Registration and error estimation in correlated multimodal imaging

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Context

Image registration methods are used in a wide range of applications, in particular in correlated multi-modal imaging in life science. In this multimodal context, there may be an important discrepancy in the intensity based features between the two images. For this reason, fiducial based methods (artificial or natural) are often preferred. Yet we often lack an estimate of the associated registration error. Cross-validation and in particular leave-one-out methods are often used to assess the quality of the registration process as seen in [1] *Schorb et al. 2014* and [2] *Kukulski et al. 2011*. These methods only use a fraction of available fiducial points to compute the transformation. The associated registration error is estimated using the remaining fiducial points by measuring the distance between fiducial points and their registered position. [3] *Fitzpatrick et al. 2001* demonstrates that registration error at a given location directly depends on the distance from this particular location to the principal axes of the fiducial points cloud. Therefore leave-one-out based methods for estimating registration error might not give accurate results. In this work we aim to provide registration error estimates as a quality metric for image registration. Our method relies on multivariate multiple linear regression analysis which provides both image registration itself and registration error estimates. Since linear regression is flexible, models can be extended to integrate constraints such as rigid transformations. This is also known as the orthogonal Procrustes problem. We provide an implementation of our registration framework as a plugin for the Icy software ([5] *de Chaumont et al. 2012*).

Expectation

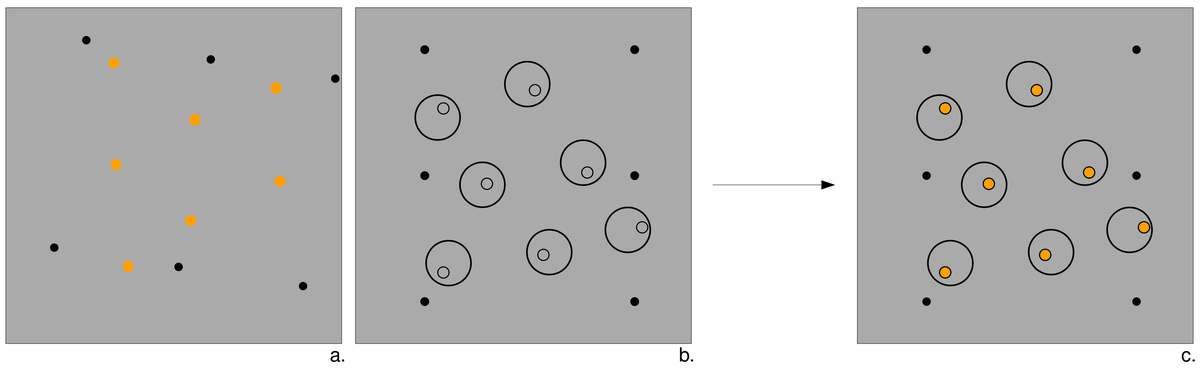


Figure 1 : Ideal case registration example. An image aquired using fluorescence microscopy (a) is registered on an image aquired using electron microscopy (b). The result is a merged image (c). Black dots are fiducial points and are perfectly aligned during resgistration process.

Reality

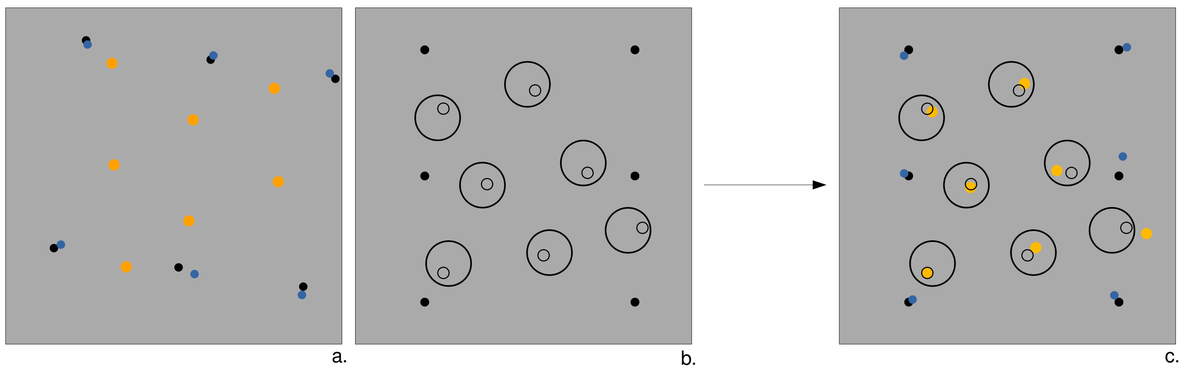


Figure 2 : Noisy case registration example. An image aquired using fluorescence microscopy (a) is registered on an image aquired using electron microscopy (b). The result is a merged image (c). Black dots are fiducial points. Blue dots are the localized fiducial points during the registration process. Fiducial points does not match perfectly.

