WELLCOME / EPSRC CENTRE INTERVENTIONAL AND SURGICAL SCIENCES

Deep Sequential Mosaicking of Fetoscopic Videos

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1. Introduction

Fetoscopic laser photocoagulation is the most effective treatment for regulating the blood flow during Twin-to-Twin Transfusion Syndrome (TTTS) treatment [1].
During treatment, the clinician first visually explores the placenta using fetoscopic video to identify vascular anastomoses, building a mental map and treatment plan.
Limited field-of-view, poor visibility and limited maneuverability of the fetoscope introduce challenges that increase procedural time and can lead to complications [2].
Mosaicking can align multiple overlapping images to generate an image with increased field-of-view and ease the localization of the vascular anastomoses' sites.

2. Proposed Deep Sequential Mosaicking

Deep Image Homography (DIH) model [3] estimates the relative 4-point homography ${}^{4p}\widehat{H}_B^A$, between pairs of image patches P_A and P_B extracted from a single image.

${}^{4p}\widehat{H}_B^A$ to $\widehat{H}_B^A$ conversion is obtained by applying Direct Linear Transform.

Mosaic from an image sequence is generated by finding the pairwise homographies between adjacent frames, followed by computing the relative homographies *w.r.t* a reference frame.

Our proposed **Deep Sequential Mosaicking** method adopts DIH by proposing:

I. Controlled Data Augmentation (CDA)

We assume that the pairwise homography between frames F_k and F_{k+1} is related by translation and rotation only. This helps to minimize the error in relative homography and consequently reduce the drift in mosaicking.

II. Outlier Rejection

For each F_k and F_{k+1}, we compute ${}_n\widehat{H}_{k+1}^k$ for *N* iterations by selecting random patch pairs at each iteration and computing the decompose parameters $\mathcal{D}_n$ by applying Singular Value Decomposition. To obtain a consistent prediction $\widehat{H}_{k+1}^k$, we apply median filtering on $\mathcal{D}_n$.

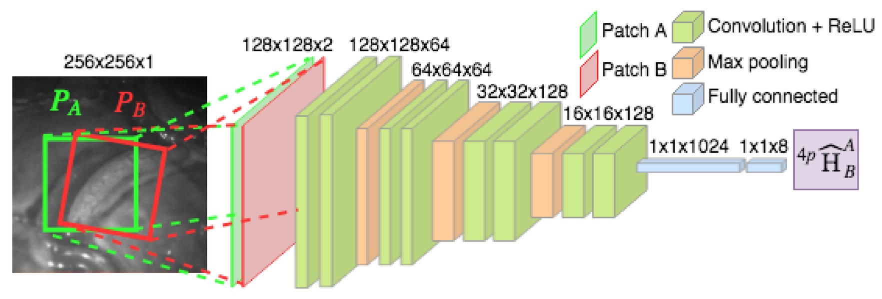


Fig 1. Deep Image Homography with Controlled Data Augmentation.

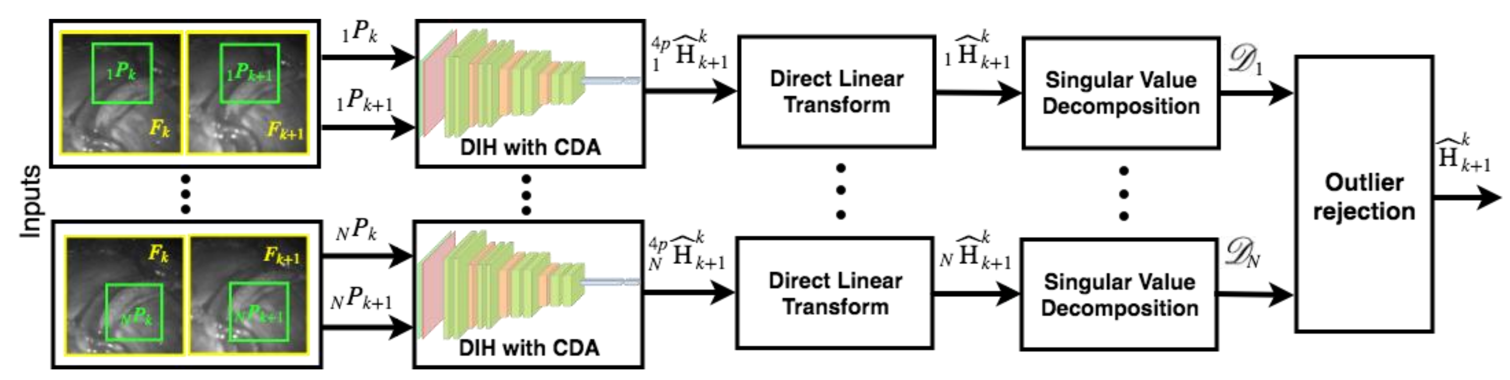


Fig 2. Overview of the proposed Deep Sequential Mosaicking method.

