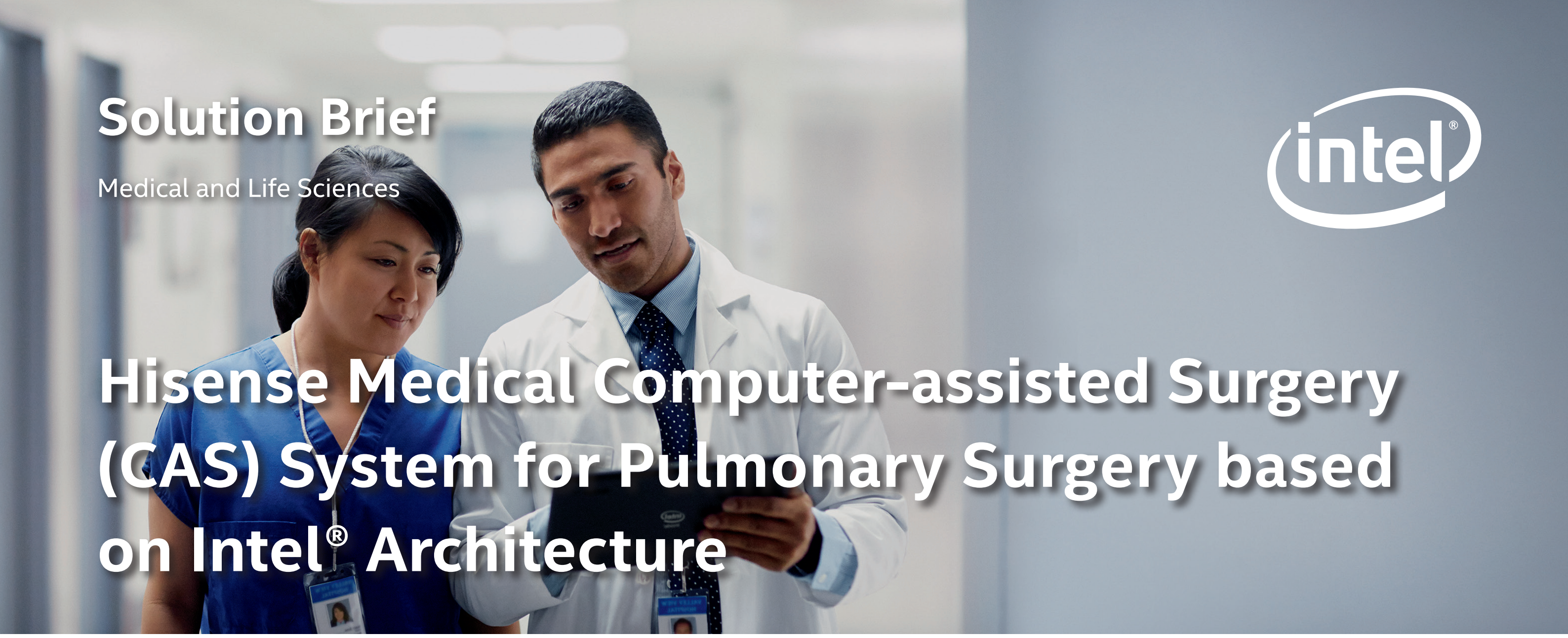

Solution Brief

Medical and Life Sciences

Hisense Medical Computer-assisted Surgery (CAS) System for Pulmonary Surgery based on Intel® Architecture

Hisense Medical

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"We performed as many as 200 precision segmentectomy operations in 2018, and at least 20 to 30 such operations every month in the second half of 2019. During these operations, Hisense Medical CAS system demonstrated its convenient and practical advantages, helped us with preoperative planning and intraoperative real-time guidance with an adjustable user interface at any time."

– Dr. Zhongmin Peng
Director of Thoracic Surgery Department
East Campus, Shandong Provincial Hospital

Overview

Digital technologies including Artificial Intelligence (AI) are profoundly reshaping the medical industry. With applications in medical imaging, disease prediction, health management, drug research & development and many others, digital technologies play an important role in enabling smart, efficient, and accurate diagnosis and treatment methods. In particular, by providing intelligent segmentation, 3D reconstruction and anatomical structure rendering, 3D surgery planning systems help doctors with surgical site location, surgery feasibility evaluation, and optimal surgical path planning. These systems help to optimize surgery plans, reduce operation time and bleeding, improve tumor resection rate and surgery safety, and therefore benefit patients.

