Hybrid-feature-guided Lung Nodule Type Classification on CT Images

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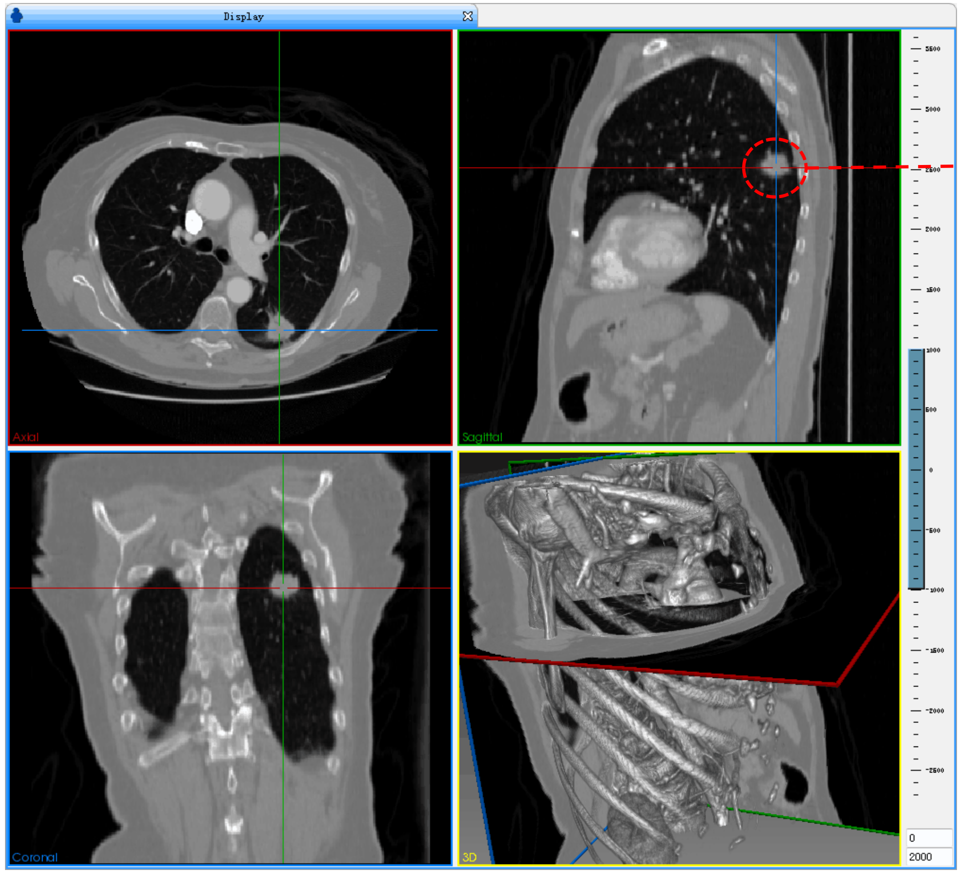
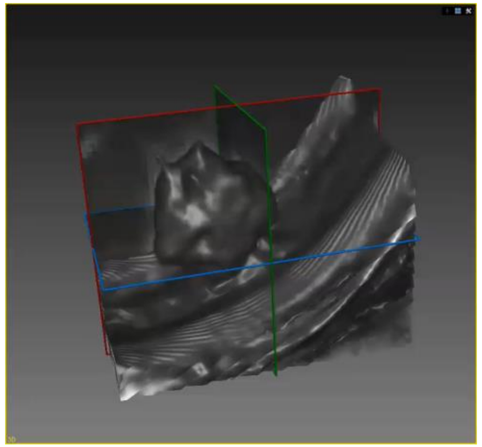
Outline

- Introduction
- Methods
- Results
- Conclusions & Discussion

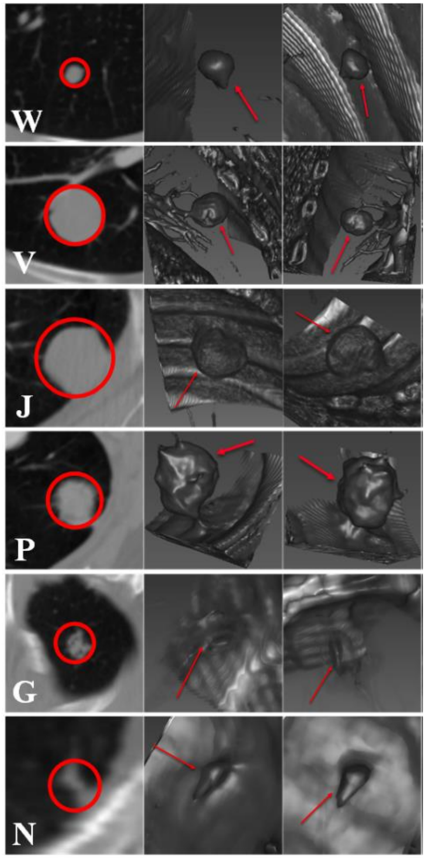
What is Lung Nodule?



Original pulmonary CT



3D model for nodule



Typical cases for nodule types

Related Work

- Enhancement towards original medical images
  - [Yao et al. IEEE Trans Biomed Eng(2013)]
  - [Song et al. IEEE Trans Med Imag (2013)]
  - [Mansoor et al. EMBC (2014)]
  - [Gao et al. ICNC (2007)]
- Feature to describe nodules' characteristics
- CNNs-based method in the field of medical analysis
- Researches on nodule type classification

Related Work

- Enhancement towards original medical images
- Feature to describe nodules' characteristics
  - [Galaro et al. EMBC (2011)]
  - SIFT:[Zhang et al. EMBC (2013)]
  - HOG:[Unay et al. ISBI (2011)][Song et al. IEEE Trans Med Imag (2012)]
  - LBP:[Jacobs et al. MICCAI (2011)][Sorensen et al. IEEE Trans Med Imag (2010)]
  - [Ciompi et al. IEEE Trans Med Imag (2015)]
  - [Kim et al. Investigative Radiology(2015)]
  - [Chen et al. MICCAI (2016)]
- CNNs-based method in the field of medical analysis
- Researches focus on nodule type classification

Related Work

- Enhancement towards original medical images
- Feature to describe nodules' characteristics
- CNNs-based method in the field of medical analysis
  - [Rongjian et al. MICCAI (2014)]
  - [Roth et al MICCAI (2014)]
  - [Arnaud et al IEEE Trans Med Imag (2016)]
  - [Prasoon et al MICCAI (2013)]
  - [Dou et al IEEE Trans Med Imag (2016)]
- Researches focus on nodule type classification

Related Work

- Enhancement towards original medical images
- Feature to describe nodules' characteristics
- CNNs-based method in the field of medical analysis
- Researches focus on nodule type classification
  - [Farag et al. ISBI (2011)]
  - [Zhang et al. IEEE Trans Biomed Eng (2014)]
  - [Song et al. ISBI (2012)]

Challenges

- How to precisely capture nodules characteristics ?