(a) Ground-truth *(b)* DIH (tracking lost) *(c)* DIH with CDA (noticeable drift) *(d)* Proposed DSM (drift minimized)

Fig 3. Comparison visualization on the synthetic sequence.

3. Experimental Analysis

Experimental Setup

Dataset used for validation contain five videos, which include synthetic (SYN), ex-vivo in water (EXVIVO), placenta phantom (PHN1), TTTS phantom in water (PHN2) and in-vivo TTTS procedure (INVIVO) videos.

Training is performed using a subset of 600 images not containing any data from EXVIVO.

Comparison of the proposed DSM is performed with DIH [3] and FEAT [4].

Observations

DSM is capable of handling varying visual quality (varying illumination, specular highlights and low resolution), planar and non-planar views with heavy occlusions.

Validation on the unseen EXVIVO dataset verified the robustness and generalization capabilities of the proposed DSM.

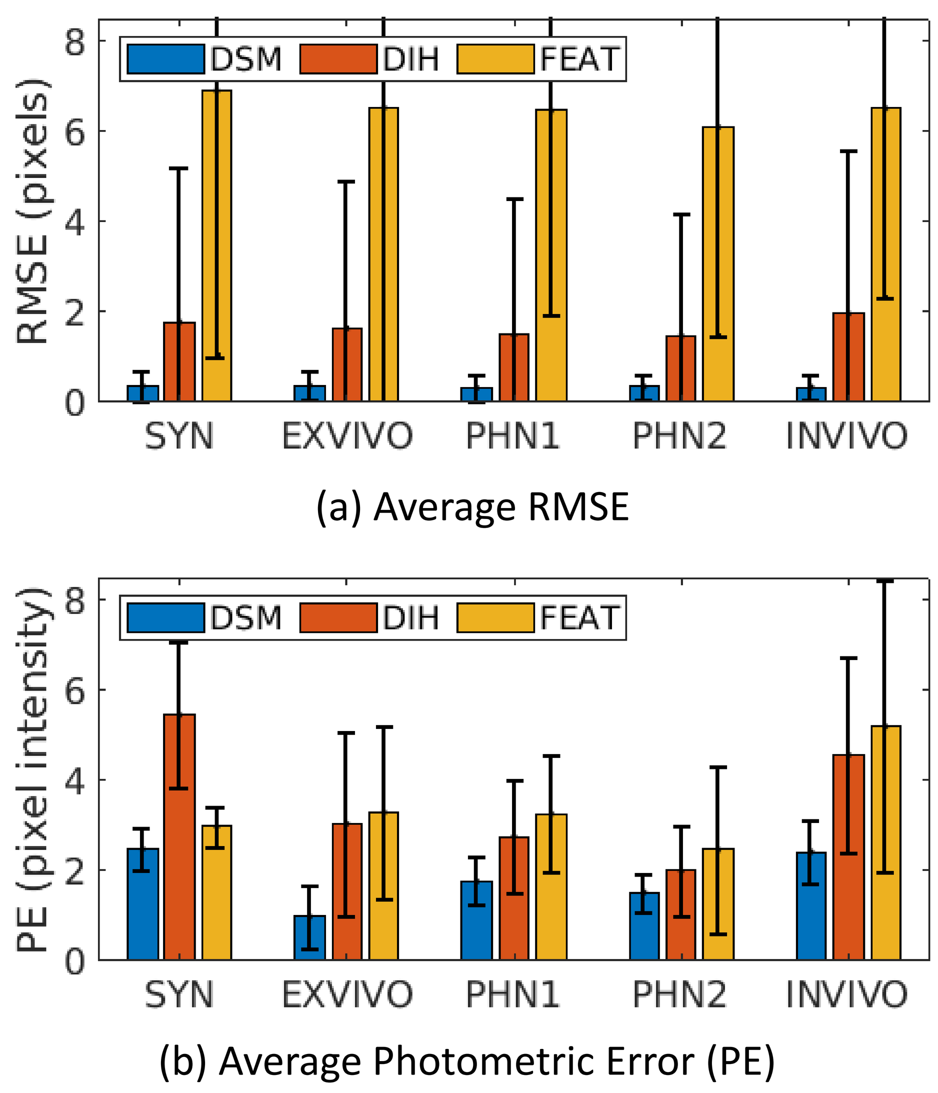