Qingdao Hisense Medical Equipment Co., Ltd. ("Hisense Medical") is a wholly-owned subsidiary of Hisense Group. Hisense Medical has established the Provincial Key Laboratory of Digital Medicine and Computer-Assisted Surgery with Qingdao University, focusing on the development of AI-assisted medical imaging technology. Hisense Medical's business units include research and development, manufacturing and production to sales and marketing. It possesses core technologies ranging from medical imaging, AI, information exchange, hospital dashboard display, and hospital IT solutions including CAS system, intelligent imaging center, digital surgical room etc. With years of R&D efforts on AI for medical imaging, Hisense Medical has successfully developed the CAS system covering chest, lung, liver, gallbladder, pancreas, spleen and urinary system. It has been deployed in more than 100 hospitals in China with over 9,000 patients served as of February 2020. The Hisense Medical CAS system produces social and economic benefits and has bright prospects for more clinical applications.

For the efficiency of AI-based organ segmentation on computerized tomography (CT) images, and low-cost large-scale deployment with flexibility, Hisense Medical adopted Intel® Xeon® Scalable processors and OpenVINO™ toolkit in the CAS System for Pulmonary Surgery to accelerate their deep learning algorithm and achieve their goals in surgery optimization.

Background: Status and prospect of CAS in China and worldwide

With the increasing number of early screening using low-dose spiral CT in recent years, more small nodules of precancerous lesions are able to be detected. Meanwhile, the surgical treatment of lung cancer has also developed and evolved from one-side pneumonectomy, anatomical lobectomy to wedge resection.

Anatomically, a pulmonary segment is a complete and independent unit. Each lung segment has its own independent supply of arteries, veins and bronchial branches. Precise resection of the pulmonary segment with tumor ensures the complete tumor removal with maximum retainment of the normal lung tissues. Moreover, precise segmentation helps with sampling and dissect of inter and intra-segment lymph glands to assist in anatomical resection and radical tumor treatment. Studies showed that, for the treatment of diseases like non-small cell lung cancer (NSCLC) at clinical stage I, anatomical segmentectomy can provide similar local and nonlocal control compared to a traditional lobectomy[1,2]. Therefore, precision segmentectomy is ideal for patients with small pulmonary nodules or contraindications for lobectomy.

As arteriovenous and bronchial branches at the edge area of the lung are complicated and lack visible anatomical boundaries, there are many technical and anatomical difficulties in performing segmentectomies with precision. The precise 3D reconstruction of lungs based on automatic segmentation using a deep neural network can identify and analyze the structure and spatial distribution of lung tissues, lesions, pulmonary blood vessels, and bronchial tubes, among others, and achieve intuitive and accurate visualization[3]. The surgical plan using 3D reconstruction technology based on CT images is shown to be useful for robot-assisted segmentectomy[4], and helps to reduce complications and improve surgical efficiency.

The preoperative 3D reconstruction with precision can offer an effective display of tumor and anatomical structure of surrounding organs, which results in the maximum preservation of lung function for cancer patients. For early-stage lung cancer and precancerous lesions, precision segmentectomy allows clinical intervention or lesion removal at minimal cost with increased long-term survival rate and improved quality of life. Practical cases have shown that anatomical lung segment analysis can help doctors effectively determine the tumor size, location, and estimate surgical margins. The 3D computed tomography analysis provided a positive predictive value of 87% in predicting a marginal clearance greater than 1 cm and a 75% positive predictive value in predicting a margin to tumor diameter ratio greater than 1 in relation to the surgical pathology assessment.[5] It can assist doctors in a better prediction of the feasibility of segmentectomy for peripheral lung cancer.

To support automatic segmentation of medical images, researchers make use of frameworks such as NiftyNet, which enables quick development and distribution of deep learning based solutions for applications such as segmentation, regression, image generation, and representation learning, or extends the platform to new applications[6].

According to a research report by Allied Market Research, the global preoperative surgical planning software market is estimated to be $84.09 million in 2018, and projected to reach $127 million by 2026 with a CAGR of 5.2%.

The 3D reconstruction from pulmonary CT images is a typical AI application in the medical industry. In fact, the outstanding advantages of AI in the diagnosis and treatment procedure has warranted itself as an important direction for many hospitals to drive digital innovation and the promotion of smart hospital. The *White Paper on Medical Imaging AI in China* shows that AI has broad prospects in clinical applications, which can improve diagnostic accuracy and efficiency, shorten waiting time, and reduce treatment cost[7].

The primary difficulty in performing precision segmentectomy is individual anatomical differences. Distinguishing the veins, arteries, bronchi and intersegment plane of the pulmonary segment is the key to precision surgery. With advancements in AI, a small number of hospitals in China have built 3D digital organ models by importing CT data and images into computer workstations, which rebuild as close as possible the shapes of patients' arteries, veins and bronchi. During operations, these models can be rotated for observation, which provides precise lesion location and resection, and greatly improves the operation safety.

