

Knowledge Representation in Noninvasive and Invasive Comprehensive Intelligent Cardiovascular Diseases Diagnosis in e-Home Healthcare

Tai Chun Tang, Mu Bo Chen, Bin Bin Fu, Ming Chui Dong, Zhao Xiong Fang, and Zhen Hua Xiao

Abstract—A cardiovascular diseases (CVDs) knowledge hierarchical representation (KHR) is pioneered to perform noninvasive and invasive comprehensive diagnosis in e-home healthcare, thus to achieve high-precise diagnostic accuracy. The clinical diagnosis actually maps the sampled cardiovascular parameters (CPs) into the relevant CVDs through using medical knowledge and depending on pathological characters of the disease. The CPs include noninvasive physical information such as electrocardiography (ECG), sphygmography (SPG), and heart sound (HS) data as well as invasive chemical information such as blood test parameters (BTPs) data. CVDs are divided into different categories with the allowance of producing new variants. Tackle such complex and diversified data, a frame-based KHR is proposed which represents the CPs, disease categories and their pathological relationships hierarchically. It is noteworthy that such a KHR is suitable to knowledge changes with the re-usable shell design structure. In addition, a versatile KHR inference mechanism (KHR-IM) is introduced to realize this KHR. With such an organic combination of noninvasive and invasive diagnosis, it establishes not only a solid mainstay for realizing more accurately the functionality of entire system, but also provides people with a reliable health monitor and management.

Index Terms—Cardiovascular diseases, cardiovascular parameters, frame-based knowledge hierarchical representation, inference mechanism, noninvasive and invasive comprehensive diagnosis, symptom-disease mapping relationship.

I. INTRODUCTION

Cardiovascular diseases (CVDs) are globally known as the number one killer of health [1]. For offering early prevention, and proactive detection of CVDs, various e-health applications have been flourishing, such as telemedicine, remote monitoring, and mobile health (m-health) [2]-[4].

As [5] proposed, adapting the noninvasive and invasive comprehensive intelligent CVDs diagnoses in e-home

healthcare can guarantee high-precise diagnostic accuracy. The proposed intelligent diagnosis system includes three entities, namely upstream (hospital server), midstream (local computers), and downstream (embedded-link devices, such as smartphone, iPad, etc.), which can satisfy users with diversified backgrounds and requirements [6].

To achieve high-precise diagnostic accuracy, the integration of noninvasive e-home healthcare with invasive clinical diagnosis must be established. The clinical diagnosis actually maps the sampled cardiovascular parameters (CPs) into the relevant CVDs through using medical knowledge and depending on pathological characters of the disease. The CPs include noninvasive physical and invasive chemical information. At the aid of pervasive body sensor network, multi noninvasive signals such as electrocardiography (ECG), sphygmography (SPG), and heart sound (HS) waveforms can be obtained. Through signal pre- and post-processing, the sampled waveforms are converted into noninvasive parameters (NiP). With the aid of hospital clinical biochemical detection, multi invasive blood test parameters (BTPs) such as total cholesterol (TCH) and aspartate (AST) etc., which are a-part-of invasive parameters (InP), can be obtained. Noninvasive or invasive diagnoses are actually to infer the CVDs based on patients' NiP or InP individually. The unit, scale, value-range, describing method, and storage method of these two types of parameters are quite different; consequently the knowledge representations and relevant inference machines are quite different.

Tackle the bottleneck problem of designing a knowledge hierarchical representation (KHR) scheme, and expressing such complex and diversified data, many aspects must be considered systematically and scientifically. For instance, the confirmation of some diseases may refer to other new CPs such as creatine kinase (CK), or other relevant parameters such as brain wave parameters (BWPs), ultrasound parameters, lung-heart parameters, etc. Moreover, CVDs are divided into different categories with the allowance of producing new variants. For example, in the coronary heart disease (CHD) category it may produce a new disease called as latent coronary heart disease (LCH).

In this paper, a frame-based KHR with re-usable shell structure [7] is proposed which is expandable and adaptable for representing such complex and diversified data. In addition, a versatile KHR inference mechanism (KHR-IM) is introduced to realize this KHR.

II. METHODOLOGY

A. Knowledge Hierarchical Representation

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1) Architecture of KHR for cardiovascular parameters

The designed architecture of KHR for CPs is illustrated in Fig. 1, in which four-layer parameter categories are concerned, namely, grand-parent, parent, child and grand-child.

In detailed, the hemodynamic parameters (HDPs) which are derived from noninvasive signals SPG waveforms, can be divided into three child parameter categories: sensitive (SSE), auxiliary (AXY), and replenish (RPH) according to their

diagnostic importance [8].

