Range-Doppler Hand Gesture Recognition using Deep Residual-3DCNN with Transformer Network

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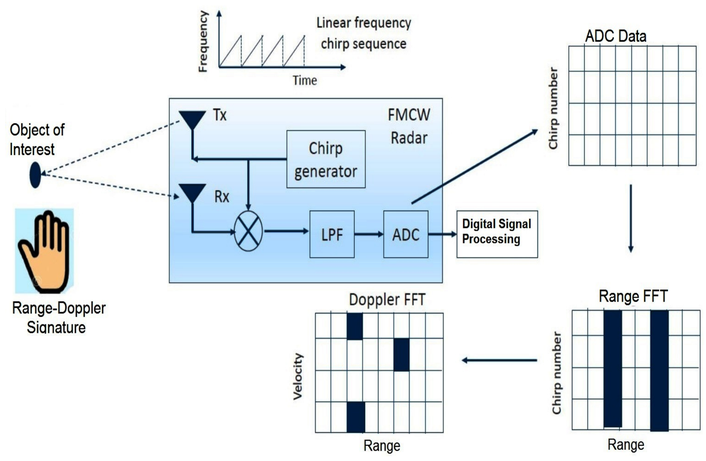
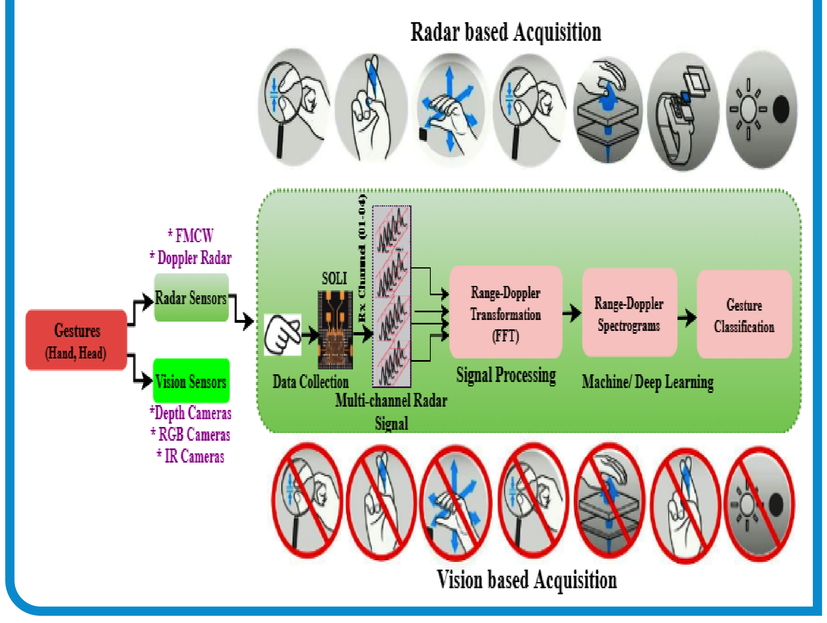
1. Motivation

- How can we use a small set of fine finger gestures or hand movements to control everything around us?
- Existing keyboard or touch based interaction paradigm is slow.
- Natural, low effort and high precision interaction paradigm is urgently needed. For example, hand gestures.
- Camera or vision sensors for hand gestures acquisition cause sensitivity to lighting conditions, occlusion, and typically require dedicated processing power.
- Radar sensors emerged as new HCI technology that offer micro gesture interaction with low energy consumption.