– Dr. Zhongmin Peng
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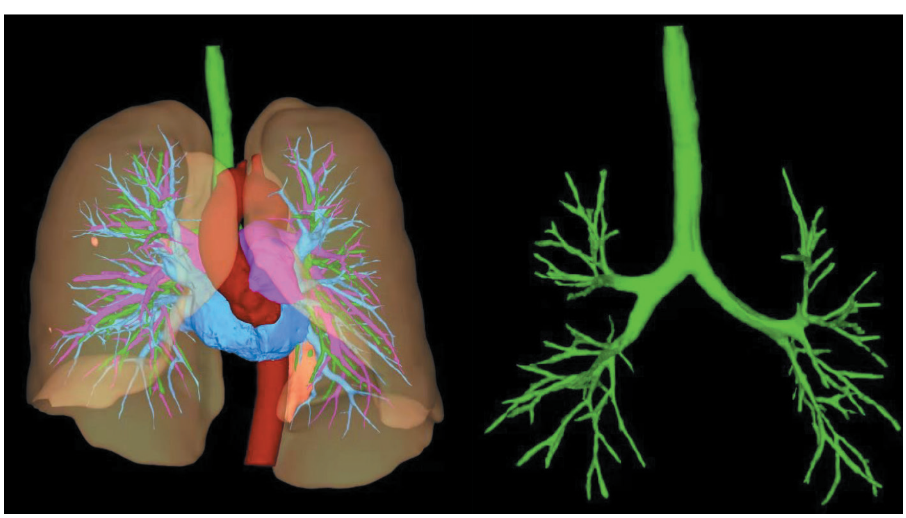

Figure 1: 3D model of pulmonary arteries reconstructed from CT images by Hisense Medical CAS system
Image Source: Hisense Medical

Hisense Medical accelerates 3D neural network prediction based on Intel architecture

For precision abdominal surgery, Hisense Medical CAS system can provide a complete image reconstruction solution with efficiency, precision, easy user interface, quantitative simulation and analysis. The CAS system is able to preprocess and segment CT/MR images of abdominal tissues and organs, output the reconstruction of liver, tumors, blood vessels and peripheral organs with high precision and clarity, and provide a variety of surgical simulation tools for direct 3D cutting, 2D mapping cutting and blood-flow analysis, which helps clinicians with quick and accurate diagnosis and operation plans.

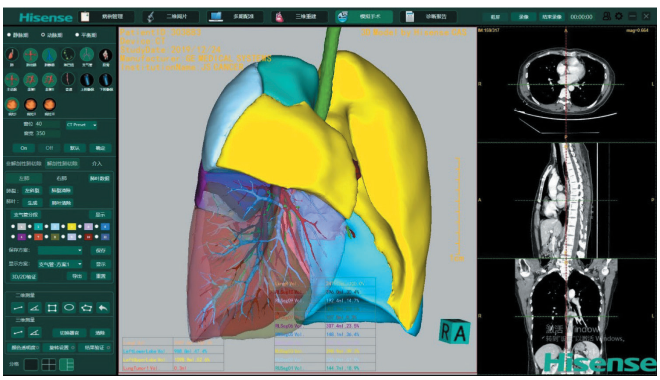

Figure 2: Hisense Medical CAS System for Pulmonary Surgery
Image Source: Hisense Medical

A survey of CAS systems for major liver diseases shows that Hisense Medical CAS system and other similar products have already provided assistance to clinical medical staff[8].

The development of Hisense Medical CAS System for Pulmonary Surgery went through the steps of functional prototype design, performance optimization, and accuracy verification. The CAS system made use of V-Net neural network architecture for 3D segmentation of fully convolutional neural network and NiftyNet framework for rapid design algorithm prototyping. It also leveraged Intel tools to optimize performance and validate prediction results before and after optimization, to ensure the consistency of results of neural networks after optimization.

V-Net

As most medical imaging data is 3D by nature, 3D feature extraction is crucial for the segmentation of tubular organs, such as blood vessels and bronchi, which often appear as round or oval cross-sections on a single CT image. The major shape features can only be found in the z-axis direction. Meanwhile, medical image segmentation often faces the challenge that the volume of the focus target is too small compared with the overall anatomical structure and the number of samples for deep learning training is unbalanced, e.g. bronchial branches and small pulmonary nodules vs. pulmonary parenchyma, which leads to prediction bias.

