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**ELECTRICAL ENGINEERING
AND COMPUTER SCIENCE**



Almekkawy Lab
Ultrasound in Imaging and Therapy

Arterial Wall motion Estimation in Carotid Artery Using Deep Learning with Extended Kalman Filter

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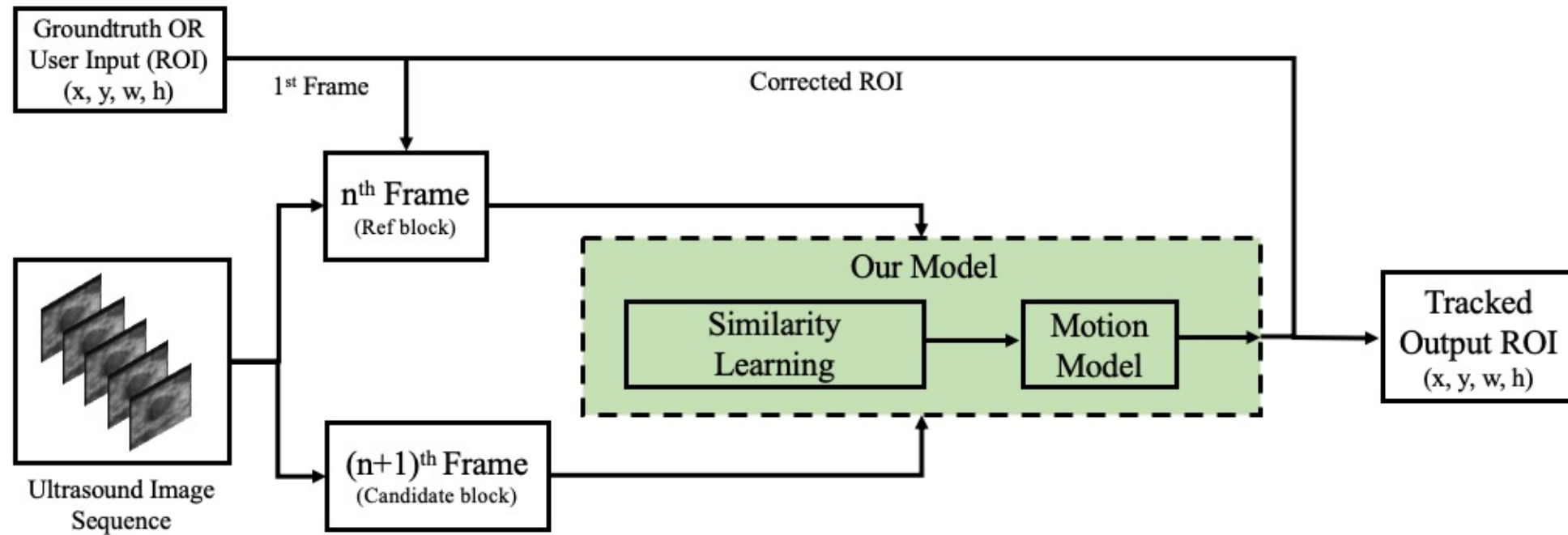
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Speckle Tracking: Background and Motivation

- Speckles, in ultrasound images, are formed by the combination of constructive and destructive interference of echoes from scatterers in the observed tissue.
- Tracking speckles has multiple applications in image-guided radiation therapy.
- We explore deep neural networks to improve motion tracking in ultrasound images.

