Research Statement

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My research vision is to enhance the capabilities of vision learning systems with a comprehensive understanding of medical images, focusing on **anatomical shape coding in specifically low-resource conditions**. The fundamental questions guiding this endeavor involve automating the quantification, interpretation, and personalization of anatomical shapes, even working with *limited-scale datasets*, *low-quality imaging modalities*, and *sparse expert annotations*. Addressing these questions is essential for understanding the diagnostic decision-making process in computer-assisted interventions. The knowledge derived from these inquiries is communicated through a variety of information sources, including text, images, videos, audio, and electronic records, irrespective of their modalities of presentation.

To acquire anatomical shape knowledge, I focus on **shape segmentation** and **tracking**, introducing a low-resource shape coding approach to transform conventional low-level shape saliency knowledge into high-level anatomical consistency knowledge. Unlike traditional shape learning methods that concentrate on **specific targets** (such as *organs, vessels, bones, or abnormal tumors*) within vast image datasets, my research empowers machines to comprehend high-level **geometrical structures** with **anatomical guarantees**. These guarantees encompass aspects such as *motion, deformation, and topology*, which are challenging to derive directly from images but constitute essential knowledge. The proposed methodology addresses the consolidation of complex anatomical structures in a multitask and multi-modality framework, providing a significant advancement beyond recent research focused on low-level shape knowledge.

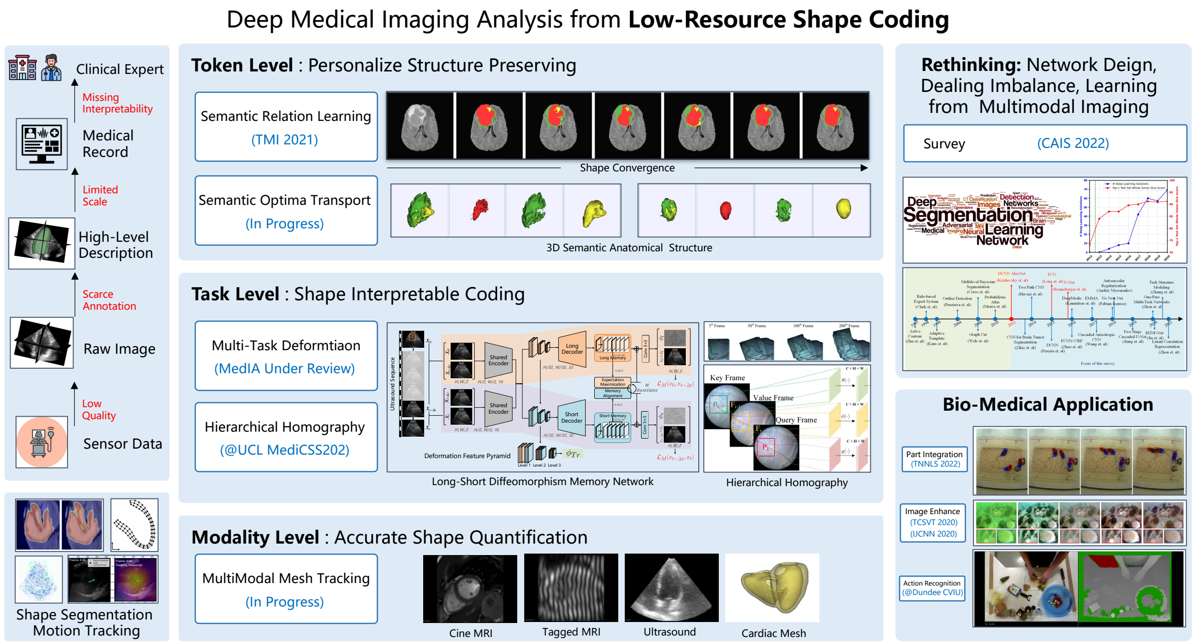

Figure 1: My research is focused on *Low-Resource Shape Analysis*. Our novel shape coding paradigm bridges shape representation across *Token*, *Task*, and *Modality* levels, providing accurate, personalized, and interpretable quantification generalized across applications.

The transformation under low-resource conditions presents notable challenges in terms of robustness, including issues like out-of-distribution generalization, interpretation difficulties such as trustworthy explanation and visualization, and concerns related to transferability, encompassing deployable and recyclable representation. To tackle these challenges, we explore efficient and effective frameworks from various coding perspectives:

