Discrete & Continuous Models
& Applied Computational Science
ISSN 2658-7149 (Online), 2658-4670 (Print)

2222, 230 (1) 1-11
http://journals.rudn.ru/miph

Review

DOI: 10.22363/2658-4670-2222-230-1-1-11

Modern Methods of Non-invasive Determination of FFR Based on Computed Tomography Data

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(received: December 31, 2025; revised: December 31, 2025; accepted: December 31, 2025)

Abstract. This article provides a review of contemporary methods for constructing three-dimensional models of internal organs and blood vessels based on computed tomography (CT) imaging data in the context of non-invasive determination of fractional flow reserve (FFR). The study covers various algorithmic approaches aimed at improving the accuracy and reliability of reconstructing the surface geometry of internal organs and vessels. Key modern approaches, including segmentation algorithms, boundary detection methods, and machine learning techniques in image processing, are discussed.

Key words and phrases: Fractional Flow Reserve (FFR), non-invasive imaging, computed tomography (CT), 3D reconstruction, image segmentation, coronary artery disease (CAD), machine learning

1. Purpose of the Article

The aim of this article is to provide a review of modern algorithmic approaches for constructing three-dimensional models of internal organs and blood vessels based on computed tomography (CT) data in the context of non-invasive fractional flow reserve (FFR) estimation, with a focus on segmentation methods, boundary detection techniques, and the application of machine learning to improve the accuracy and reliability of geometric reconstruction.

2. Introduction

Non-invasive determination of fractional flow reserve (FFR) is essential for accurately assessing the condition of coronary arteries without the need for invasive procedures. This approach enables the identification of stenoses that may require treatment, thereby reducing the risk of complications and improving patient outcomes. FFR derived from angiography serves as a valuable tool in decision-making for the diagnosis and treatment of coronary stenosis in catheterization laboratories. This technology assists cardiologists in evaluating and managing moderate stenoses by integrating both physiological and anatomical parameters of the coronary arteries.

Moreover, non-invasive methods reduce patient discomfort and stress, as they do not require catheter insertion into the arteries. Ultimately, this facilitates earlier and safer detection of coronary artery disease. As a result, non-invasive FFR estimation has become one of the most in-demand technologies in both domestic and global clinical practice.

3. Applicability of Non-invasive Approaches for FFR Determination

Study [1] compares non-invasive FFR estimation methods based on CT imaging with invasive techniques, investigating whether combining the two improves the predictive accuracy for various conditions such as stenosis and ischemia. The authors conclude that incorporating data obtained through modeling leads to more accurate disease prediction, indicating the positive impact of non-invasive FFR assessment in clinical practice.

Similar findings are reported in publications [2–9]. Specifically, study [2] demonstrates significantly lower mortality in the group of patients with negative non-invasive FFR results compared to those with positive results. Meanwhile, publication [5, 10] shows that the use of non-invasive FFR methods yields high diagnostic accuracy and performs well in comparison to invasive FFR in assessing the significance of coronary stenotic lesions. These studies emphasize that non-invasive FFR techniques are still evolving and require further refinement and clinical validation before widespread clinical implementation.

4. Methods of Non-invasive FFR Determination

Traditionally, non-invasive FFR estimation relies on various vessel segmentation algorithms [11], which are used to build a blood flow model and perform fluid dynamics simulations within the reconstructed geometry using specialized software such as Ansys.

One of the main types of segmentation algorithms is the family of region-growing algorithms. These take a series of CT images and a set of initial coordinates (seeds) as input and expand regions from these seed points. The output is typically a set of voxels forming the region of interest [12]. Due to the need for manual seed selection, these algorithms are considered semi-automatic. They are commonly used to segment internal organs and their components. For example, study [13] describes the process of constructing a patient-specific heart model based on high-resolution CT data. The publication demonstrates the possibility of segmenting the region of interest into separate components such as the heart, blood vessels, and others. A similar approach is also described and applied in [14].

Some studies are limited to constructing one-dimensional vessel models directly from CT data. Such an approach is presented in [15], but its applicability is limited due to the inability to account for certain individual anatomical features or the presence of plaques in the vessels, as explicitly noted in the study. Moreover, according to publication [16], taking into account features like vessel branching is highly desirable, as it significantly affects the simulation results.