Big Picture Overview

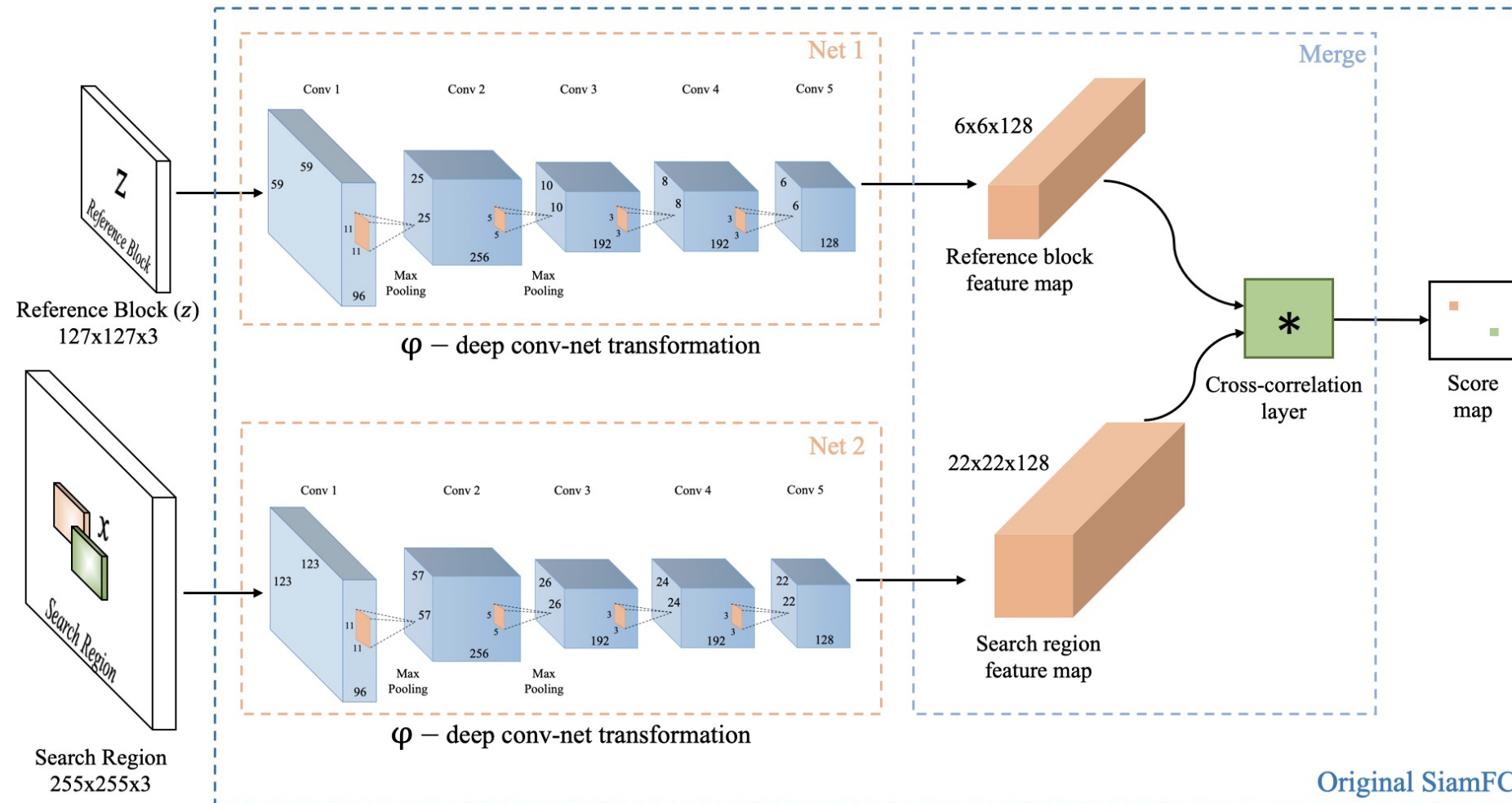




Speckle Tracking: A Deep Learning Approach

- Conventional techniques – Exhaustive Search-based Similarity Matching (ES-SM)
 - Expensive or less accurate (trade-off)
- Requirement: Faster similarity matching techniques without compromising accuracy
 - Deep learning techniques – fast (similarity learning) and accurate.
- Ultrasound images pose challenges –
 - Could be RF data
 - Hardly any difference between foreground and background
 - Lack of annotated data
 - Needs exhaustive testing to prove validity

SiamFC: Architecture



Siamese Architectures: Fully-Convolutional Siamese Tracker (SiamFC)

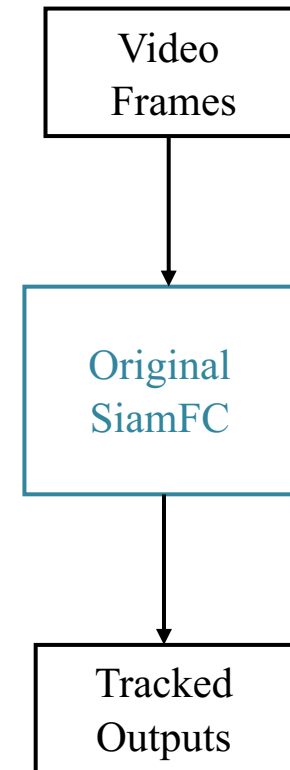
Fully-Convolutional Siamese Tracker (SiamFC) was developed by Bertinetto et al¹.

- Siamese networks use same transformation function (φ) on two different inputs to compare the similarity between them.
- Siamese architectures formulate motion estimation as convolutional feature cross-correlation between a reference block and a search region.
- Given a reference image z , the network compares it with candidate image x of the same size and returns a high score if two images depict same image and a low score otherwise.
- In SiamFC, convolutional stage resembling the architecture of AlexNet² is adopted as the embedding function (φ) for the reference block and the candidate blocks from within the search region.

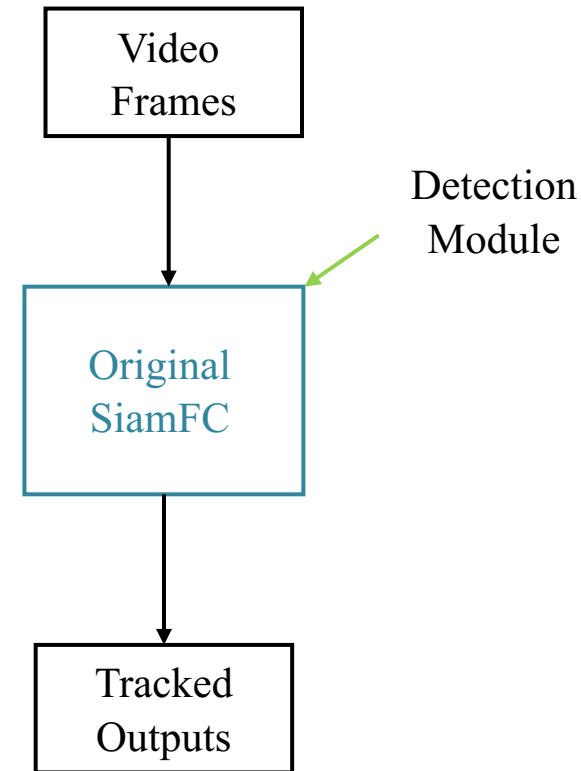
1. Luca Bertinetto, Jack Valmadre, Joao F Henriques, Andrea Vedaldi, and Philip HS Torr, “Fully-convolutional siamese networks for object tracking,” in *European conference on computer vision*. Springer, 2016, pp. 850–865.
2. Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton, “Imagenet classification with deep convolutional neural networks,” in *Advances in neural information processing systems*, 2012, pp. 1097–1105.