- How to take both statistical features and geometrical features into consideration for better classification ?

Contributions

- A normalized **spherical sampling** pattern, a nodule **radius estimation** method and a best **view selection** method
- A **multi-view multi-scale CNN** to extract the most discriminative statistical features from original data automatically
- An approach to combine CNN features and FV encoding features into **hybrid features** and use to classify nodule types accurately

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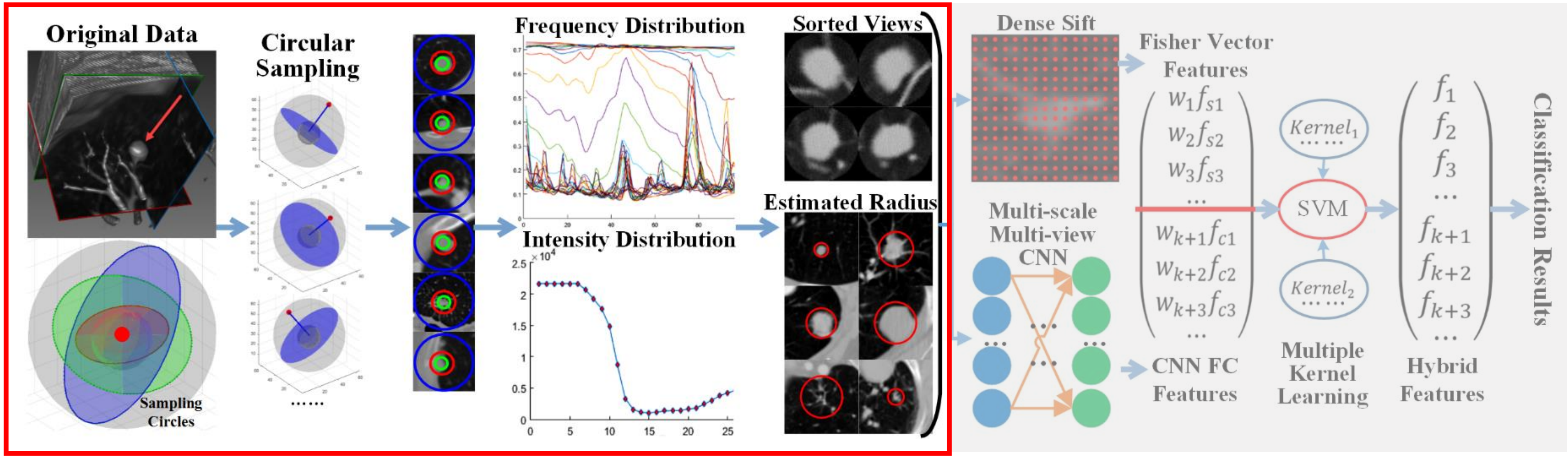
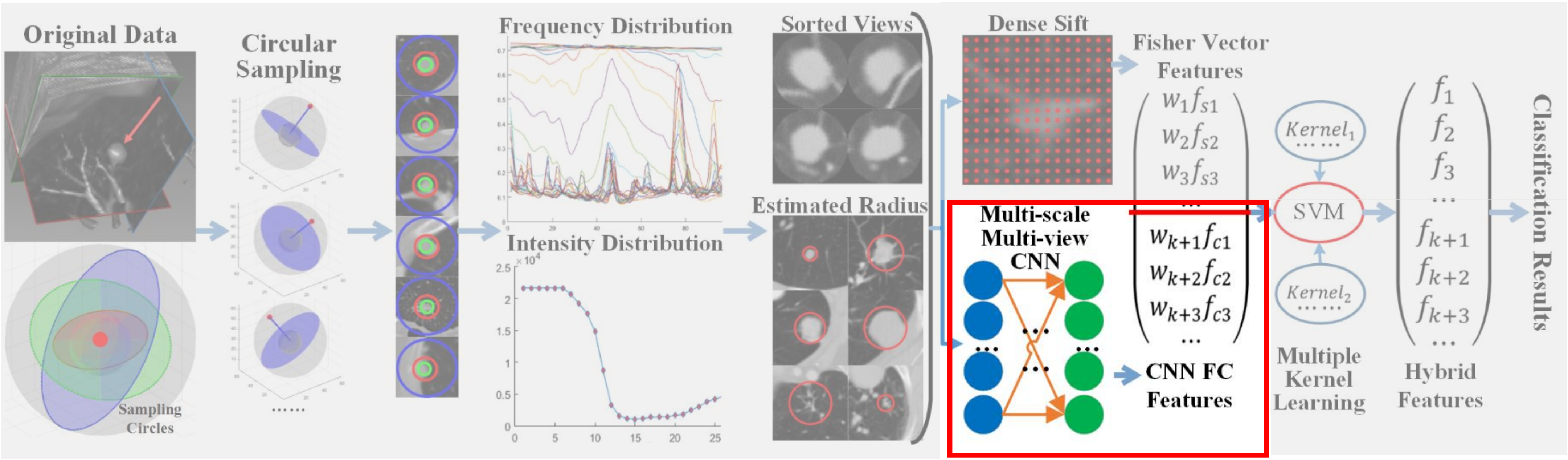
Overview