Undoubtedly, constructing a more precise 3D model of the vascular system improves the accuracy of simulations and FFR estimation. Consequently, such technologies are in high demand and have become widespread.

In addition, boundary detection-based algorithms are also employed. Study [17] proposes a method for constructing a model of the heart and its adjacent vascular system using a parameterized boundary detection algorithm. The proposed method begins segmentation from an initial state based on an idealized, patient-averaged heart model and iteratively converges to a state that represents the individual geometry of a specific patient's heart. The transition from one state to the next is performed so as to optimize a predefined quality functional. The study also includes a validation phase that assesses the accuracy and quality of heart segmentation. Based on tests on data from three patients and comparisons between automatically generated and manually created segmentations, the authors claim that their approach is sufficiently accurate for practical use and can facilitate and accelerate quantitative analysis of CT data for the diagnosis and treatment of cardiovascular diseases.

A method for constructing a three-dimensional region by ”inflating” a deformable body is described in study [18]. The authors employ a parameterized energy functional that models the behavior of the elastic surface of the expanding body, along with a system of differential equations that governs the process of filling the region of interest, which is bounded by the walls of internal organs or blood vessels. Laplace equations are used to describe the behavior of the body under the influence of both the expanding force and surface tension forces. The system is solved using a finite element mesh specifically designed for the task, consisting of triangular elements in the space $\mathbf{C}^1$.

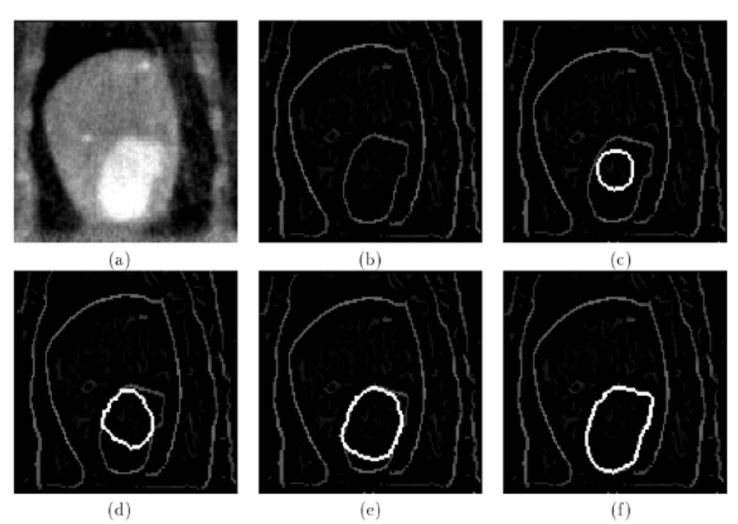

Figure 1. The process of filling the region of interest with a deformable body [18–22]

Another method involves the interpolation of the boundaries of the heart and blood vessels using splines, resulting in a smooth surface that segments the region of interest [23]. Compared to polygonal models, such a representation may be more suitable for simulating fluid flow for FFR estimation, as it allows for more precise and interactive control over the generation of the finite element mesh. This, in theory, can lead to greater accuracy of the simulation results [24–26].

The algorithm described in publication [27] enables vessel geometry reconstruction by first generating an intermediate one-dimensional structure, similar to the approach in study [15]. The central lines of the vessels are constructed first, and then the vessel walls are reconstructed based on individual anatomical features using Frenet formulas. The output of the algorithm is a three-dimensional vessel model with a smooth surface, which can be used to run simulations and model blood flow dynamics.

Such reconstruction methods are particularly valuable in the context of patient-specific modeling, where anatomical variability plays a critical role in both diagnosis and treatment planning [28]. Unlike generic or population-based models, individualized vessel reconstructions account for the unique topological and morphological features of a patient’s vascular network, including curvature, bifurcations, and local variations in diameter. These parameters are essential for achieving accurate hemodynamic simulations, especially when calculating pressure gradients for non-invasive FFR estimation [29]. Furthermore, the use of Frenet frames to reconstruct vessel walls based on extracted centerlines allows for the generation of smooth and anatomically consistent geometries, which are well-suited for finite element meshing and subsequent computational fluid dynamics (CFD) analysis [30]. This approach not only enhances the physiological relevance of simulations but also reduces numerical instabilities during flow modeling, thereby improving the robustness and reliability of diagnostic predictions [31].