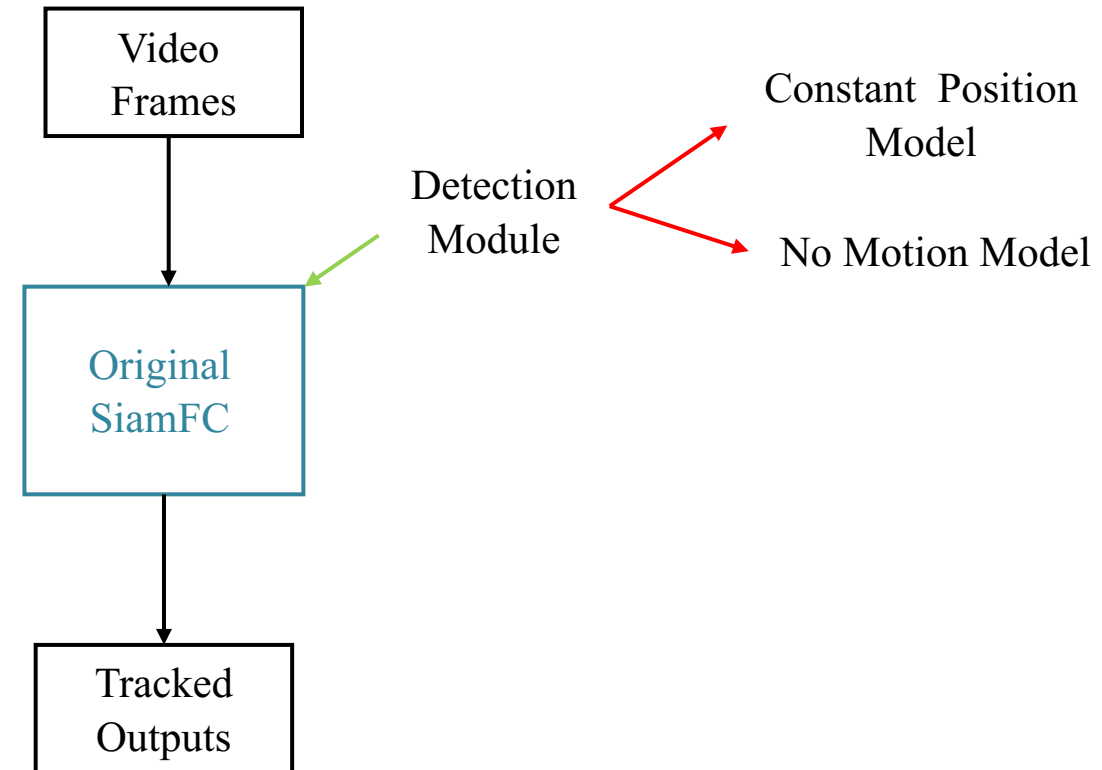
SiamFC: Upgraded SiamFC



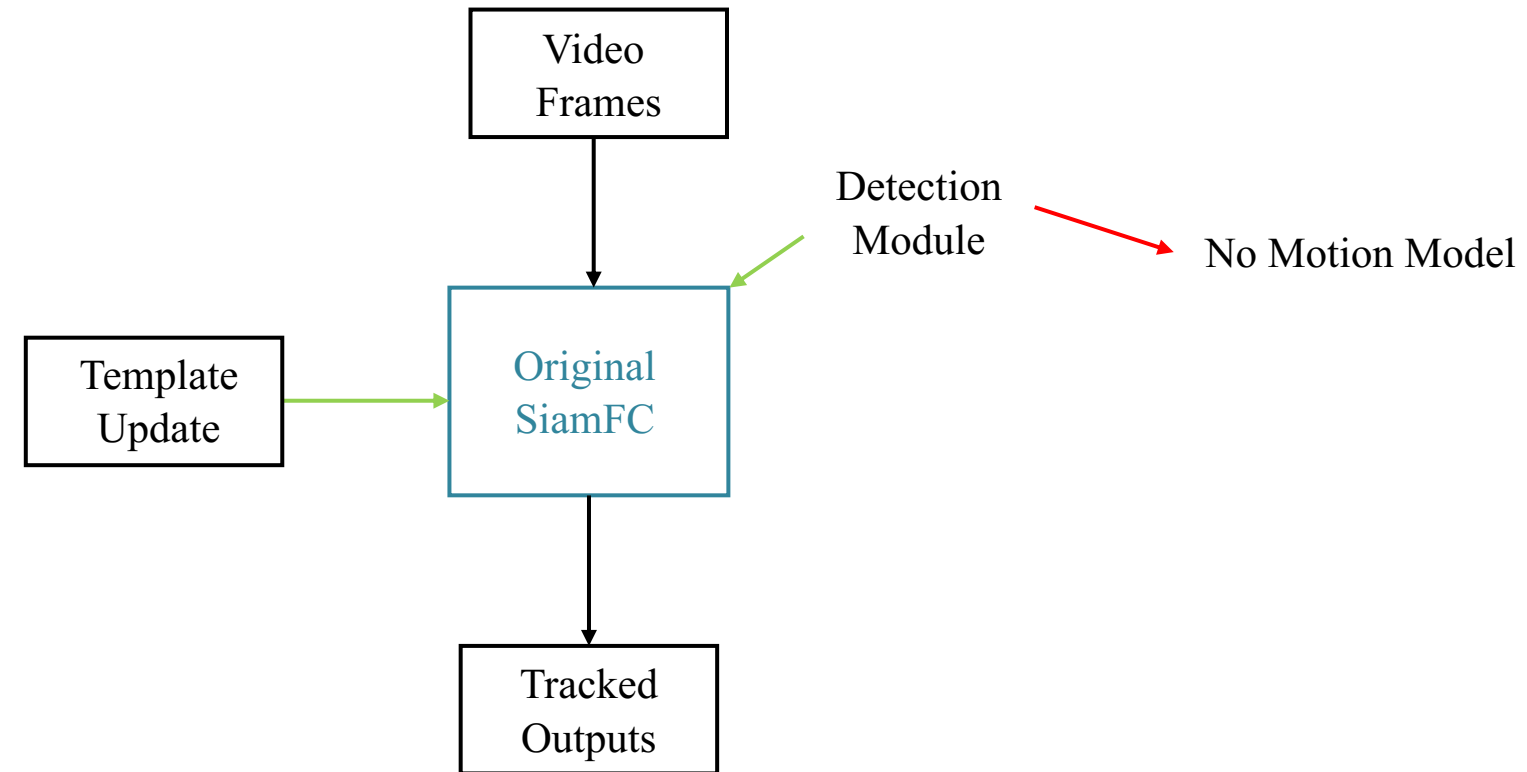
Upgraded SiamFC



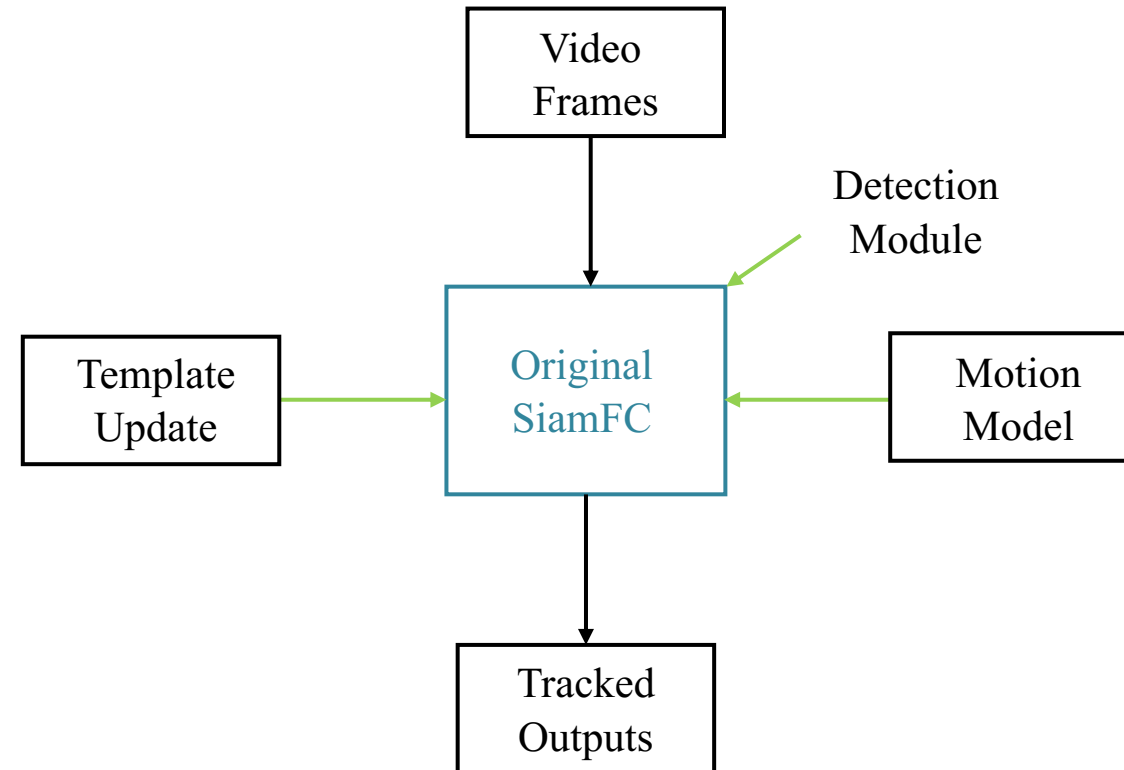
