max} \} \)
8: return \( \langle \tilde{a}, M'' \rangle \)
9: end function

Algorithm 2 describes the new pseudo motion method in detail. Step 2 is an initial estimate of the compensated motion. Several possibilities for such an estimate exist:

1. Initialize \( (u_c, v_c) = 0 \) for every pixel.
2. Initialize \( (u_c, v_c) \) with the compensated motion from the previous frame according to Eq. (4).
3. Call Kourogi’s method for a small number of iterations to get an initial estimate of \( (u_c, v_c) \).

In any way, we start with an initial estimate for \( (u_c, v_c) \) and define a set of \( N \) landmarks. We use in line 6 the logarithmic search method to relocate the landmarks in the object image, starting from the displacement given by \( (u_c, v_c) \).

In order to select only reliable landmarks, there is a two-stage filter in lines 9-19 of Algorithm 2:

1. First we eliminate all landmarks with final correlation coefficient below a threshold, \( C_L < c_{min} \).
   We have however a request for a minimum of \( a_{min}N \) landmarks in total. If there are not enough landmarks above threshold, we take the \( a_{min}N \) landmarks with highest \( C_L \).
2. Based on the landmarks accepted in the first stage, we recalculate \( (u_c, v_c) \) with the help of Eq. (3) and Eq. (4). We now measure for each landmark the Euclidean distance between its displacement vector \( (u_p, v_p) \) and its compensated motion \( (u_c, v_c) \). Outliers (landmarks having a distance larger than \( e_{max} \)) are discarded. Again, care is taken to retain at least \( a_{min}N \) landmarks.

The finally accepted landmarks in \( M'' \) are the basis for the least-squares estimate of transformation \( \tilde{a} \).

\(^3\)To avoid any instabilities in this initialization method, we usually restrict Kourogi’s method to the class of purely translational transformations.
Given the resulting transformation $\vec{a}$ from algorithm \textsc{PMotionLog}, the object image is now warped into the reference image frame. If there is a whole video sequence, these steps are repeated in a loop and step-by-step an image mosaic is formed.

The actual implementation is a little bit more complicated, since only a certain masked area of the image frame contains pixel from the endoscopic view. Furthermore, valid locations $(u, v)$ for template $A$ in the reference or template $B$ in the object image are only those locations where these templates are fully inside the masked area. Those valid locations are computed beforehand with the help of suitable erosion operators.

3 Results

Fig. 2 shows some image mosaicking results. The left image is an early result with Kourogis’s method from Konen et al. [2007b] (CARS conference), based on neuroendoscopic videos from an older Wolf endoscope. The right image is from the more recent study of Liebig et al. [2014] where a Storz endoscope with better lighting and better image quality was available. Here the logarithmic search algorithm is used. A clear improvement in quality is visible. For details the reader is referred to the relevant publications [Konen et al., 2007b; Liebig et al., 2014].

4 Discussion

Advantages of pseudo motion based on logarithmic search:

- It is invariant against local intensity and local contrast changes in the images.
- A good match is well recognizable by its high correlation coefficient $C_L$.
- Localization is usually more precise than with the pixel-based method of Kourogis. (Problems with the pixel-based method of Kourogis are: (a) the gray level of a pixel can fit at multiple places; (b) it may not fit at the correct place because the overall intensity in both images is different.)
- It avoids the problematic acceptance test in step (B) of Kourogis’s method (see Sec. 2.3).
• It is sufficient to match a small set of landmarks. (In principle, 3 landmarks would be sufficient to estimate the 6 parameters of $\vec{a}$. For more robust operation in practical applications, we usually take 10-20 landmarks, which is still considerable less than the number of pixels.) A small set of landmarks allows fast calculation although the individual logarithmic search method is more costly than the pixel acceptance test.

• Most importantly, there is no loop with 10-30 iterations as in Kourogi’s method. It was found that for difficult image pairs (large distortions or difficult lighting conditions), these iterations may cause divergent solutions (e.g. with unrealistically large scale factors). In contrast to that, logarithmic search is considerably more stable.

Disadvantages of pseudo motion based on logarithmic search:

• It is not applicable to (larger) rotations. But in video images there are usually no large rotations from frame to frame.

• Cross correlation accuracy decreases if there is a larger scale factor between two images to be matched. But scale factors up to 10-15% will be usually tolerated.

• It does not calculate a dense pseudo motion field ($u_p$, $v_p$) as Kourogi’s method does. Instead, $(u_p, v_p)$ is only calculated for the accepted landmarks. Thus it cannot express the discontinuities in motion fields as they appear in images from natural scenes when a nearer object with sharp boundaries moves in front of a more distant background. But it was found that endoscopic video sequences often do not exhibit such discontinuities, because the near-far-transition is often gradually. This is of course only a first approximation, and there might be other endoscopic applications, where a 3D reconstruction of nearby objects is necessary to create visually acceptable image mosaics. But for a first approach where the image mosaic gives the surgeon some orientation in the scene, it might be more important to have an algorithm which works fast and robustly. This holds for the logarithmic search method.

Logarithmic search was also used for tracking landmarks in neuroendoscopic video sequences [Konen et al., 1997; Scholz et al., 1998; Konen et al., 1998; Scholz et al., 2005]. Logarithmic search was found to work robustly and a tracking error of 0.7 mm could be obtained [Konen et al., 1997]. Tracking operates at 8 frames per second and thus can be performed under real-time conditions in the operating theatre.

Besides its applications in neuroendoscopy, logarithmic search was also applied with very good success to image stabilization of facial video sequences in the diploma thesis of Bloemendal [2009] (in German). It was shown that it operates reliable enough to allow super-resolution.4

A survey of more work on image processing in neuroendoscopy is found in Konen [2016].

5 Conclusion

This technical report presented a short introduction into the logarithmic search algorithm for image mosaics. A few iterations of Kourogi’s algorithm were used to initialize the motion field, but the central motion field estimation with logarithmic search requires no iterations. In a variety of applications [Bloemendal, 2009; Liebig, 2011; Liebig et al., 2014] it was shown to operate robustly and fast.

The PhD thesis of Liebig [2011] and the paper Liebig et al. [2014] investigated image mosaics based on Kourogi’s algorithm and on the logarithmic search method in neuroendoscopy under clinical conditions. With large image sizes (720x576 pixels) and color image processing, a frame rate of 3-4 fps could be established. Three clinical observers graded the quality of the image mosaic in terms of usefulness for surgery. It was found that the logarithmic search method showed significantly better results than Kourogi’s method. The logarithmic search method was reliable in operation and provided higher-quality mosaics. There is however a need for faster frame rates to create a smooth panorama image for practical use during surgery.

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4A super-resolution image provides more image detail than each image of the original image sequence.
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