Privacy Preserving Image Registration

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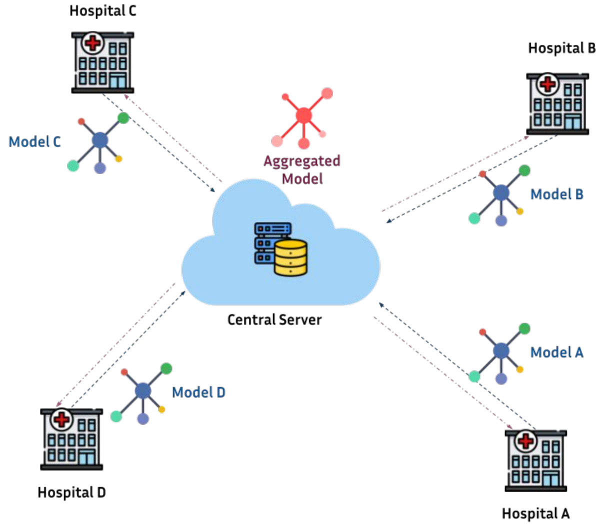
Introduction

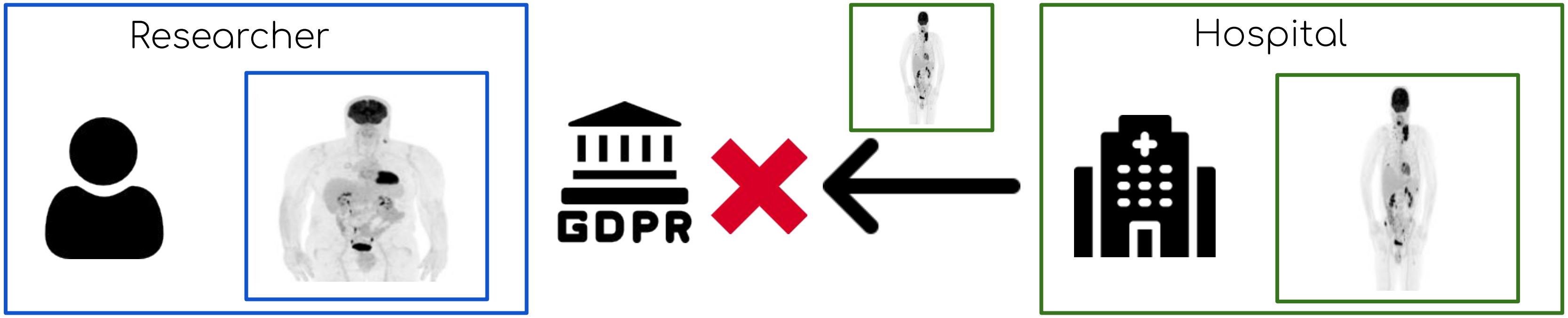
Image registration (IR) is the workhorse of many real-life medical imaging software and applications:

- Public web-based services for medical images segmentation [1];

- Federated Learning (FL) [2] where medical images can be jointly analyzed in multi-centric scenarios.



Problem



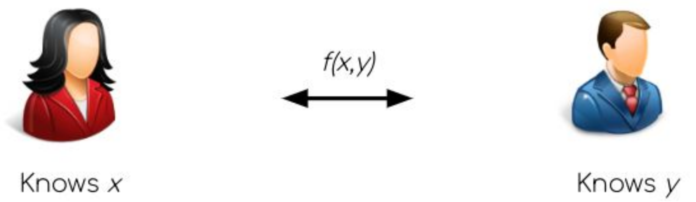
Medical imaging information falls within the realm of personal health data and its sensitive nature, these applications of image registration are no longer compliant with regulations currently existing in many countries, such as the GDPR [3], or HIPAA [4].

Contribution

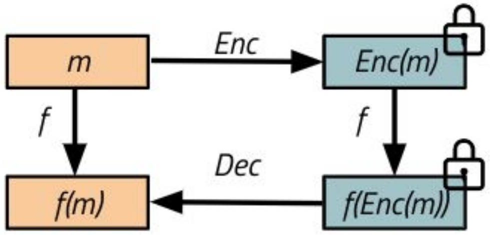
We formulate the problem of **IR** under a privacy preserving regime, where **images** are assumed to be **confidential** and **cannot be disclosed in clear**.