Registration error

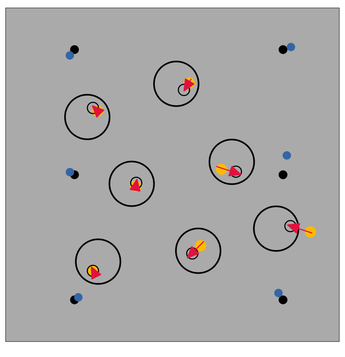


Figure 3 : Registration error represented by red arrows.

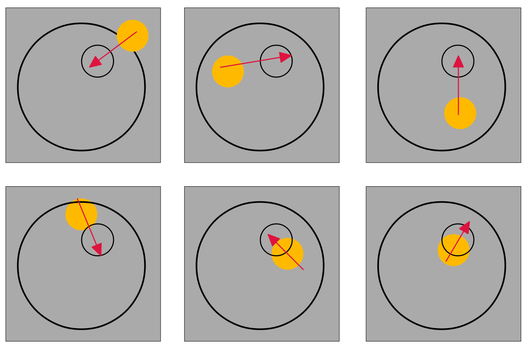


Figure 4 : Registration error is a zero-mean vector.

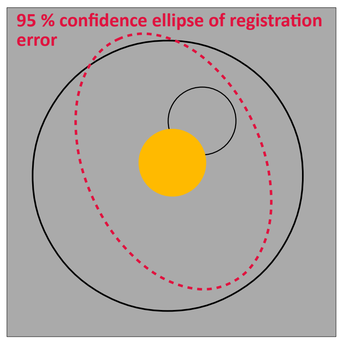


Figure 5 : Confidence ellipse constructed using registration error variance.

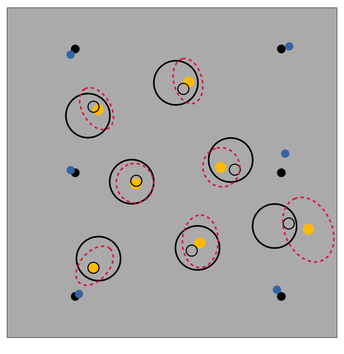


Figure 6 : Confidence ellipse constructed at different locations in an image.

Registration models

Rigid model

✔ Rotation ✗ Scaling
✔ Translation ✗ Shear

Can be solved by :

Maximum likelihood optimization

Registration error variance estimated by :

Cramer-Rao lower bound

Affine model

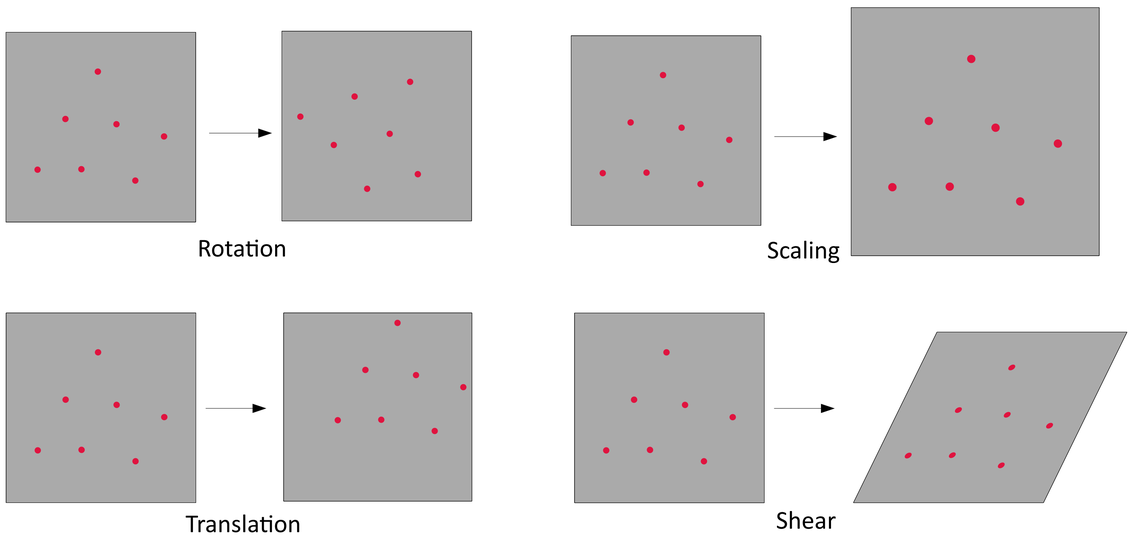
✔ Rotation ✔ Scaling
✔ Translation ✔ Shear

Can be solved by :