The V-Net neural network architecture was proposed by Milletari et al. in 2016. The input images go through a compression path for feature extraction and down-sampling, and then a following decompression path to restore the original image size. Hence, the neural network architecture presents a left to right symmetrical V-shape. The fine-grained details that would be otherwise lost in the compression and decompression path is kept by using feature forward shortcut connection to improve the quality of the final contour prediction. By introducing a novel objective function based on Dice coefficient and its optimization, the challenge of a strong imbalance between the number of foreground and background voxels is resolved.

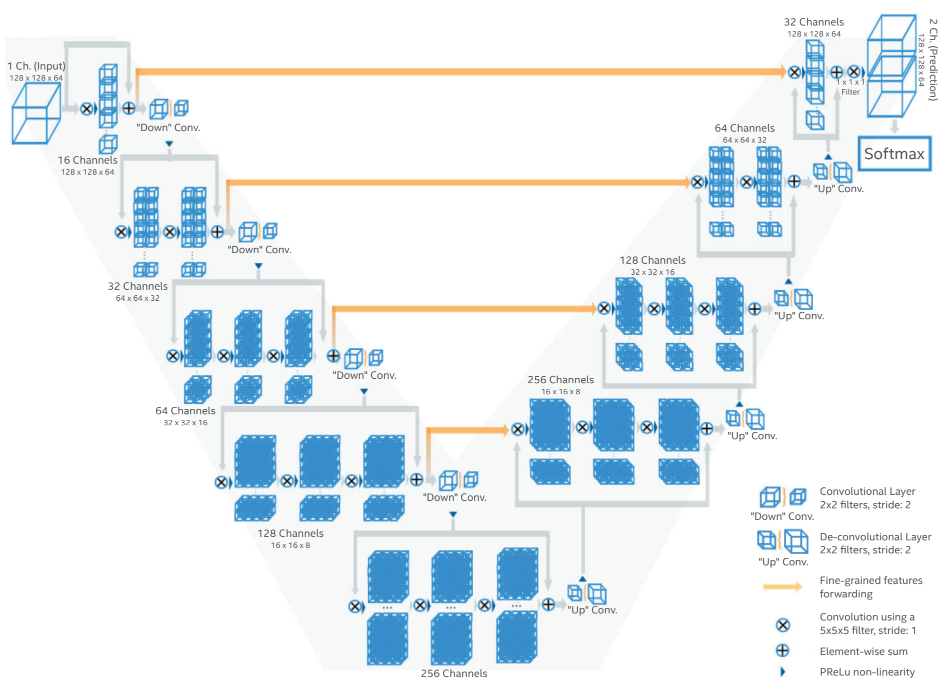

Figure 3: V-Net neural network architecture[9]

NiftyNet

NiftyNet is a TensorFlow-based open-source convolutional neural network (CNN) platform for research in medical image analysis and image-guided therapy[6]. Hisense Medical uses NiftyNet and Dense-Vnet from the NiftyNet open model zoo for segmentation of multiple organs using abdominal CT images. This network can do segmentation for eight organs from abdominal CT: the gastrointestinal tract (e.g. esophagus, stomach, duodenum), the pancreas, and nearby organs (e.g. liver, gallbladder, spleen, left kidney)[10].

Based on TensorFlow, the NiftyNet open model zoo provides steps to conduct model training using a standard public dataset and trained weights (checkpoint file) for inference result validation and performance evaluation. For Hisense Medical CAS system, Intel helps to modify the NiftyNet open source code to serialize TensorFlow graph and generate frozen .pb file with weights. This is not a step from the standard OpenVINO toolkit workflow. During the graph serialization steps, the correct input and output node needs to be specified so that the frozen files with weights only contain the model structure diagram from the relevant nodes between input and output. The flowchart below shows how the toolkit helps the NiftyNet open model to achieve inference acceleration. The orange blocks are from the NiftyNet source file, while the blue blocks are from the OpenVINO toolkit optimization process:

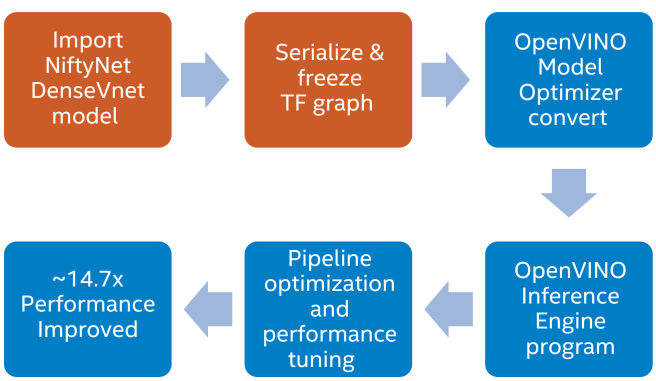

Figure 4: Accelerate NiftyNet model inference performance using OpenVINO. Please refer to Figure 9 for the details of 14.7x performance improvement.