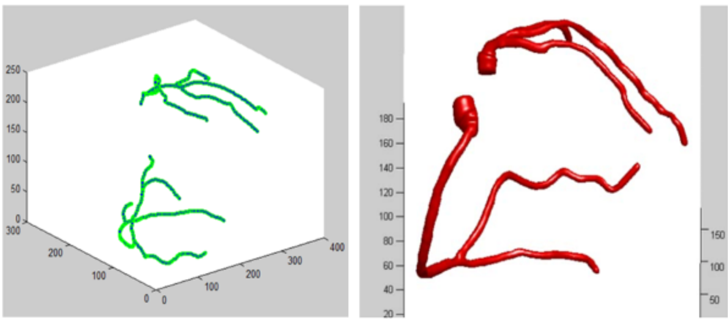

Figure 2. Centerline of the vessels and their reconstructed geometry [27]

Recently, convolutional neural network (CNN)-based approaches have also been used for reconstructing the geometry of internal organs and blood vessels and building their three-dimensional models. For instance, the U-net model [32], specifically developed for biomedical image segmentation tasks, is applied in study [33]. The study compares the segmentation results produced by U-net with those of a Ground Truth algorithm that relies on manual pre-processing, and concludes that U-net—and deep learning in general—shows high applicability and significant potential for medical image segmentation tasks.

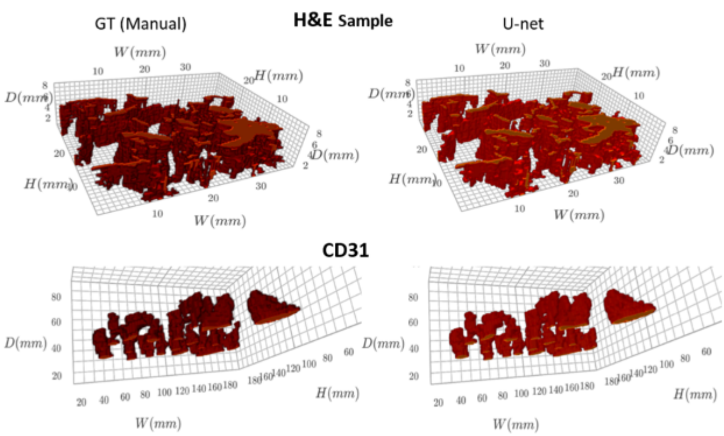

Figure 3. Comparison of segmentation results using the GT algorithm and U-net [33, 34]

Study [35] presents a fast, end-to-end, and fully automated method for determining FFR using a convolutional neural network (CNN) architecture, transfer learning, and a pre-trained DenseNet169 model to estimate FFR values from angiographic images. The model architecture consists of feature extraction and classification layers, with cross-entropy used as the loss function [36]. A distinctive feature of this approach is the absence of a vessel geometry reconstruction stage — the model directly takes input images and outputs the FFR value [37, 38].

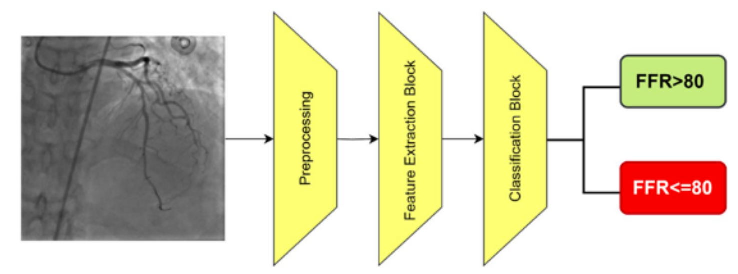

Figure 4. Architecture of the proposed model [35]

5. Current Results

The review study [39] examines the progress of technologies and methods for non-invasive FFR estimation as of 2020. The authors analyze the historical development of non-invasive FFR algorithms and summarize the current achievements in the field.