Upgraded SiamFC



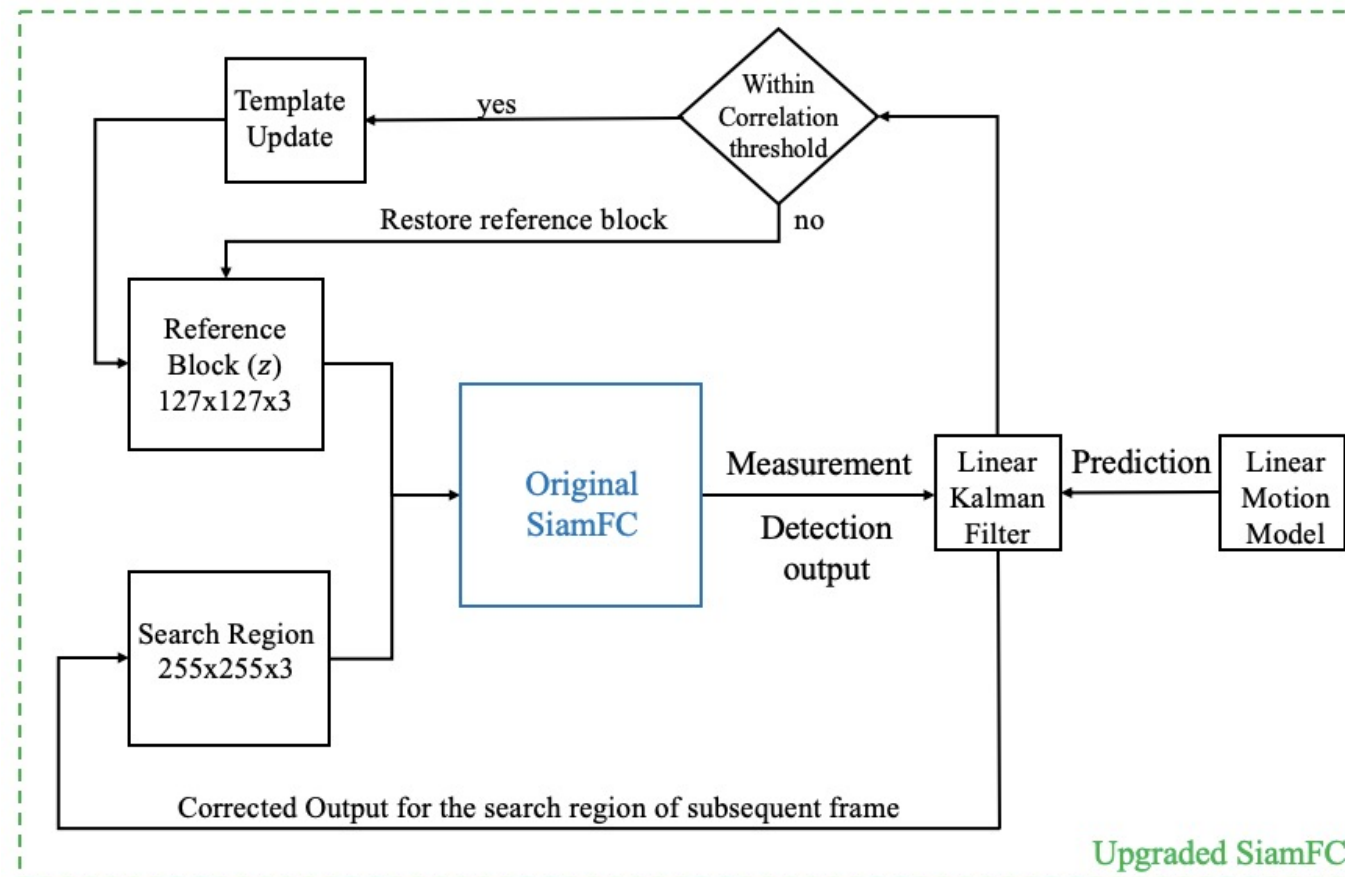
Upgraded SiamFC



Upgraded SiamFC

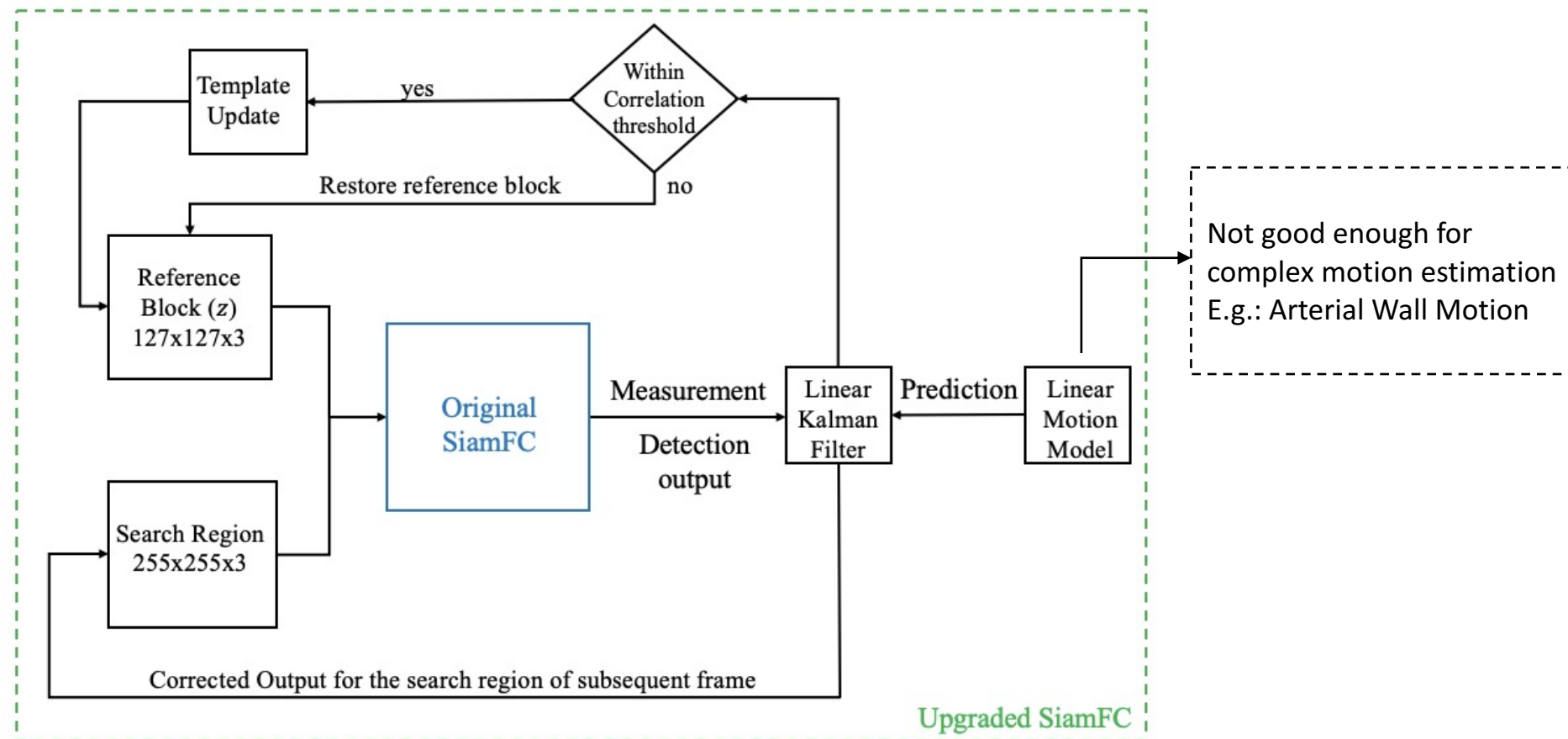


Upgraded SiamFC: Architecture