Accelerate DL models inference using the OpenVINO toolkit

The OpenVINO toolkit provides highly optimized deep learning inference computing capability; the optimization is available to Intel hardware platforms including Intel CPU, GPU, VPU, and FPGA. In this case, Hisense Medical makes use of Intel® Deep Learning Deployment Toolkit (Intel® DLDT), which is the main inference optimization module inside of OpenVINO toolkit.

As shown in Figure 5, Intel DLDT contains two modules, Model Optimizer (MO) and Inference Engine (IE). MO is a cross-platform command-line tool that facilitates the transition between the training and deployment environments, performs static model analysis, and adjusts DL models for optimal execution on end-point target devices[11]. It supports offline model conversion from popular framework model (e.g. TensorFlow) to Intermediate Representation (IR).

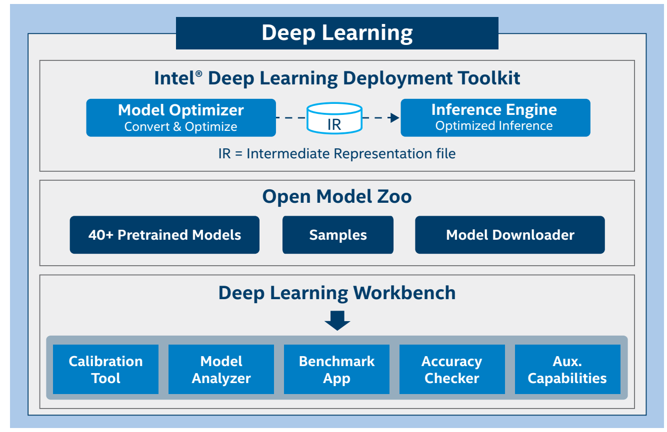

Figure 5: Product architecture related to deep learning deployment of OpenVINO toolkit

MO produces DL models in IR, which contains XML and binary files for network structures and weights/biases binary data; IE is able to load and execute the DL model on platforms such as servers based on the latest Intel Xeon Scalable Processors. IE provides unified cross-platform C++ and python API for inference acceleration and optimization. On Intel Architecture processors, the IE will automatically use runtime plugin with Intel Deep Neural Network Library (DNNL) which can detect instruction set architecture (ISA) in the runtime and use just-in-time (JIT) code generation to deploy the code optimized for the latest Intel Instruction Set Architectures (ISA)[12], to accelerate processing of neural network layers on respective hardware.

Figure 6 shows the scheme and the process of Intel DLDT's accelerated inference. The MKL-DNN (also known as Intel DNNL) plug-in used by IE defines how to implement core primitive operation layers of DL networks, including Conv (convolution) layer, Eltwise (element-wise) layer, and Concat (concatenation) layer etc.[13]

OpenVINO Async mode

To optimize the complete inference pipeline and reduce data transferring costs, Hisense Medical adopts asynchronous application programming interface (Async API) from IE to set up multiple instances of inference request, and perform inference on multi-cores in parallel. 3D CT images can be divided into multiple small blocks (64*64*64 in size for each block) for processing with no data interdependency among any blocks. Then, batches of blocks can be independently loaded at the beginning, and fed into a pool of inference requests for parallel processing, without the need to wait for completion of data loading or inference results. OpenVINO Async API provides convenient response mechanism using wait functions. Upon the execution completion from Async inference request, the results will be acquired and marked, and the next input will be pushed to the request pool for the immediate next round of inference.