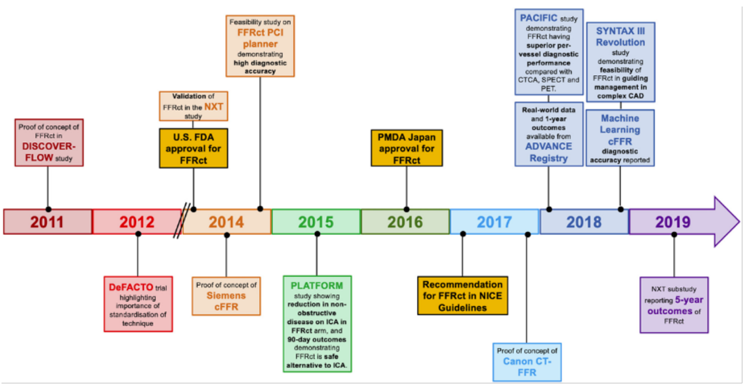

Figure 5. History of non-invasive FFR (as of 2020) [39]

The researchers highlight the following findings:

- Diagnostic accuracy: CT-based FFR has demonstrated high accuracy in diagnosing coronary artery disease, comparable to invasive methods. Studies such as DISCOVER-FLOW, DeFACTO, and NXT have shown that non-invasive FFR correlates strongly with invasive

FFR and outperforms standard CT coronary angiography (CTCA) in diagnostic performance [40, 41].
- Clinical outcomes: Non-invasive FFR allows for accurate identification of hemodynamically significant stenoses, which is essential for decision-making regarding revascularization procedures (e.g., stenting). This helps avoid unnecessary interventions in patients with non-critical stenoses [24, 42–44].
- Advantages over invasive methods: Non-invasive techniques eliminate the risks associated with surgical procedures and reduce patient discomfort [45, 46].
- Practical clinical application: Integrating non-invasive FFR into clinical practice can enhance the diagnosis and treatment of patients suspected of having coronary artery disease, reducing both diagnostic time and costs [47–49].
- Future development: The authors emphasize the need for further large-scale studies to validate the diagnostic effectiveness and safety of non-invasive FFR methods in routine clinical use.

6. Conclusion

This article has reviewed modern algorithmic approaches to the non-invasive determination of fractional flow reserve (FFR) based on computed tomography data. The discussed methods—ranging from classical segmentation algorithms and boundary detection techniques to deep learning-based models—demonstrate significant potential for improving the accuracy and efficiency of FFR estimation. Non-invasive FFR provides a clinically valuable alternative to invasive procedures, offering reduced risk, greater patient comfort, and strong diagnostic performance. While current results are promising, further development and large-scale clinical validation are needed to ensure the reliability and integration of these technologies into routine medical practice [50].

7. Future Work

Future research should focus on improving the accuracy and generalizability of non-invasive FFR estimation methods, particularly those based on deep learning [50, 51]. Expanding training datasets with diverse clinical cases and CT scan protocols will enhance model robustness.

Further efforts are needed to develop fully automated and clinically integrable pipelines that combine segmentation, modeling, and FFR calculation. Real-world validation on larger cohorts is essential to confirm diagnostic reliability and assess long-term clinical impact.

Additionally, incorporating supplementary physiological parameters, such as myocardial perfusion or vessel wall characteristics, may provide a more comprehensive and personalized evaluation of coronary artery disease.

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To cite: Leladze K. G., Alexandrova L. V., Modern Methods of Non-invasive Determination of FFR Based on Computed Tomography Data. *Discrete and Continuous Models and Applied Computational Science* **230** (1), 1-11. doi: 10.22363/2658-4670-2222-230-1-1-11. edn: (2222).

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DOI: 10.22363/2658-4670-2222-230-1-1-11

Современные методы неинвазивного определения ФРК на основании данных компьютерной томографии

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Аннотация. В данной статье представлен обзор современных методов построения трёхмерных моделей внутренних органов и сосудов на основании данных компьютерной томографии (КТ) в контексте задачи неинвазивного определения фракционного резервного кровотока (ФРК). Исследование охватывает различные алгоритмические подходы, применяемые для повышения точности и надёжности реконструкции геометрии поверхности внутренних органов и сосудов. Рассмотрены ключевые современные подходы, включая алгоритмы сегментации, методы на основании детектирования границ и методы машинного обучения в обработке изображений.

Key words and phrases: Фракционный резерв кровотока (ФРК), неинвазивная визуализация, компьютерная томография (КТ), трёхмерная реконструкция, сегментация изображений, ишемическая болезнь сердца (ИБС), машинное обучение