Multivariate linear regression

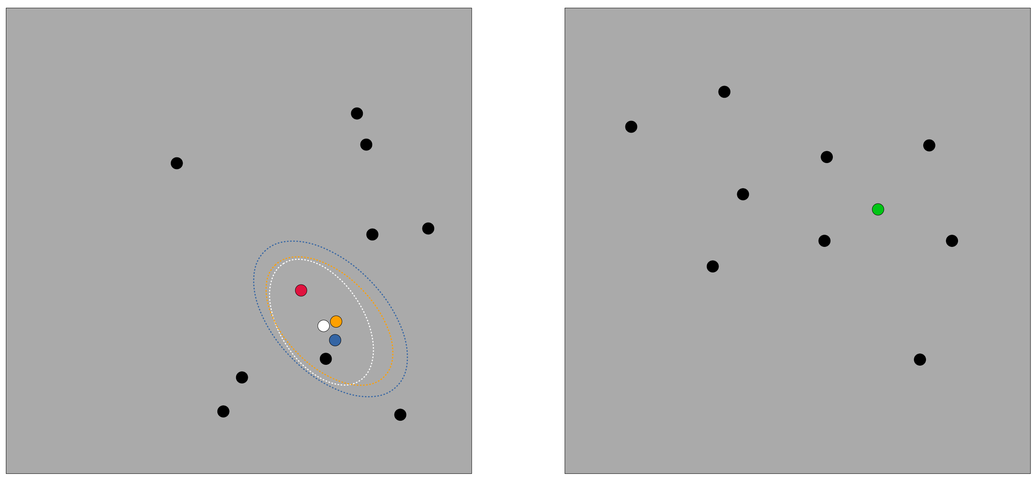
Registration error variance estimated by :

Multivariate linear regression result



Simulation protocol

Rigid model Affine model Noise model



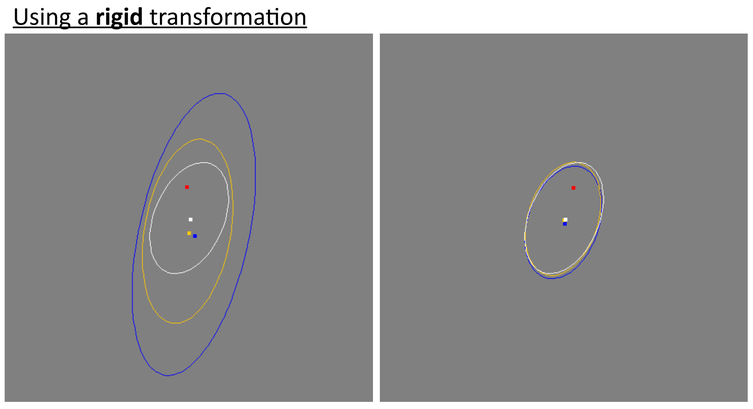
Target

Source

Known transformation

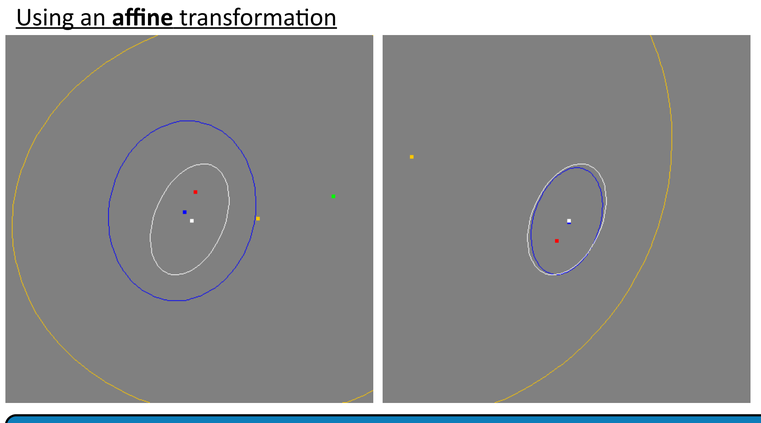
Results

Using a **rigid** transformation



Model	# Fiducials	% red point inside ellipse	Ellipse area (arbitrary unit)
Rigid	10	95,053	5 696
Rigid	25	94,183	3 779
Rigid	100	94,982	3 413
Affine	10	95,058	8 918
Affine	25	94,994	4 415
Affine	100	94,995	3 539
Noise	10	95,004	3 339
Noise	25	94,982	3 339
Noise	100	94,982	3 339

Using an **affine** transformation



Model	# Fiducials	% red point inside ellipse	Ellipse area (arbitrary unit)
Rigid	10	97,824	55 941
Rigid	25	97,792	35 719
Rigid	100	98,435	31 365
Affine	10	95,152	8 915
Affine	25	95,033	4 415
Affine	100	95,004	3 539
Noise	10	95,004	3 339
Noise	25	95,005	3 339
Noise	100	95,014	3 339

Conclusion

Cross-validation and in particular leave-one-out methods are often used as quality metrics by estimating registration error. Unfortunately theses methods may not be accurate. [4] *Moghari et al. 2009* provides a solution to estimate the registration error under the assumption of a rigid transformation. This solution requires solving a maximum likelihood optimization problem and uses the Cramer-Rao lower bound to estimate the registration error variance. We demonstrate that multivariate linear regression provides a direct closed-form solution in the more general case where the underlying transformation is affine. This solution might be faster to compute and is more robust from a practical point of view: in a real experiment one cannot be certain whether the underlying transformation is rigid or affine. Finally, we plan to extend this work by using the total least squares instead of multivariate linear regression. It might be a better fit regarding the assumptions taken on the noise of the images.

References

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