Images Generation

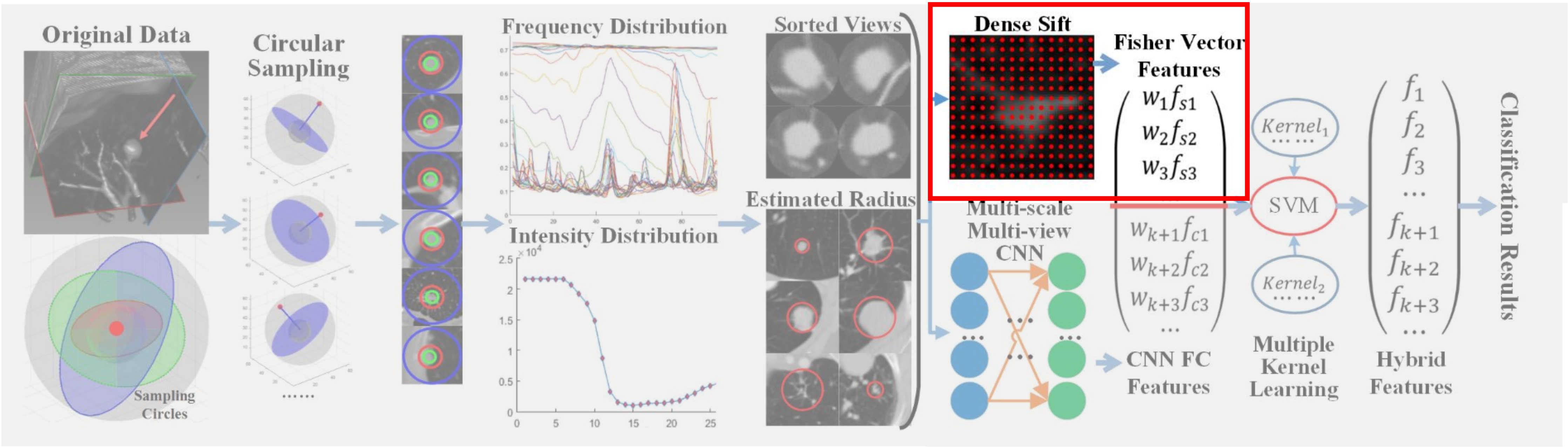
Overview



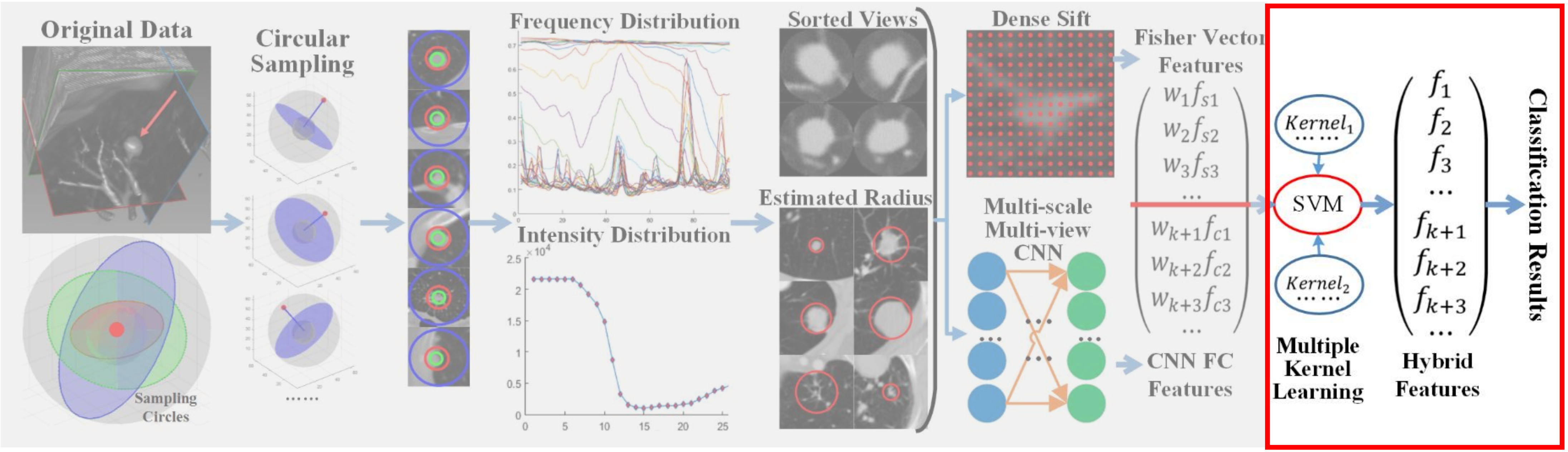
Statistical Features

Overview

Geometrical Features



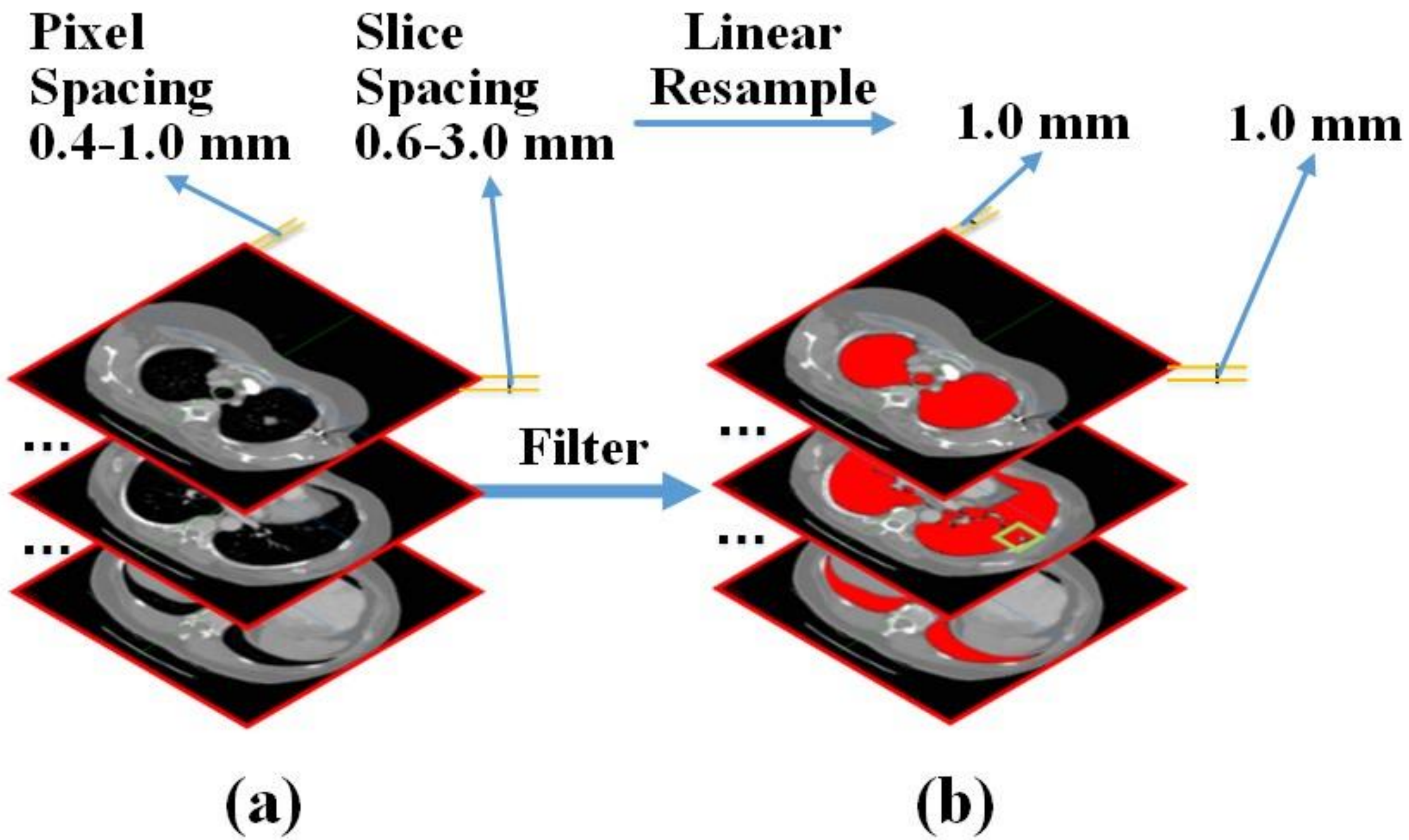
Overview



Hybrid Features and Classify

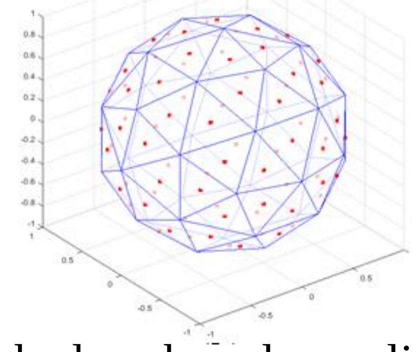
Images Generation

Preprocessing ➡ Nodule Spherical Sampling ➡ Nodule Radii Estimation ➡ View Sorting