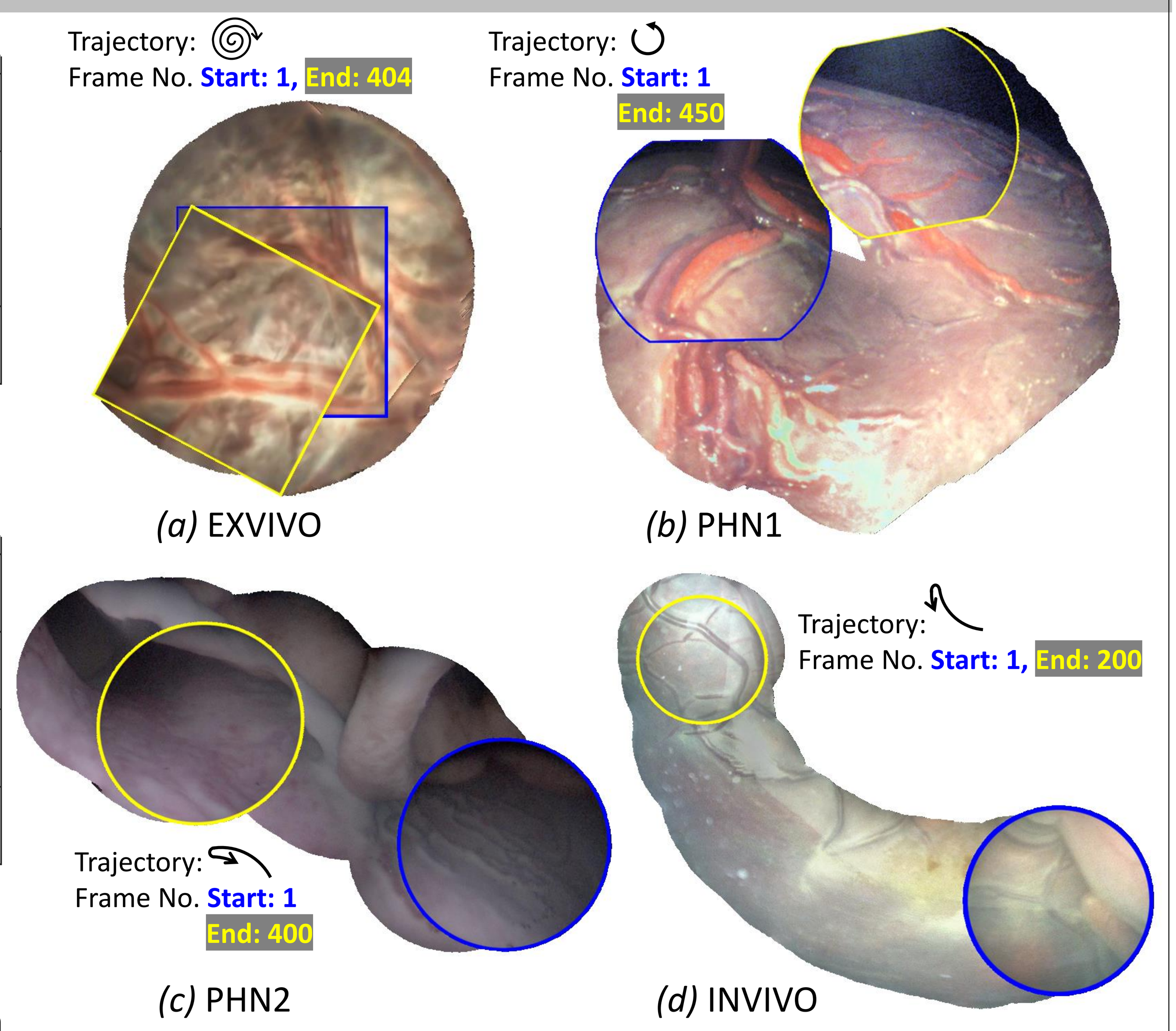


Fig 4. Quantitative evaluation and comparison on five diverse fetoscopic videos.



(a) EXVIVO *(b)* PHN1 *(c)* PHN2 *(d)* INVIVO

Fig 5. Qualitative evaluation on exvivo, phantom and invivo videos.

4. Conclusion

We proposed a deep sequential mosaicking method for fetoscopic videos acquired through various sources which to our knowledge is a first.
Experimental evaluation on five diverse fetoscopic sequences showed that, unlike existing methods that drift rapidly in just a few frames, our method produced mosaics with minimal drift even for long-range sequences.
Future work involves further validation on invivo sequences, end-to-end learning and region re-localization for field-of-view expansion throughout the TTTS procedure.

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References

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