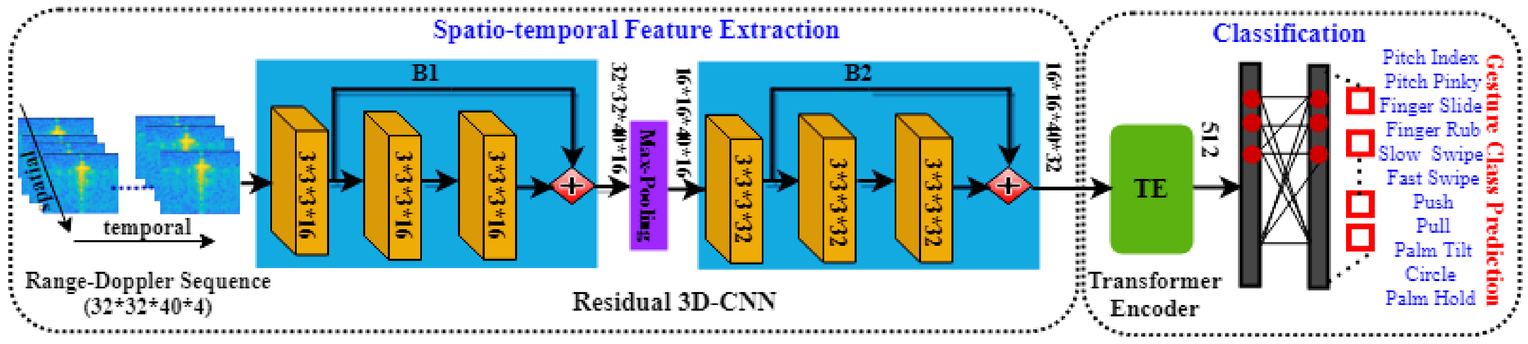
2. Major Challenges

- Low Signal-to-Noise Ratio (SNR) environments due to the presence of non-stationary and unexpected background.
- High variability of gestures in terms of scale, non-uniform frame rate, and measured distance.
- Lack of leveled data, high intra-class and low inter-class variation in features
- Sequential n/w i.e., RNN/ LSTM have limited ability to learn temporal dynamics of multi-channel range-Doppler sequences

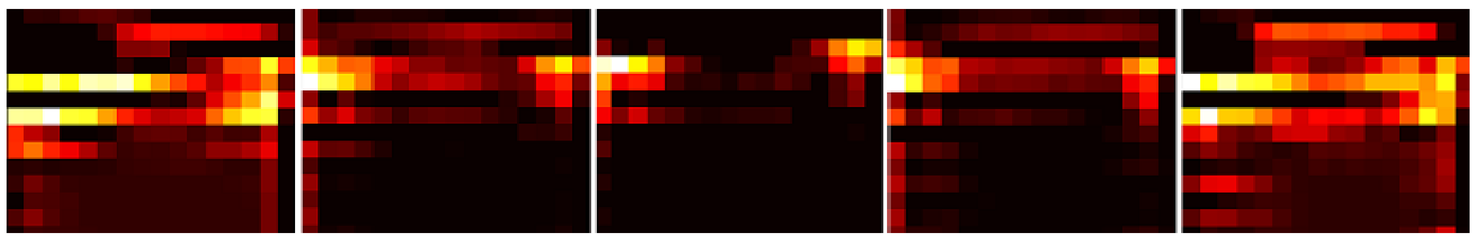


3. Res3DTENet Architecture: Hand Gesture Classification

- Res3DTENet consists of two main modules in sequential order: * Residual 3D-CNN (Res3D-CNN); * Transformer Encoder Network (TENet).
- SOLI Hand Gesture Dataset: 11 gesture classes, 10 subjects, 25 instances per subject per gesture = 2750 sequences
  - Approximately 40 frames per gesture instance/sequence
  - 11 gesture classes, 1 subject, 50 instances per subject per gesture, 5 sessions = 2750 sequences



(a) HGR network to classify spatio-temporal RD features



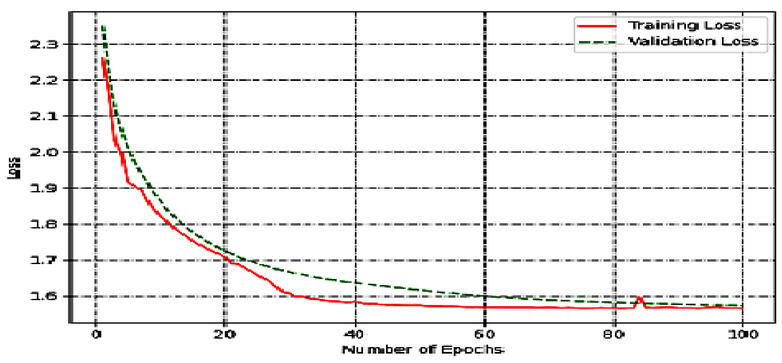
(b) Feature maps from 6th CNN Layer

4. Res3DTENet Architecture: Transformer Encoder

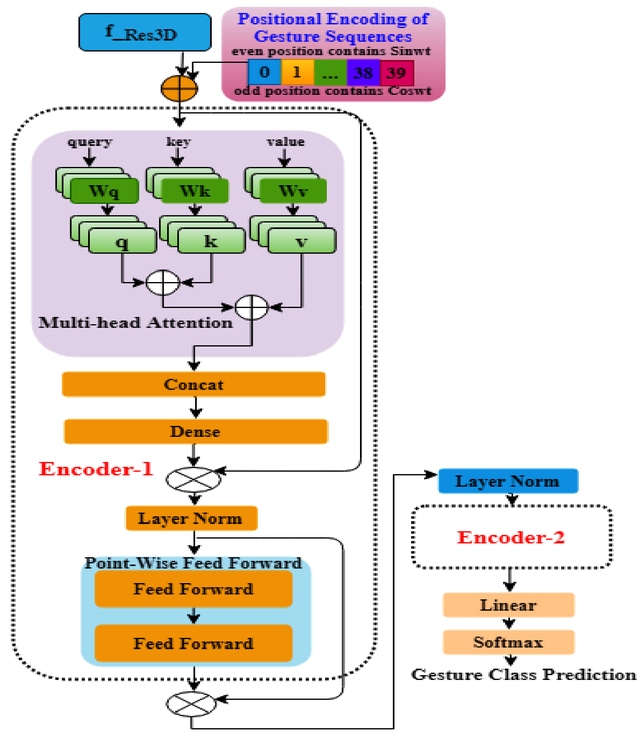
- Transformer Encoder N/W consists of 2 encoder layers and FC layer.
- Each encoder block consists of 3 attention heads, feed forward n/w, layer norm.
- Trained over spatio-temporal RD features to refine temporal inter-relationship b/w frames

