Fast 3D Registration Using the Patch Algorithm

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Introduction
With the advent of fast 2D and 3D MRI, there is a growing need to correct for patient motion artifacts, which can have a critical effect when highly accurate feature matching is required, such as in functional MRI. A method for 3D image registration is proposed, as an extension of a previously described method for 2D image registration using the ‘patch’ algorithm. It is robust to noise, and can in principle handle arbitrary distortions; here we describe the 12-parameter affine transformation for 3D images.

Method
Let $I(x) = I(x,t_0)$ and $I'(x) = I(x,t_1)$ be two images acquired at times $t_0$ and $t_1$. $I'(x) = (1+\varepsilon)I(x+u)$ is the result of changes in $I$ caused by displacement field $u(x)$ and a mean intensity change by factor $(1+\varepsilon)$. If $I$ and $I'$ are pre-filtered by the same filter $h$, and a linear approximation (assuming $u, \varepsilon$ are small) to this equation is integrated over a region ('patch') $P$ of the image, we obtain

$$\int_P I_x \, dV = \varepsilon \int_P I' \, dV + \int_P I_x \varepsilon \, dS - \int_P I_y \varepsilon \, dV \quad (1)$$

where $I_x = I*h$, $\Delta I = (I'-I)*h$, and (*) denotes convolution. In this form, derivatives of the noise-corrupted image function $I_x$ are avoided, and the problem is no longer ill-posed. If we choose $u$ as an affine transformation: $u = Ax + b$, and apply Eq. (1) to several different patches $P$ in the image domain, we may solve the resulting linear regression equations for the parameters $A, b$ and $\varepsilon$. The linear approximation (1) is valid only if $u$ is smaller than the smallest scale of features appearing in the filtered images. This problem is addressed by first solving the regression equations using a set of multiscale filters at a coarse resolution, then at progressively finer scales. The approximate solution found at a coarser scale is used to update the transformation parameters at the next finer scale. In this way, $u$ is incrementally improved. The group property of the affine transformation allows for incremental updating of the parameters instead of images, thus avoiding error accumulation caused by successive image interpolations. In the present method, the entire image was simply ‘tilled’ with rectangular patches of uniform size. For the filter set $h_i$, we use a multiscale tensor-product form of the 1D Simoncelli low-pass/high-pass filter pair in the $x,y$-plane, with no filtering in the z-direction (which usually has coarse resolution due to the slice thickness). The images $I, I'$ are filtered at scales $2^j$, for $j = j_{min}, \ldots, j_{max}$, where $j_{min}, j_{max}$ are user-specified. At each scale, the expected displacement $u$ must be smaller than $2^j$ pixels in size, and $j_{max}$ large enough that noise does not corrupt the solution.

Results
The method was applied to a pair of 256x256x64 $T_2$-weighted EPI images of a honeydew melon (only these images have large out-of-plane displacement among available images) and to a pair of 128x128x20 images of human brain. An undecimated (oversampling) set of filters was used. The difference between matching slices of the reference and of the updated images at different levels $j = 3,2,1,0$ are presented in the Figure. The error, defined as $err = |I'/I| - |J|$, diminished with each update. For iteration at finer levels no further improvement occurred, in part due to errors in linear interpolation. Cubic convolution and sinc interpolations were also tried. These usually produced comparable errors, but at much higher computational cost. However, some lower resolution images could not be registered with linear, but could with sinc interpolation. The CPU time required for registration, and registration errors at different level $j$ on a SGI computer with 180MHz clock, are shown in the Table. The CPU time may be reduced by further optimization of the program.

Discussion
The method described is efficient, robust to noise, and general enough to be extended to models of global distortion that are more elaborate than the affine case. If smaller displacements are expected, then $j_{max}$ and $j_{min}$ can also be chosen smaller, thereby reducing the time required for registration.

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References

Figure: The difference between matching slices of the reference and of the image before registration (ori), and updated images after iterations at different levels $j$ for human brain (top) and melon (bottom). Registration error $err$ is presented in the Table.