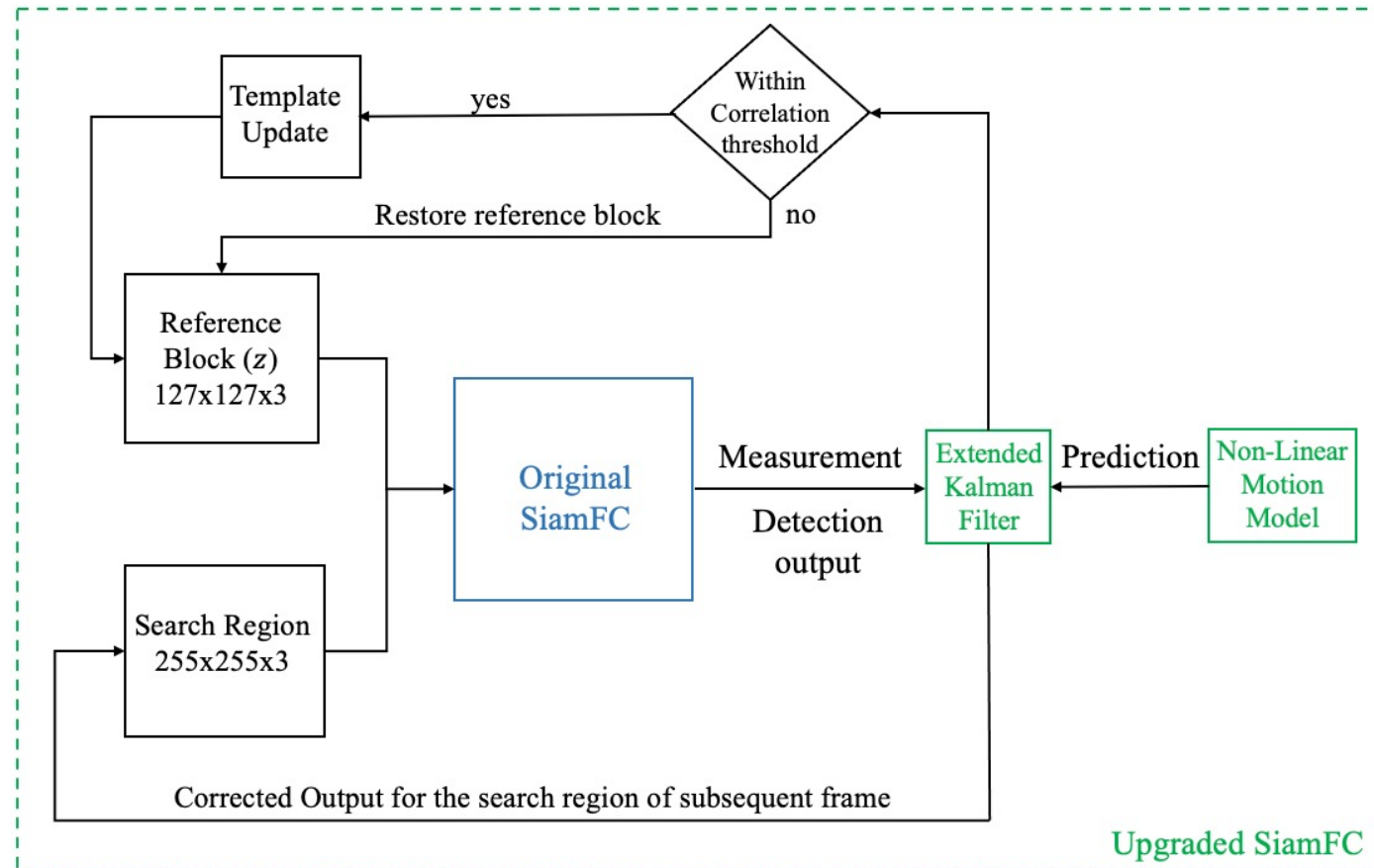
S. Bharadwaj, S. Prasad and M. Almekkawy, "An Upgraded Siamese Neural Network for Motion Tracking in Ultrasound Image Sequences," in IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control, vol. 68, no. 12, pp. 3515-3527, Dec. 2021, doi: 10.1109/TUFFC.2021.3095299.