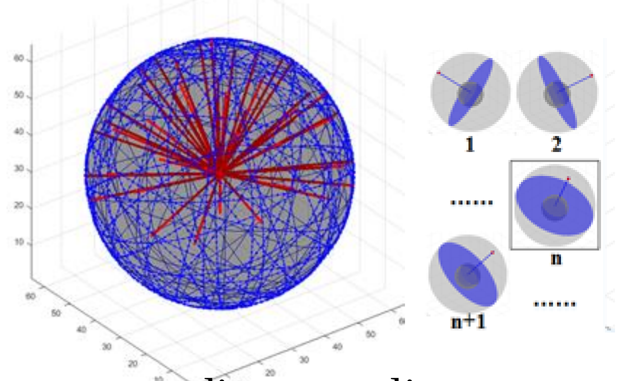


Images Generation

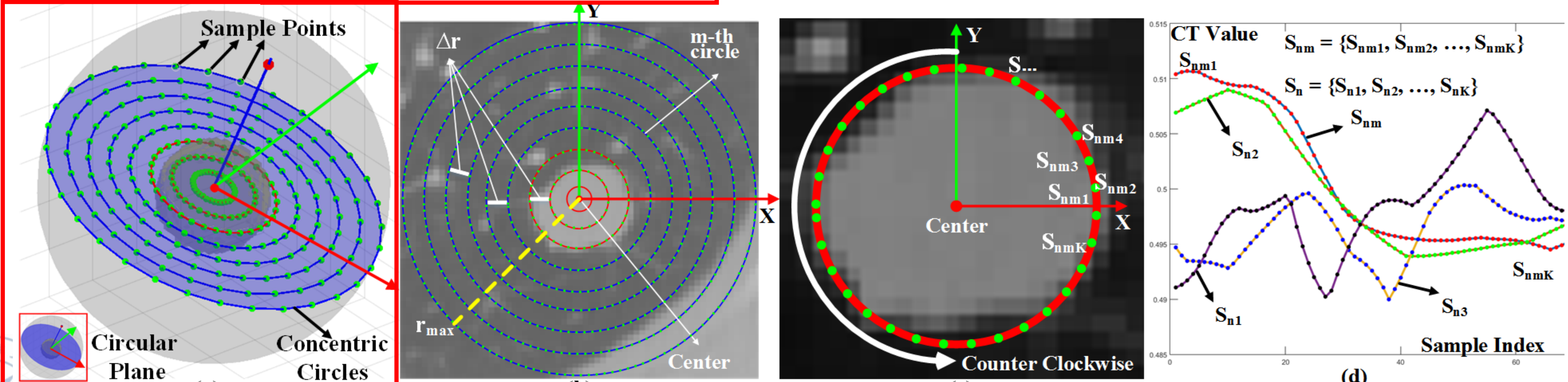
Preprocessing → Nodule Spherical Sampling → Nodule Radii Estimation → View Sorting



Icosahedron-based sampling



corresponding sampling patterns



(a) (b) (c) (d)

Images Generation

Preprocessing → Nodule Spherical Sampling → Nodule Radii Estimation → View Sorting

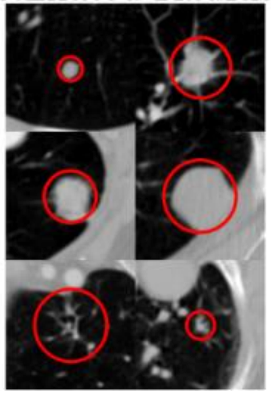
Algorithm 2: RADIUS_ESTIMATION

Input: S, sampled 3-D matrix with size $N \times M \times K$ for V.
N / M / K, specified parameters.

Output: r_{est}, estimated radius for V.

$Counter \leftarrow 0$;
for $n = 1 \rightarrow N, m = 1 \rightarrow M, k = 1 \rightarrow K$ **do**
  if $S_{nmk} > threshold$ **then**
    $Counter_{nm} = Counter_{nm} + 1$;
$R\_Counter \leftarrow 0$;
for $m = 1 \rightarrow M, n = 1 \rightarrow N$ **do**
  $R\_Counter_m \leftarrow R\_Counter_m + Counter_{nm}$;
  if $R\_Counter_m < counter\_threshold$ **then**
    $r_1 \leftarrow m$;
    break;
$r_2 \leftarrow local\_min(R\_Counter)$;
$r_{est} = min(r_1, r_2)$;
return r_{est};

Estimated Radius



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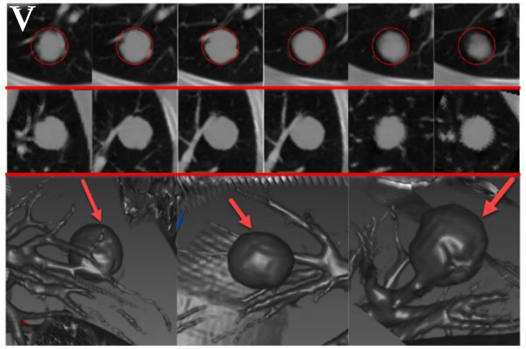
Images Generation

Preprocessing → Nodule Spherical Sampling → Nodule Radii Estimation → View Sorting

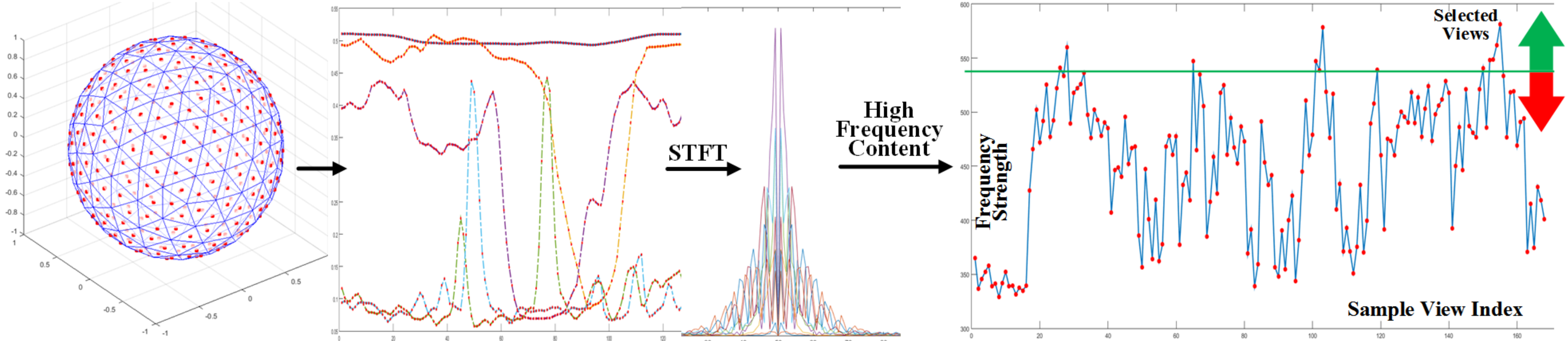
$$\boxed{freq_n = \sum_{m=1}^{M} D_C(S_{nm})\ ,}\quad D_c(S_{nm}) = \frac{1}{K}\sum_{k=1}^{K} |\hat{X}_k - X_k|$$