Privacy Preserving Tools

Multi Party Computation (MPC)



Fully Homomorphic Encryption (FHE)



Background

We consider a scenario with two parties, $\boxed{party_1}$ and $\boxed{party_2}$, whereby owns $\boxed{party_1}$ image I and $\boxed{party_2}$ owns image J .
The cost function to optimize the registration problem is the sum of squared intensity differences (SSD):

$$\mathrm{SSD}\left(I, J, \mathbf{p}\right) = \arg\min_{\mathbf{p}} \sum_{\mathbf{x}} \left[I\left(W_{\mathbf{p}}\left(\mathbf{x}\right)\right) - J\left(\mathbf{x}\right)\right]^2$$

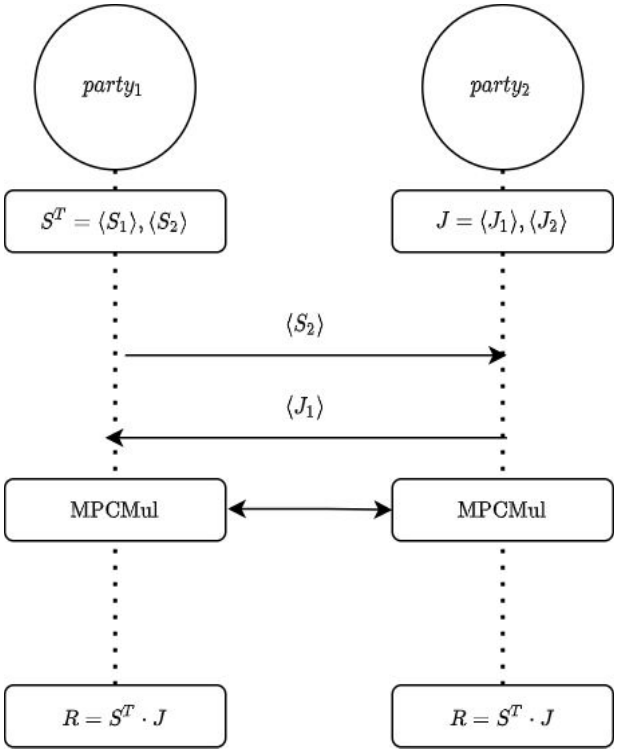
Under Gauss-Netwon optimization scheme, the parameters of the spatial transformation can be computed as:

$$\Delta \mathbf{p} = \underbrace{H^{-1}}_{\boxed{party_1}} \cdot \sum_{\mathbf{x}} \underbrace{S\left(\mathbf{x}\right)}_{\boxed{party_1}} \cdot \left(\underbrace{I\left(\mathbf{W}_{\mathbf{p}}\left(\mathbf{x}\right)\right)}_{\boxed{party_1}} - \underbrace{J\left(\mathbf{x}\right)}_{\boxed{party_2}} \right)$$

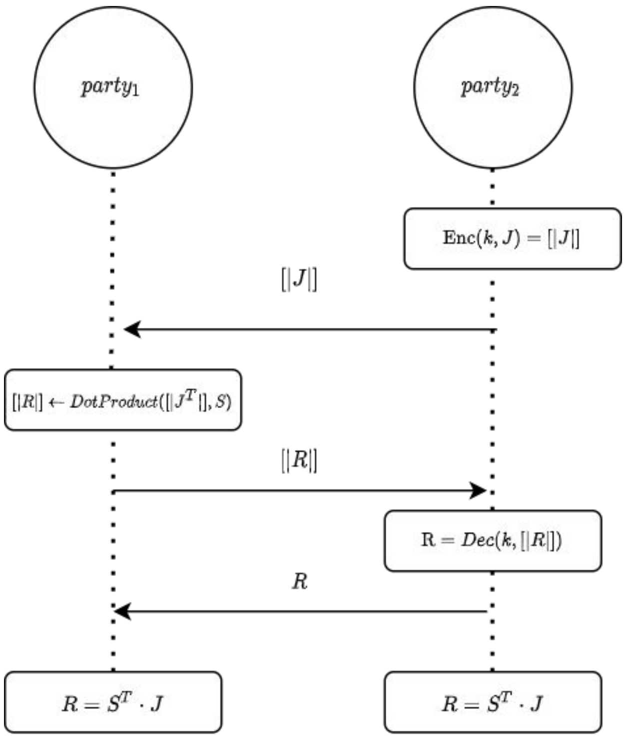
To compute the registration update the only operation requiring the joint availability of information from both parties is the term $R = \sum_{\mathbf{x}} \underbrace{S\left(\mathbf{x}\right)}_{\boxed{party_1}} \cdot \underbrace{J\left(\mathbf{x}\right)}_{\boxed{party_2}}$
in vectorized form $R = \underbrace{S^T}_{\boxed{party_1}} \cdot \underbrace{J}_{\boxed{party_2}}$

Privacy Preserving Image Registration (PPIR)

Multi Party Computation (MPC)



Fully Homomorphic Encryption (FHE)



Scalability of privacy preserving tools is achieved using gradient approximations, i.e. Uniformly Random Selection (URS) [5] and Gradient Magnitude Selection (GMS) [6].