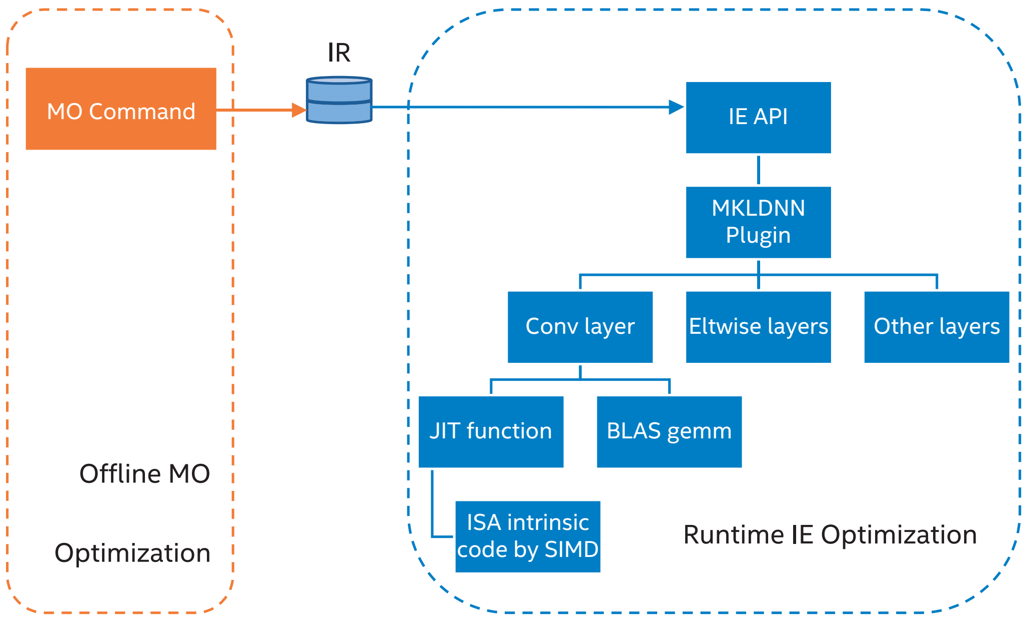

Figure 6: Intel DLDT's optimization mechanism for CPU platform

Figure 7 shows that the original inference engine Sync API is analyzed by the Intel® VTune™ toolkit using the hotspot analysis option. The network layers execute on the main thread, and Intel DNNL creates Intel Threading Building Blocks (TBB) threads for each network layer on multiple cores[14]. Starting with the OpenVINO toolkit 2019 R1, DLDT transitioned the parallelism scheme from OpenMP to TBB to further increase inference performance in multi-network scenarios, and for asynchronous and throughput modes[15].

In Figure 7, the bar marked by the yellow oval represents the main thread, the horizontal axis represents duration, and the orange bar indicates that the main thread is in the idle status of spin and overhead, and occupies system resources. This is because the main thread needs to wait until TBB worker threads to complete one layer after another, and can only release resources after the input data of each block is computed serially.

Unlike Sync API, the OpenVINO Async API can create several instances of inference request to execute DL network inference concurrently. As shown in Figure 8, sub-threads with several inference requests are created at the same time, each one performs inferences with different blocks of input data independently. The red circles represent the same layer on different inference instances executed in parallel. As a result, the latency between main and sub-threads will be reduced.

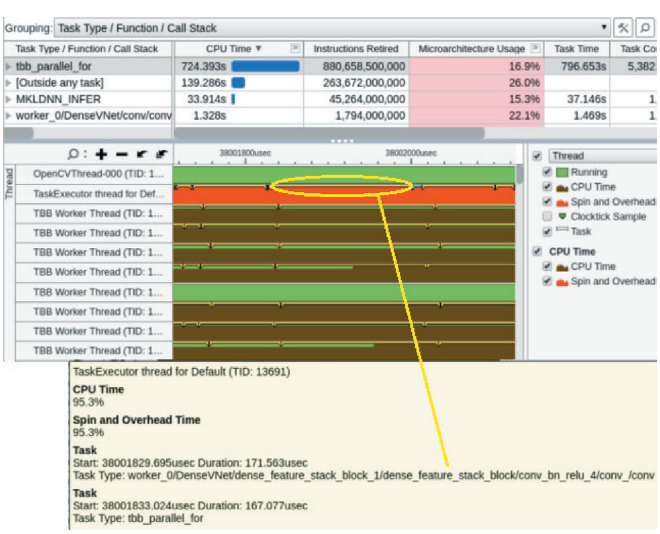

Figure 7: IE Sync API computation flow shown in Intel VTune Tool

Figure 8: IE Async API computation in "throughput" mode shown in Intel VTune Tool

Meanwhile, Hisense Medical also uses the throughput mode of IE to run multiple inference requests on the CPU simultaneously, which significantly improves the system throughput[16]. In this mode, the execution resources are pinned to execution "streams", which are tired to the respective physical cores on CPU. This feature can get even higher performance especially on multiple-core server system.

Hisense Medical CAS performance verification based on OpenVINO toolkit

To perform 3D reconstruction of medical image data including CT scans, it is required to collect point cloud data (PCD) of the target, and go through the steps of depth image enhancement, point cloud computing and matching, data fusion, and surface generation to complete 3D target reconstruction. As this process involves automatic segmentation and image reconstruction, which need DL networks deployment to provide AI predictions, it is a huge demand for resources such as computing, storage and network.