Original axial slice

View sorting slice

View Sorting Results



CT Sampling Results

CT Value Distributions

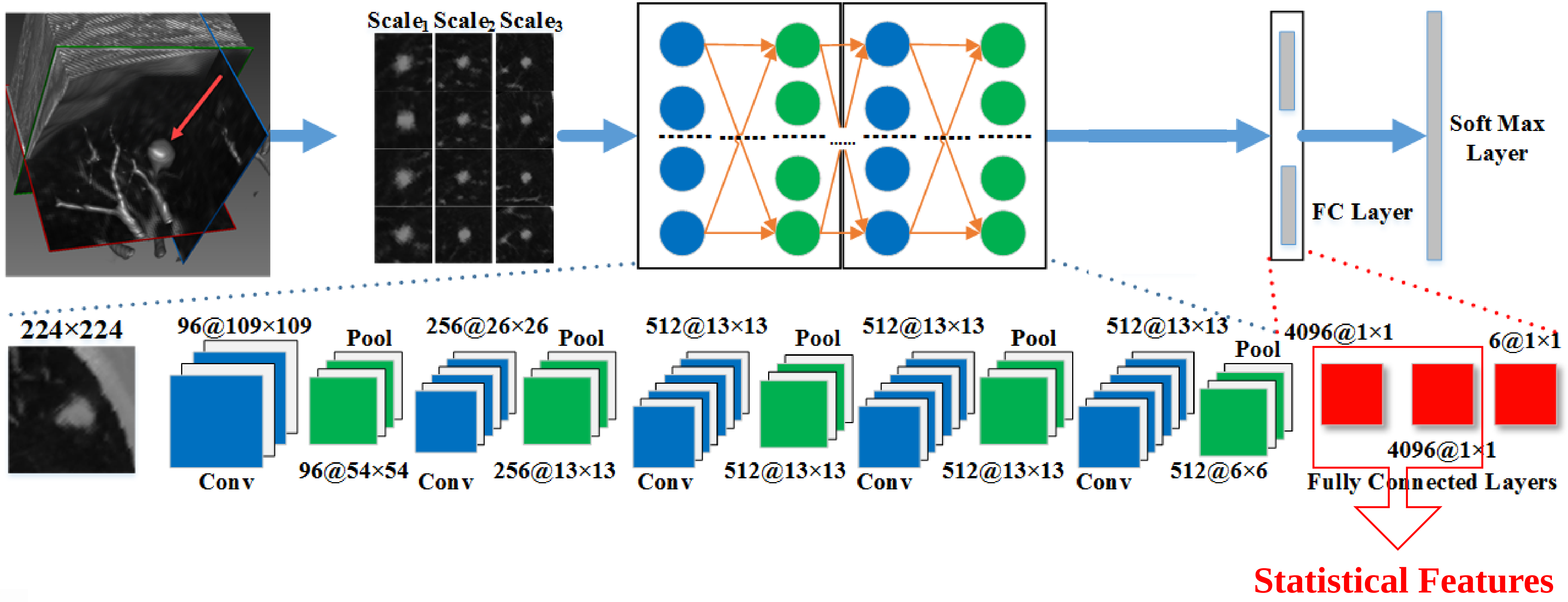
Frequency Domain

Frequency Variation Accumulation

View sorting based on high frequency content analysis

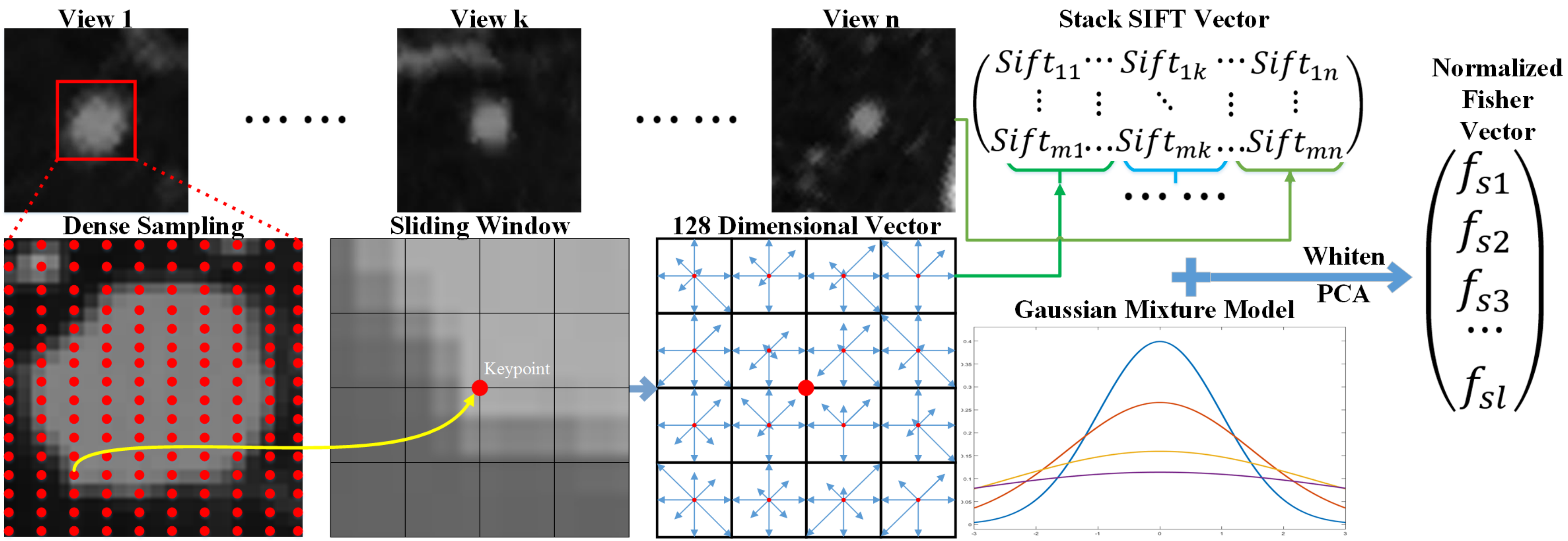
Hybrid Feature Extraction

Multi-view Multi-scale CNN Feature Extraction + Fisher Vector Feature Extraction → Feature Fusion based on Multiple Kernel Learning and Classification