Experimental Results

We demonstrate and assess **PPIR** based on **linear** (Figure 1, Table 1) and **non-linear registration**, by comparing the registration results with respect to the ones obtained with standard registration on clear images (Clear).

Affine registration metrics				
Solution	Intensity Error (SSD)	Num. Interation	Displacement RMSE Clear vs PPIR (mm)	
Clear	4.34 ± 0.0	118 ± 0.0	-	
SPDZ	4.34 ± 0.0	114.8 ± 4.0	1.81 ± 0.02	
CKKS	✗	✗	✗	
Clear + URS	4.38 ± 0.0	61 ± 0.0	-	
SPDZ + URS	4.34 ± 0.0	60.4 ± 6.85	16.49 ± 3.74	
CKKS ($D = 128$) + URS	4.34 ± 0.10	61.80 ± 4.82	23.31 ± 2.72	
Clear + GMS	4.34 ± 0.0	63 ± 0.0	-	
SPDZ + GMS	4.34 ± 0.0	59.80 ± 6.20	6.21 ± 1.49	
CKKS ($D = 128$) + GMS	4.34 ± 0.05	60.4 ± 5.12	5.17 ± 1.40	
Affine efficiency metrics				
Solution	Time $party_1$ (s)	Time $party_2$ (s)	Comm. $party_1$ (MB)	Comm. $party_2$ (MB)
Clear	0.0	0.0	-	-
SPDZ	0.13	0.13	1.54	1.54
CKKS	✗	✗	✗	✗
Clear + URS	0.0	0.0	-	-
SPDZ + URS	0.02	0.02	0.20	0.20
CKKS ($D = 128$) + URS	2.55	0.02	0.06	0.01
Clear + GMS	0.0	0.0	-	-
SPDZ + GMS	0.02	0.02	0.20	0.20
CKKS ($D = 128$) + GMS	2.51	0.02	0.06	0.01

Table 1: quantitative results for affine registration, where SPDZ = MPC and CKKS = FHE

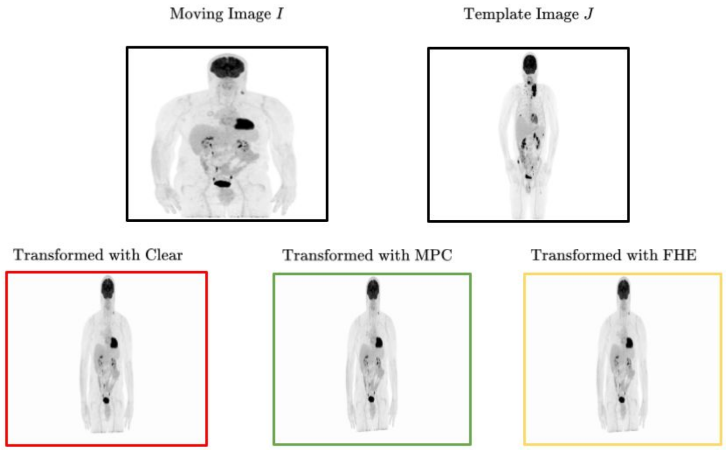


Figure 1: qualitative results for affine registration

Conclusion & Future Extensions

This work introduces **PPIR**, a novel framework to allow IR when **images cannot be disclosed in clear.** Future extensions are:

- Improve FHE time complexity;
- Apply to others cost function, i.e. Mutual Information

References

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[3] Regulation (EU) 2016/679 of the European Parliament and of the Council.

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[5] Mattes et al. : Pet-ct image registration in the chest using free-form deformations. IEEE transactions on medical imaging 22(1), 120–128

[6] Sabuncu et al. : Gradient based non-uniform subsampling for information-theoretic alignment methods. In: The 26th Annual International Conference of the IEEE Engineering in Medicine and Biology Society. vol. 1, pp. 1683–1686. IEEE (2004)

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Thanks!

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