- **Token Level** Analysis to Answer *Personalize Shape Anatomical Information* : Accurately quantifying and understanding the structure of anatomical shapes poses significant challenges in medical image analysis, playing a crucial role in achieving personalized diagnoses. Existing efforts in medical image analysis face difficulties in preserving structural relationships across segments and often lack robust strategies to incorporate essential contextual information. In response, my work introduces novel approaches to enhance semantic correspondence. As the first to introduce semantic structure learning into brain glioma segmentation(**CANet**)[6], I first propose deep region relational learning within the regional embedding graph, which resolves anatomical structure preserving problems and supports semantic transport learning in paired image anatomical information extraction.
- **Task Level** Analysis to Answer *Interpretable Shape Coding* : Challenges arise in medical imaging due to varying shape information requirements across different tasks. Current approaches often focus on a singular task, limiting their adaptability and interpretability. To overcome this limitation, we introduce an innovative multi-task approach designed to accommodate diverse shape analysis needs. Within this framework, we propose the long-short diffeomorphism memory network (**LSDM**)[3], which incorporates an auxiliary learnable deformation prior to enhancing accurate landmark tracking. Additionally, we extend spatial shape analysis through a hierarchical homography estimation network, demonstrating its efficacy in achieving accurate medical image mosaicing [1]. This network learns explicit spatial relationships between adjacent frames, generating high visual cues for understanding Fetoscopy Placenta image mosaicing.
- **Modality Level** Analysis to Answer Accurate Shape *Deformation Quantification* : The wealth of information offered by multi-modality imaging is crucial for comprehending and precisely quantifying shape deformation. In the context of myocardial motion tracking using mesh-based analysis, we introduce a **cross-modality mesh mapping** to seamlessly fuse motion information from diverse imaging modalities. This innovative approach enhances the overall interpretation of myocardial motion by effectively leveraging the benefits of multi-modality imaging. Furthermore, our study extracts valuable insights from the multimodal data, categorizing the learning process into two crucial aspects: **learning from the full modality spectrum** and **learning from the missing modalities** [2].

Research Philosophy. I firmly believe that the role of AI in medical imaging extends beyond overfitting to specific metrics, tasks, or disease indices. Instead, its purpose is to augment physician capabilities in real-world clinical scenarios. This includes tasks such as analyzing extensive medical datasets, identifying subtle patterns and anomalies, creating personalized treatment plans, and generalizing to individual variations in genetics, lifestyle, and medical history. My commitment lies in anchoring these techniques in a social good context, fostering effective communication of knowledge between AI and physician experts. This involves presenting trustworthy, interpretable learning representations aimed at improving patient care, enhancing diagnostic accuracy, and ultimately contributing to saving lives.

Future Research Agenda

My **long-term** goal is to equip machines with the capability to comprehend anatomical shapes as physician experts do, focusing particularly on concrete geometry structures such as landmarks, segments, and surface norms, alongside abstract semantic structures. This understanding is intended to span across populational and longitudinal studies. **Adopting a structural view of shape knowledge, machines can advance their ability to comprehend, reason, and communicate knowledge through medical imaging to the healthcare system.** To pursue this goal, I plan to continue my research in the following directions.

Out-of-distribution Shape Analysis and Assistant Diagnosis. I aim to construct a robust open-world shape analysis system capable of generalizing to understand and diagnose shapes or patterns beyond the training population distributions. I aim to propose a probabilistic learnable approach that can compositionally evolve and learn new shape concepts with transferable representation. This approach can be regarded as utilizing life-long learning to model geometry distribution, providing anomaly detection within a transparent assistant diagnosis process. I am passionate about working with excellent researchers in **Computer Vision, Machine Learning, and Clinical Medicine** towards the joint understanding of anatomical shape on novel structures and concepts.

Learning Shape Beyond Imaging. Fine-grained multimodal knowledge proves effective in extracting shape deformation for accurate diagnosis decision-making and precision medicine. I am highly interested in identifying shape-related information from pathology records, electronic health records, and medicine prescriptions. This interest extends to reducing abnormal shape bias and establishing effective shape associations. I am open to collaboration with researchers in **Natural Language Processing, Data Mining, and Neural Science** to automatically extract patients' demographic characteristics, region-level factors, geographical indicators, and medical records. This collaborative effort has the potential to contribute to a societal fair healthcare system.

Interacting Shape Analysis with Feedback from Physical World. The grounding of medical imaging devices, surgical robotics, and wearable equipment requires anatomical shape information such as motion, deformation, and high-level statistics. My previous research collaboration shows the potential of integrating shape representation into interdisciplinary research projects[4, 5, 7]. I aim to extend medical shape analysis by incorporating feedback from real-world scenarios, including signal validation for affordable imaging devices, expert human feedback for human-in-loop healthcare processes, and symbolic rewards for dynamic robotic control. I am excited to collaborate with researchers in **Surgical Robotics, Robotics and Embodied AI, Human-Computer Interaction, and Symbolic AI** to enhance the safety of medical imaging analysis. This involves integrating real-world feedback into automated vision systems for autonomous task planning and execution.

Collaboration

The research directions that I intend to explore require collaborations with expert researchers in many fields, including computer vision, computer graphics, natural language processing, machine learning, data mining, robotics, human-machine interaction, numerical analysis, and also in medical subfields including but not limited to cardiovascular science, oncology, radiology, neural science, and clinical medicine. I have rich experience in leading and managing large Interdisciplinary projects across institutions and organizations. During my past research career, **I am very fortunate to have close collaborations with 20 professors from 12 universities and industrial research institutes**, such as University Hospitals of Leicester NHS Trust, the University of Edinburgh, Queen Mary University of London, Xidian University, University of Surrey, University of London, University of Dundee, Philips Research Netherland, AstraZeneca Research Cambridge. I plan to continue existing collaborations and foster new connections in order to develop well-established principles underlying medical image analysis research. I will continue to seek funding opportunities in the future from multiple funding agencies and industries.

References

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