Upgraded SiamFC: Architecture



S. Bharadwaj, S. Prasad and M. Almekkawy, "An Upgraded Siamese Neural Network for Motion Tracking in Ultrasound Image Sequences," in IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control, vol. 68, no. 12, pp. 3515-3527, Dec. 2021, doi: 10.1109/TUFFC.2021.3095299.

Upgraded SiamFC: Architecture





Upgraded SiamFC: Template Update

- Allow reference image to change within permissible range – Anchoring
- Similarity cost function: Normalized Cross – Correlation –

$$G = \frac{\sum_i \sum_j (z_{ij} - \bar{z})(x_{ij}^k - \bar{x}^k)}{\sqrt{\sum_i \sum_j (z_{ij} - \bar{z})^2} \sqrt{\sum_i \sum_j (x_{ij}^k - \bar{x}^k)^2}}$$

z – represents the reference block,

x^k – represents a candidate block within the search region x .



Upgraded SiamFC: Linear Kalman Filter

- **State Space Equation:** $\mathbf{x}_{k+1} = f(\mathbf{x}_k, \mathbf{u}_k) + \mathbf{n}_k$ $\mathbf{z}_k = h(\mathbf{x}_k) + \mathbf{v}_k$

f : Motion of
Van der Pol Oscillator

- **Governing Equation:**

$$x_k = x_{k-1} - \frac{T}{5}y_{k-1} + Tu_1$$

$$y_k = \left(1 - \frac{T}{5}\right)y_{k-1} + Tx_{k-1} - \frac{T}{373}x_{k-1}y_{k-1} + Tu_2$$

(u_1 and u_2 are shown
in the next slide)

- **State Equation and Measurement Model:**

$$\mathbf{x}_k = \mathbf{F}\mathbf{x}_{k-1} + \mathbf{B}\mathbf{u}_k + \mathbf{n}_k$$

$$\mathbf{z}_k = \mathbf{H}\mathbf{x}_k + \mathbf{v}_k$$





Upgraded SiamFC: Linear Kalman Filter

- Control Signal: $[u_1, u_2]^T = g_1(k) + g_2(k)$

$$g_1(k) = \begin{bmatrix} \tanh(1.22(k - 0.4T))(1 - \tanh(1.22k))\sin^2 \frac{\pi k}{3.5T} \\ \tanh(2.07(k - 0.4T))(1 - \tanh(2.07k))\sin^2 \frac{\pi k}{3.5T} \end{bmatrix}$$

$$g_2(k) = \begin{bmatrix} (1 + \tanh(1.22(k - T)))(1 + \tanh(1.22(0.4T - k)))(20 - \frac{20}{T}k) \\ (1 + \tanh(2.07(k - T)))(1 + \tanh(2.07(0.4T - k)))(17 - \frac{17}{T}k) \end{bmatrix}$$

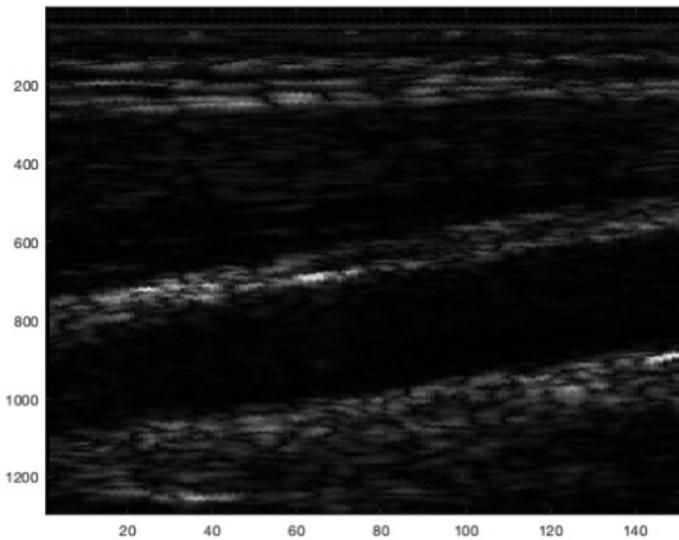
- Brief Summary of Kalman Matrices:

$$\mathbf{F} = \begin{bmatrix} 1 & -dt/5 \\ dt - (\frac{dt}{373}y_k) & (1 - \frac{dt}{5}) - (\frac{dt}{373}x_k) \end{bmatrix} \quad \mathbf{B} = \begin{bmatrix} dt \\ dt \end{bmatrix} \quad \text{and} \quad \mathbf{H} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