Hybrid Feature Extraction

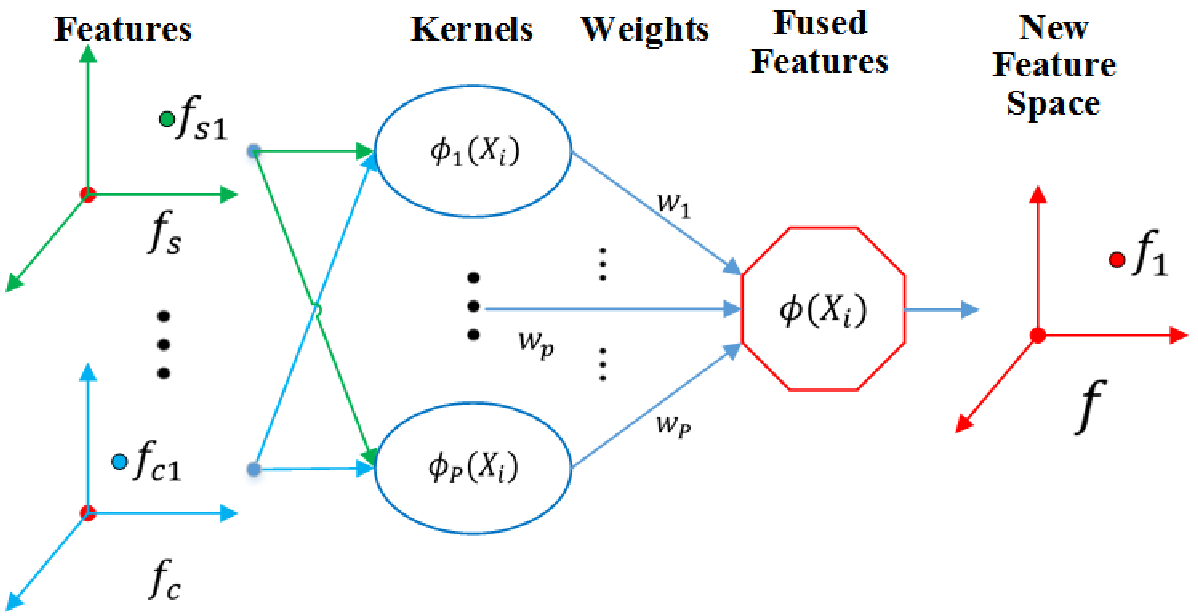
Multi-view Multi-scale CNN Feature Extraction + Fisher Vector Feature Extraction → Feature Fusion based on Multiple Kernel Learning and Classification



Hybrid Feature Extraction

Multi-view Multi-scale CNN Feature Extraction + Fisher Vector Feature Extraction → Feature Fusion based on Multiple Kernel Learning and Classification

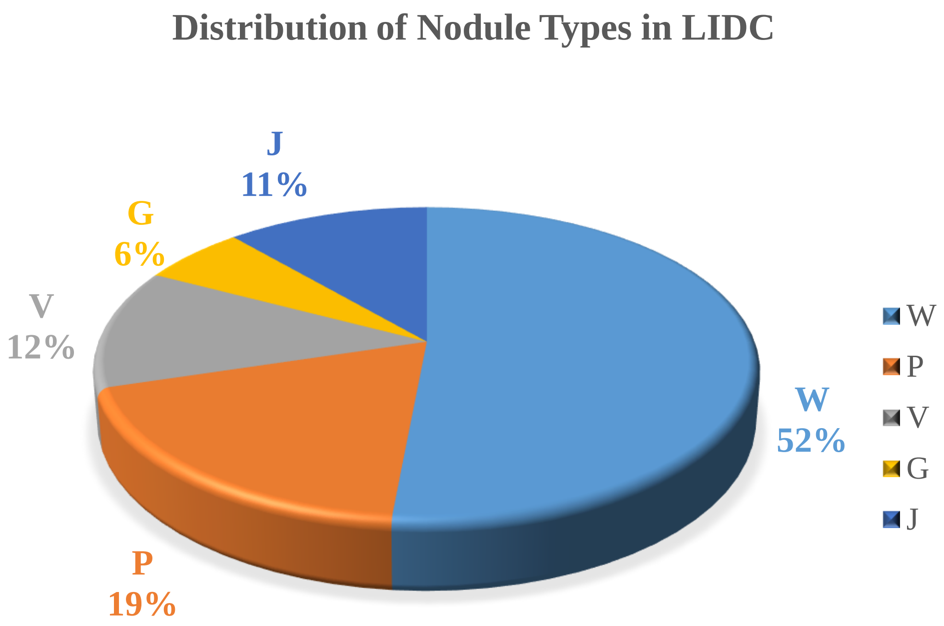
$$F(x_i, x_j) = \sum_{k \in K} w_k \cdot f_k(x_i, x_j)$$



The multiple kernel learning approach for feature fusion

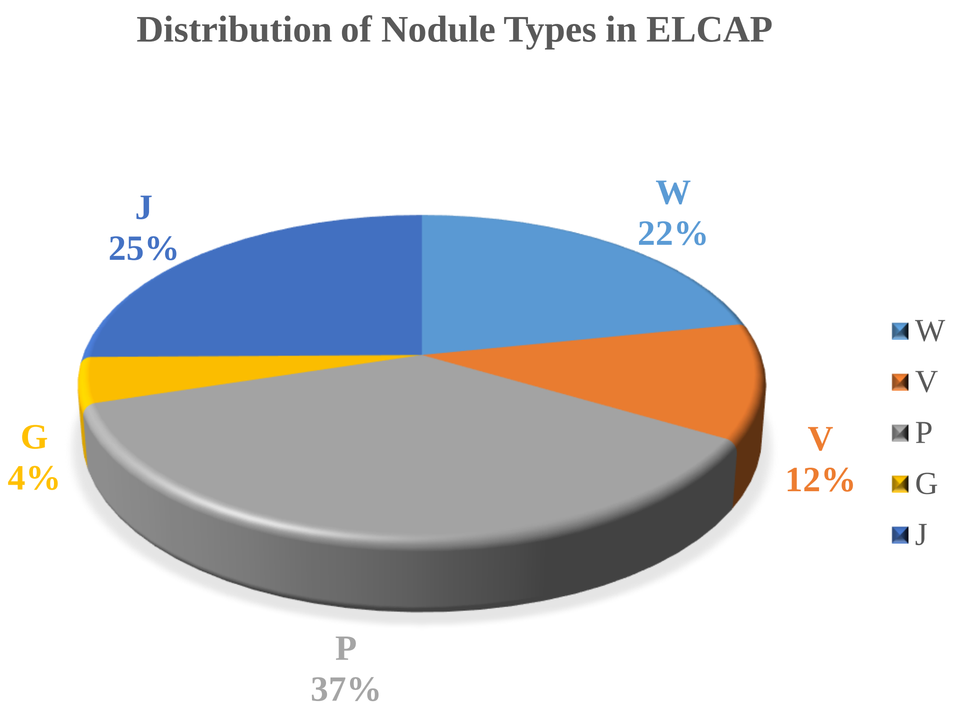
Materials

- LIDC-IDRI
  - Nodule agreement levels ≥ 2
  - 1738 nodules, 1000 non-nodules from 744 chest CTs
    - W: 905, 52.0%; P: 329, 19%
    - V: 219,12.5%; G: 82, 6%; J: 203, 11.5%
  - Original CT
    - 512×512 pixels
    - In-plane spacing, 0.4-1.0 mm
    - Slice thickness, 0.5-3 mm