To build hardware infrastructure for DL network AI inferences, product designers often find it difficult to choose between CPUs and GPUs. Due to architecture differences, external GPUs may find some wide usages in image processing algorithms and DL training. However, due to the special nature of medical usage scenarios, external GPUs may not be the best choice for AI prediction networks targeting 3D image reconstruction:

- The deployment of AI functions in hospitals is often limited to local area networks, and cloud GPU resources in public networks can hardly be accessible. To meet the concurrency requirements, multiple high-performance GPUs need to be deployed locally, which leads to high hardware cost.
- As GPU memory is generally limited, to process a large amount of 3D neural network prediction data, the patch-based method (split-separate prediction-merging) needs to be applied. But the context information of the predicted target in this scenario is easily lost which leads to emergence of noise. For example, in dynamic and static pulmonary segmentation, the data volume size is 512 * 512 * 400; with a GPU with only 11GB of memory in Hisense Medical's evaluation setup, the maximum patch size can only be 232 * 232 * 232. In this context, the GPU deployment adaptability will be limited.
- Specifically for this paper, the AI algorithm of Hisense Medical CAS system has an advanced feature of batch processing with minimal human interactions, which allows for acceptable user experience with slightly longer processing time.
- In addition, GPUs have limited universal applicability for all usage scenarios. It may be applicable only to customized AI operations, but not to general purpose computing. Meanwhile, CPU-based servers can be effectively utilized to provide resources to other digital services like digital image diagnostic room or operating room while not performing AI related tasks.

In sum, when deploying surgery planning system based on 3D image reconstruction, these important factors need to be considered: an appropriate hardware infrastructure platform for 3D neural network prediction and inference performance improvement by using DL acceleration toolkit.

Based on Intel Xeon Scalable processors and OpenVINO toolkit, Hisense Medical and Intel have jointly optimized the algorithms for AI segmentation and reconstruction of pulmonary CT, greatly reducing the deployment cost and enhancing the CAS system flexibility for Pulmonary Surgery.

After discovering the possible limitations of the GPU solution, Hisense Medical decided to build an infrastructure platform based on Intel Xeon Scalable processors and evaluate the performance of this solution. Intel Xeon Scalable processors provide powerful general-purpose computing capabilities and integrate innovative technologies, such as enhanced Single Instruction Multiple Data (SIMD) and Intel® AVX-512. These innovations deliver both general-purpose and parallel computing capabilities that empower AI training with excellent performance as well. Compared with previous generations, Intel Xeon Scalable processors provide high performance for both AI training and inference workload.

In addition, Hisense Medical used the OpenVINO toolkit for AI inference acceleration. By importing pretrained models from standard training frameworks, the model optimizer (MO) can convert DL models into a unified intermediate representation (IR) format, and perform inference using inference engine. This helps medical SW applications to be scaled to different Intel hardware targets, including CPU and accelerators such as VPU, iGPU, FPGA, without any additional software changes.

To verify the performance, Hisense Medical performed comparative tests (the CPU solution on Intel Xeon Scalable processors, equipped with Intel SSE4.2, Intel AVX, Intel AVX2, and Intel AVX -512 instruction set, and optimized by OpenVINO toolkit; the results are shown in Figure 9). The original size of CT image is (284, 512, 512), i.e. 284 CT scan slices each with size of 512 * 512. Hisense Medical CAS system used the GridSampler function in NiftyNet to divide the original CT scan slices into 1,001 small blocks of size (64*64*64) for deep learning inference.

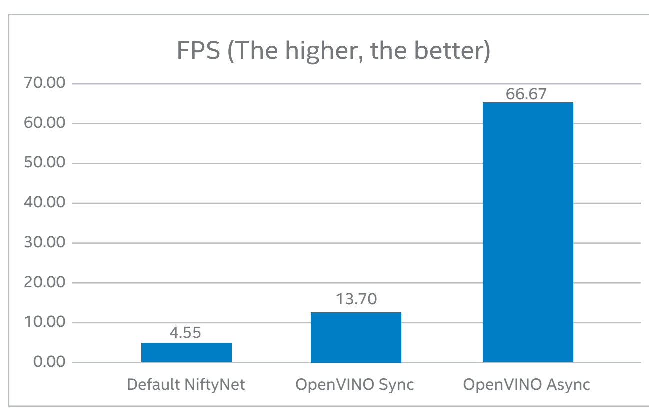

Figure 9: Inference performance of default NiftyNet and OpenVINO toolkit before and after optimization. Data source: Hisense Medical, January 2020[17]

The test results prove that the CPU solution features a higher system deployment and application flexibility for a wider range of workloads with lower total cost of ownership (TCO).