Res3D-CNN				
Layer name	Residual block	Kernel size	No. of filters	Output size
Input	-	-	-	32 × 32 × 40 × 4
Conv1	-	3 × 3 × 3	16	32 × 32 × 40 × 16
Conv2	R1	3 × 3 × 3	16	32 × 32 × 40 × 16
Conv3	R1	3 × 3 × 3	16	32 × 32 × 40 × 16
Max-pooling	-	2 × 2 × 1	-	16 × 16 × 40 × 16
Conv4	-	3 × 3 × 3	32	16 × 16 × 40 × 32
Conv5	R2	3 × 3 × 3	32	16 × 16 × 40 × 32
Conv6	R2	3 × 3 × 3	32	16 × 16 × 40 × 32
Output	-	-	-	16 × 16 × 40 × 32

(a) Res3D-CNN



(c) Training and validation loss

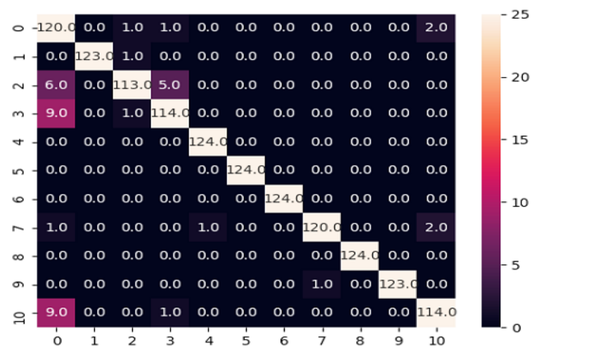


(b) Transformer Encoder

5. Important Findings

- Transformer n/w outperforms the LSTM network in terms of faster training and capturing long-term dependencies.
- Residual learning helps in training deep network more easily and leads to better generalization.
- Micro motion gestures like finger slide and finger rub are least classifying gesture classes.
- Smaller training data may reduce n/w convergence and its generalization capability.

6. Experimental Analysis



(a) Confusion matrix: 50:50 training and testing

Network	Avg.	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10	G11
Accuracy based on 50:50 training and testing split of the data												
Res3DTENet	96.99	96.77	99.19	91.13	91.94	100	100	100	96.77	100	99.19	91.94
3DCNNTENet	93.03	93.55	100	77.42	78.23	91.94	100	100	91.13	100	99.19	91.94
TENet	78.92	62.22	64.88	45.07	89.30	67.20	94.62	94.89	87.34	92.50	85.78	84.39
Res3D-LSTM	91.12	87.90	96.77	83.87	83.06	87.10	95.16	88.71	91.13	97.58	91.94	99.19
Soli (CNN-LSTM) [6]	87.17	67.72	71.09	77.78	94.48	84.84	98.45	98.63	88.89	94.85	89.56	92.63
Soli (RNN-shallow) [6]	77.71	60.35	62.25	38.72	89.45	66.77	92.52	94.93	86.89	91.39	85.52	86.22
GVLAD [2]	96.77	97.58	100	98.38	83.06	100	100	99.19	99.19	96.77	98.38	91.93
Accuracy using leave one subject out: cross Subject Validation on 10 subjects												
Res3DTENet	92.25	89.12	93.34	92.20	83.43	84.66	93.50	97.68	100	95.78	93.22	91.84
Soli [6]	79.06	58.71	67.62	64.80	91.82	72.31	72.91	93.40	89.99	95.16	82.80	80.24
GVLAD [2]	91.38	84.80	98.40	88.00	78.40	87.60	99.20	90.00	99.20	96.40	93.99	89.20
Accuracy on leave one session out: cross Session Validation on 1 Subject												
Res3DTENet	92.98	92.03	100	92.00	60.15	98.24	100	100	100	100	100	80.42
SOLI [6]	85.75	56.69	61.98	76.43	96.83	92.73	81.38	98.42	97.79	95.33	96.92	89.10
GVLAD [2]	97.75	94.33	99.33	97.76	90.33	97.66	100	100	99.66	100	99.66	96.66

(b) Classification Performance

References

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