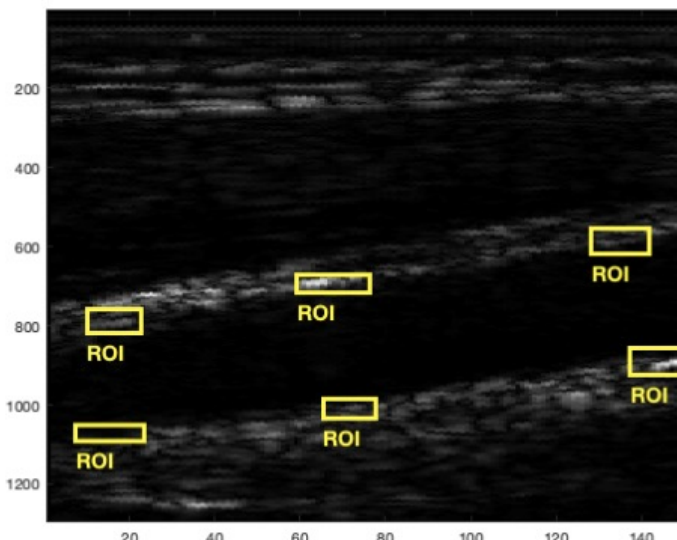


Upgraded SiamFC: Experiments

- Proposed approach was tested on 17 ROIs from 8 image sequences.
- ROIs → User input the first frame and track throughout the image sequence.
- Compare accuracy and speed between SiamFC-EKF and ES-SM.



(a) Sample frame



(b) Multiple ROIs

Sonix RP (LA14-5/38)
7.5 MHz



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Upgraded SiamFC: Results

Accuracy

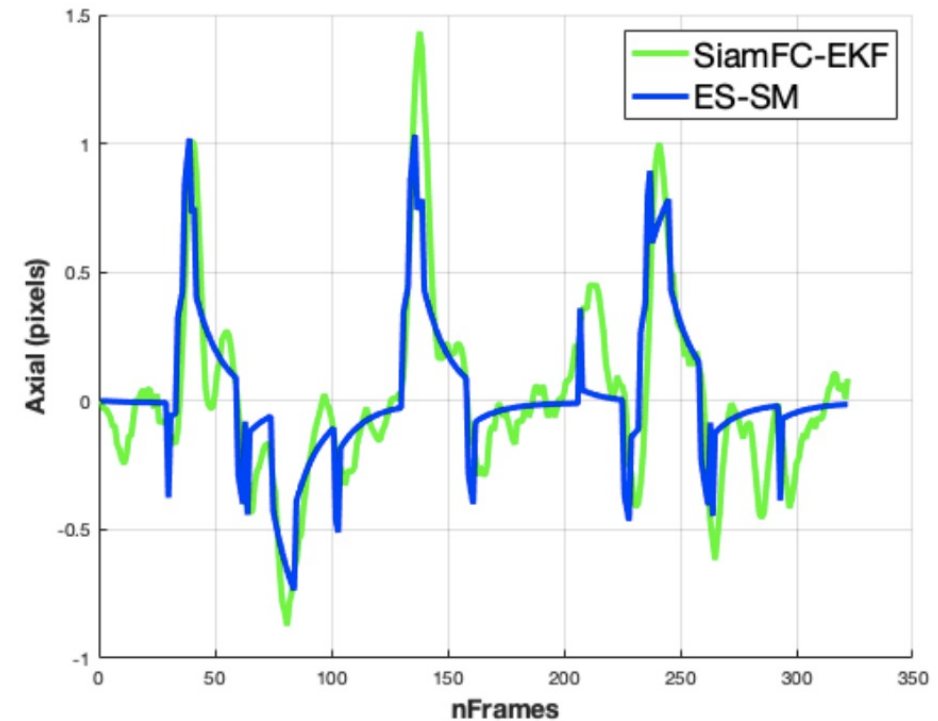
	RMSE
Axial	0.1188
Lateral	0.3433

RMSE between
SiamFC-EKF and ES-SM

Speed

	Computational time per frame
ES-SM	1.69s
SiamFC-EKF	0.33s

Computational Time per Frame
between SiamFC-EKF and ES-SM



Axial Displacement Trajectory
Between SiamFC-EKF and ES-SM



Conclusion and Future Work

Conclusion

- Arterial wall motion estimation was performed using Siamese architecture-based deep learning network incorporated with Extended Kalman Filter.
- We compared with the conventional ES-SM technique.
- SiamFC-EKF outperforms ES-SM in speed with no trade-off in accuracy.

Future Work

- Improve SiamFC by incorporating transfer learning.
- More sophisticated Siamese architectures could be used in place of the vanilla model.



Thank you