Practical example: 8 minutes to complete key surgical procedures for a rare disease

Powered by Intel Xeon Scalable processors and OpenVINO toolkit and optimized AI segmentation for pulmonary CT images, Hisense Medical CAS system provides efficiency and accuracy in real clinical settings. With 3D reconstruction of pulmonary CT image, the CAS system produces a stereoscopic 360-degree, quantifiable, observable, and interactive image model. Doctors and surgeons can have more close-up views by rotating the image model, adjusting the transparency, and zooming in and out. It offers important supports to preoperative planning and intraoperative reference.

Yongjian Chen, Deputy General Manager of Hisense Medical, pointed out that in a recent clinical operation of "renal cancer with inferior vena cava tumoral thrombosis and infiltrated vena cava wall" at the Urology Department of the First Affiliated Hospital of Chongqing Medical University in China. The patient's condition was too complicated for doctors to refer to any previous case as reference and very risky for conventional operation. By using Hisense Medical CAS system for 3D reconstruction, doctors had a careful preoperative planning preparations, and finally spent only 8 minutes completing the most crucial surgical steps.

By combining Hisense Medical's profound experience in the medical industry and the high performance, flexibility of Intel architecture, the CAS system has great potential in the diagnosis and treatment of pulmonary diseases to assist doctors to improve the quality of clinical surgery. For hospital, these CAS solutions based on CPU and OpenVINO toolkit can provides the general-purpose compute resources with lower cost.

In January 2020, the research program "Development, Clinical Application and Industrialization of Computer-Assisted Surgery System for Pediatric Hepatic-Biliary-Pancreatic Surgery" built upon Hisense Medical CAS system won the second prize of 2019 China National Science and Technology Progress Award[18]. This program was jointly developed by the Affiliated Hospital of Qingdao University and Hisense Medical.

Outlook: Intel and Hisense Medical will promote the implementation of smart healthcare

"The 3D reconstruction plays an increasingly prominent role in the diagnosis of diseases with efficiency and accuracy advantages. We have ensured the operation efficiency and agility of the CAS system by collaborating with Intel. In the future, we will also cooperate with Intel in exploring the application of 3D printing, mixed reality and other technologies in the medical industry, providing greater support for accurate preoperative diagnosis, precise intraoperative surgery, and rapid recovery of patients", said Yongjian Chen, Deputy General Manager of Hisense Medical.

To promote the adoption of AI in the medical and healthcare industry, Intel has introduced a wide array of hardware (e.g. CPU, FPGA, VPU, GPU) along with a range of software development tools (e.g. OpenVINO toolkit and Intel VTune Profiler). With a comprehensive end-to-end AI product portfolio, Intel provides a variety of flexible and optimized solutions which allow ecosystem partners such as Hisense Medical to excel in their respective application areas.

About Hisense Medical

Technology First, Quality First

Qingdao Hisense Medical Equipment Co., Ltd. (Refers as "Hisense Medical"), established in Feb. 28th 2014, is a wholly-owned subsidiary of Hisense Group, China. Relying on profound experiences and R & D capabilities of Hisense Group in technologies such as multimedia display and network information, we are committed to developing five major categories including Medical Displays, Hisense Computer Assisted Surgery System (CAS), Smart Hospital System Solutions (e. g. Digital OR), Clinical Nursing Operation Mobile Terminal and Color Doppler Ultrasound Instrument. Adhering to the purpose of "technology first" and "quality first", Hisense Medical is responsible to complete the national medical display module research and development projects. All related display products including consultation display, diagnostic displays, as well as endoscopic monitors have passed a rigorous product quality and performance test, obtaining the German Rhine TUV ISO 13485 medical device quality management system certification, the EU CE certification and the United States FDA certification.

About Intel

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You may know us for our processors. But we do so much more. Intel invents at the boundaries of technology to make amazing experiences possible for business and society, and for every person on Earth.

Harnessing the capability of the cloud, the ubiquity of the Internet of Things, the latest advances in memory and programmable solutions, and the promise of always-on 5G connectivity, Intel is disrupting industries and solving global challenges. Leading on policy, diversity, inclusion, education and sustainability, we create value for our stockholders, customers, and society.

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[17] FPS: Frames per second. The size of each frame is (64, 64, 64). The higher the number, the better the performance. Configuration of test system: Intel® Xeon® Gold processor 6140, 187 GB of memory, operating system Ubuntu 16.04, OpenVINO™ toolkit development edition (2019R2, IE call parameters: -niter=20, -nireq=50) , NiftyNet (v0.5.0).

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