Materials

- ELCAP
  - 46 cases with 421 nodules
    - W:92, 21.8%; V: 49, 11.6%;
    - P: 155, 36.8%; J: 106, 25.2%, G: 19,4.6%



- Data Augmentation
  - Classical methods
    - Image rotation, scaling, flipping
  - Random selection based on the estimated nodule radii and sorted views

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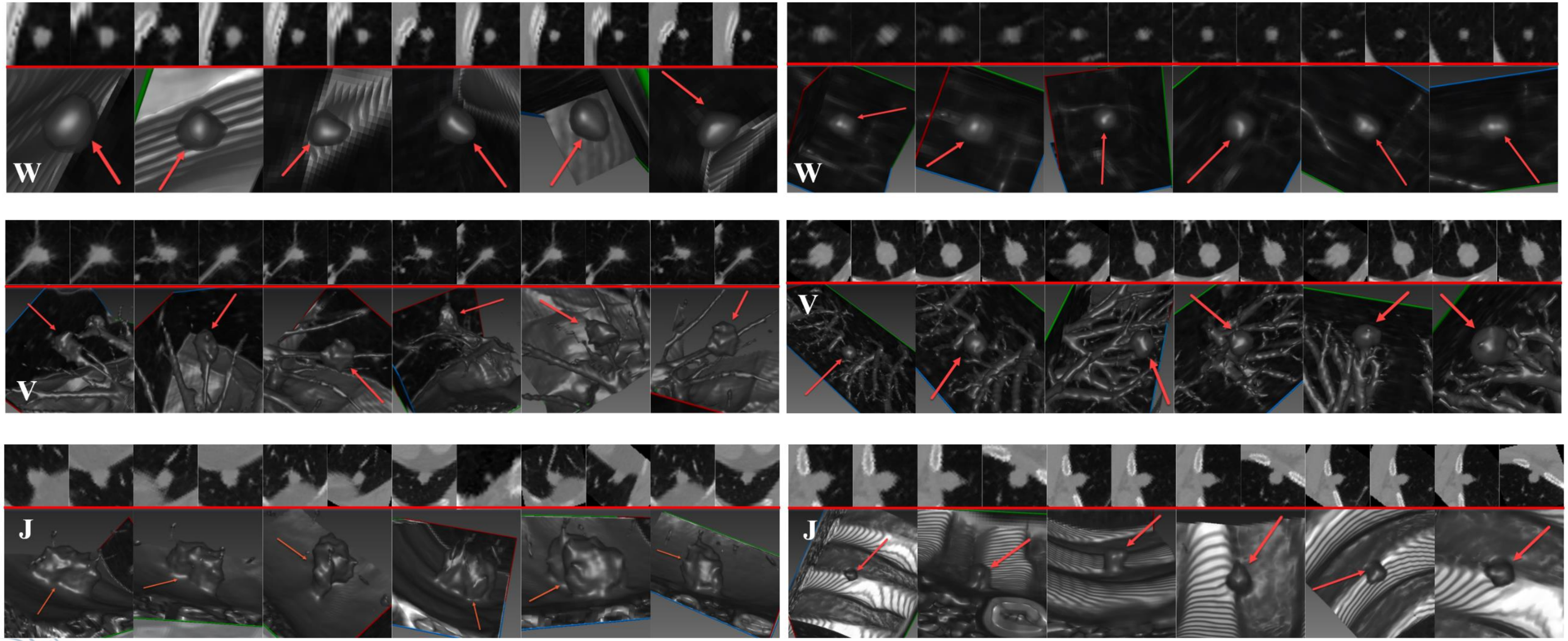
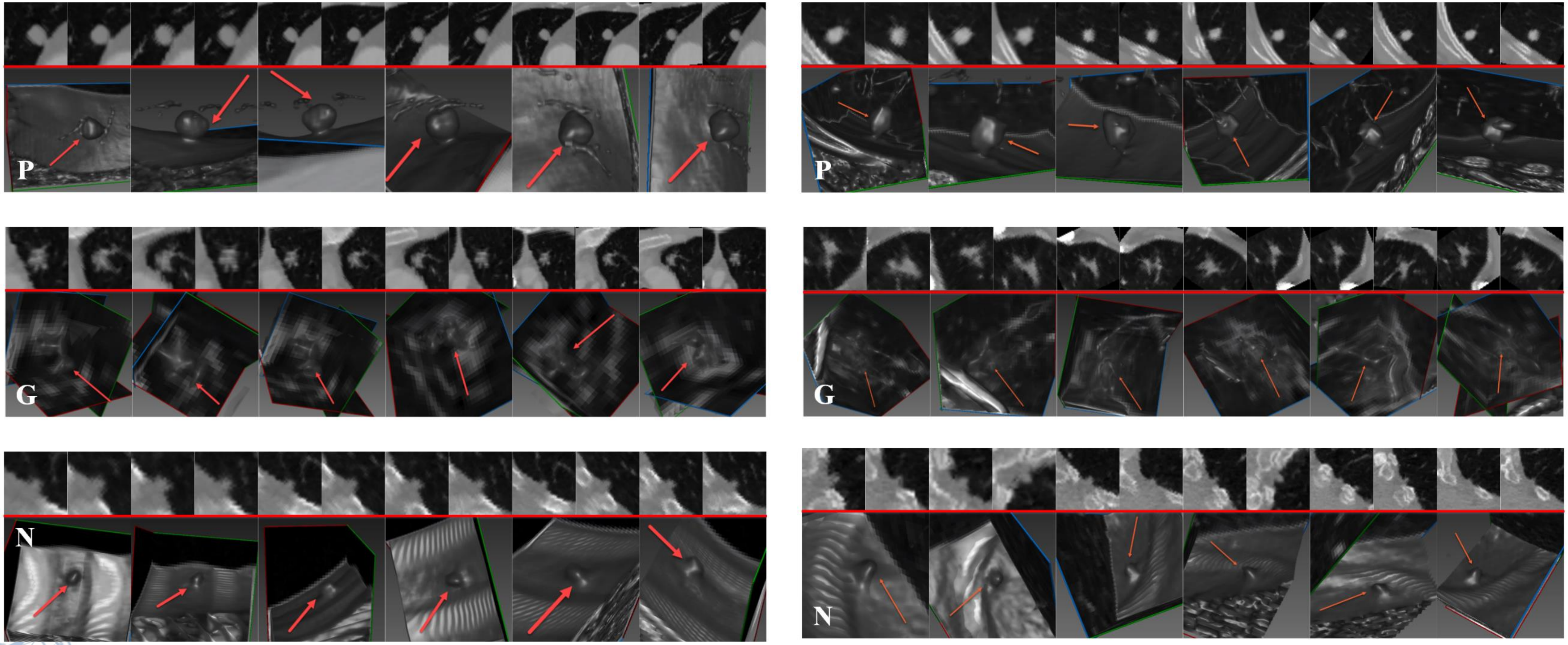
Results

Classification Results for Typical Cases



Results

Classification Results for Typical Cases



Comparison

TYPE/METHOD		G	W	N	P	V	J
G	PB	N/A	N/A	N/A	N/A	N/A	N/A
	The Proposed	**0.793**	0	0.138	0	0	0.069
W	PB	N/A	0.89	N/A	0.06	0.04	0.01
	The Proposed	0	**0.961**	0.039	0	0	0
N	PB	N/A	N/A	N/A	N/A	N/A	N/A
	The Proposed	0	0.028	**0.972**	0	0	0
P	PB	N/A	0.03	N/A	0.91	0.03	0.03
	The Proposed	0	0	0.063	**0.938**	0	0
V	PB	N/A	0.05	N/A	0.06	0.86	0.03
	The Proposed	0	0	0.068	0	**0.932**	0
J	PB	N/A	0.03	N/A	0.06	0.04	**0.87**
	The Proposed	0	0	0.169	0	0	0.831

Prop = Proposed method **PB = Patch-based [40]** **P = Pleural-tail**
W = Well-circumscribed **V = Vascularized** **J = Juxta-pleural**

Overall classification rate 89%(PB)\93.9%(Ours)

Confusion matrix for comparison with PB method on ELCAP

Comparison

- CNNs
  - classical pure CNN + soft-max
- CNNs+Pooling
  - with max-pooling layer
- CNNF
  - multi-view multi-scale CNN
- CNNF+Pooling
  - with max-pooling layer
- FV+SIFT
- BOW+SIFT

Comparison

The Proposed 93.9%, CNN$_S$ 80.6%, CNN$_S$+Pooling 68.1%, CNN$_F$ 85.9%, CNN$_F$+Pooling 86.8%, FV+SIFT 65.5%, BOW+SIFT 56.6%

TYPE/METHOD		G	W	N	P	V	J
G	CNN$_S$	0.809	0.045	0.101	0	0.045	0
	CNN$_S$+Pooling	0.854	0.023	0.079	0.011	0.034	0
	CNN$_F$	0.596	0.067	0.101	0.045	0.124	0.067
	CNN$_F$+Pooling	0.809	0.034	0.112	0	0.045	0
	FV+SIFT	0.615	0.021	0.077	0.070	0.154	0.063
	BOW+SIFT	0.524	0.063	0.063	0.091	0.168	0.091
	The Proposed	**0.899**	0.011	0.079	0	0.011	0
W	CNN$_S$	0.022	0.801	0.018	0.074	0.055	0.030
	CNN$_S$+Pooling	0.011	0.867	0.011	0.066	0.033	0.011
	CNN$_F$	0.052	0.683	0.041	0.074	0.125	0.026
	CNN$_F$+Pooling	0.011	0.963	0.015	0	0.011	0
	FV+SIFT	0.022	0.735	0.040	0.036	0.157	0.009
	BOW+SIFT	0.036	0.664	0.027	0.054	0.206	0.013
	The Proposed	0	**0.993**	0.004	0.004	0	0
N	CNN$_S$	0.015	0.045	0.865	0.020	0.020	0.035
	CNN$_S$+Pooling	0.010	0.040	0.885	0.010	0.020	0.035
	CNN$_F$	0.035	0.070	0.735	0.045	0.030	0.085
	CNN$_F$+Pooling	0.005	0.035	0.885	0.010	0.030	0.035
	FV+SIFT	0.129	0.041	0.676	0.071	0.006	0.076
	BOW+SIFT	0.153	0.029	0.571	0.071	0.018	0.159
	The Proposed	0.010	0.035	**0.915**	0.005	0.025	0.010
P	CNN$_S$	0.027	0.054	0.116	0.705	0.027	0.071
	CNN$_S$+Pooling	0	0.063	0.089	0.786	0	0.063
	CNN$_F$	0.036	0.116	0.107	0.607	0.009	0.125
	CNN$_F$+Pooling	0.018	0.045	0.152	0.759	0.009	0.018
	FV+SIFT	0.067	0.044	0.081	0.659	0.015	0.133
	BOW+SIFT	0.089	0.111	0.126	0.474	0.030	0.170
	The Proposed	0	0.018	0.116	**0.866**	0	0
V	CNN$_S$	0.064	0.113	0.043	0	0.780	0
	CNN$_S$+Pooling	0.028	0.078	0.050	0.028	0.816	0
	CNN$_F$	0.057	0.142	0.064	0.043	0.688	0.007
	CNN$_F$+Pooling	0.007	0.085	0.078	0	0.830	0
	FV+SIFT	0.063	0.162	0.035	0.077	0.606	0.056
	BOW+SIFT	0.063	0.232	0.007	0.092	0.507	0.099
	The Proposed	0.014	0.035	0.043	0	**0.908**	0
J	CNN$_S$	0.012	0.018	0.096	0.036	0.006	0.831
	CNN$_S$+Pooling	0.012	0	0.042	0.042	0	0.904
	CNN$_F$	0.018	0.036	0.102	0.133	0.006	0.705
	CNN$_F$+Pooling	0.012	0.030	0.066	0.054	0.006	0.831
	FV+SIFT	0.048	0.030	0.139	0.157	0.030	0.596
	BOW+SIFT	0.048	0.048	0.181	0.108	0.024	0.590
	The Proposed	0.018	0.006	0.048	0	0	**0.928**

G = Ground glass optic **N = Non-nodule** **P = Pleural-tail**
W = Well-circumscribed **V = Vascularized** **J = Juxta-pleural**

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Conclusions & Discussion

- Devise a hybrid-feature-based lung nodule type classification method
- The experiments on LIDC-IDRI and ELCAP have shown we achieve an overall classification rate of 93.1% (911 out of 979) and 93.9% (647 out of 689) separately
- Limitations
  - Complex pipeline
  - Low efficiency for the feature extraction and fusion

Future work

- Estimate radius more robustly and scale in-variant towards very tiny nodules (radius < 3 mm) and juxta-pleural nodules
- Label out types, positions and sizes automatically for nodules not centered in images with few human interactions
- Design 3D CNNs to effectively reduce error results in lung nodule classification from volumetric CT scans

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Thank you!

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