Similarly, BTPs can be categorized into several child parameter categories such as blood lipid parameters (BLPs), myocardial enzyme parameters (MEPs), liver function parameters (LFPs) and renal function parameters (RFPs), which are the indicators to the metabolism of cardiovascular, liver and renal function respectively. Clinically, those parameters are quite sensitive for CVDs diagnosis.

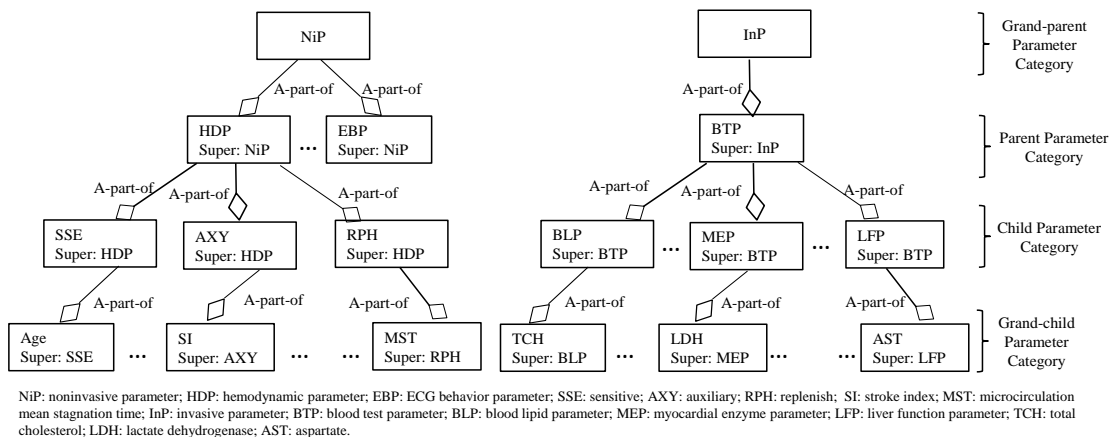


Fig. 1. Architecture of KHR for CP.

Cardiovascular Parameter (CP)	Disease Set (DS)	Symptom-Disease Mapping Relationship (SDMR)
<p>Frame: BTP in KHR Superclasses: CP, InP Subclasses: BLP, MEP, LFP, RFP, ... SLOT: Name: Blood test parameter Unit: <i>#string</i> Scale: <i>#string</i> //Normal-value-range (NVR) NVR-Max-Children: <i>#string</i> NVR-Min-Children: <i>#string</i> NVR-Max-Adult: <i>#string</i> NVR-Min-Adult: <i>#string</i> Store-method: <i>#string</i> ...</p>	<p>Frame: CHD in KHR Superclasses: DS, CVD Subclasses: UAA, NST, STE, ... SLOT: Name: Coronary heart disease Clinical manifestations: <i>#string</i> Suggestion: <i>#string</i> ...</p>	<p>Frame: SDMR_CHD in KHR Superclasses: SDMR Subclasses: SDMR_UAA, SDMR_NST, ... SLOT: Name: SDMR in CHD DS: <i>#string</i> CP₁: <i>#string</i> ... CP_n: <i>#string</i></p>
<p>Frame: TCH in KHR Superclasses: CP, InP, BTP, BLP Subclasses: None SLOT: Name: Total cholesterol Unit: mmol/L Scale: mmol/L × 38.67 → mg/dL NVR-Max-Children: 5.20 NVR-Min-Children: 3.12 NVR-Max-Adult: 6.00 NVR-Min-Adult: 2.9 Store-method: double ...</p>	<p>Frame: LCH in KHR (<i>disease variants</i>) Superclasses: DS, CVD, CHD Subclasses: None SLOT: Name: latent coronary heart disease Clinical manifestations: breathing difficulty, chest tightness, ... Suggestion: go to the hospital for further testing,</p>	<p>Frame: SDMR_STE in KHR Superclasses: SDMR, SDMR_CHD Subclasses: None SLOT: Name: SDMR in STE DS: STE CP₁: CP, InP, BTP, BLP, TCH > NVR-Max-Adult ... CP_j: CP, InP, BTP, BLP, CK > NVR-Max-Adult CP_{n+1}: CP, NiP, EBP, EBP₅ = 0 ... CP_j: CP, NiP, EBP, EBP₁₅ = 1 CP_{n+1}: CP, NiP, HDP, SI > NVR-Max-Adult ... CP_n: CP, NiP, HDP, MST > NVR-Max-Adult</p>

Fig. 2. (a) Frame instance of CP; (b) Frame instance of DS; (c) Frame instance of SDMR.

Accordingly, as an example of frame construction, Fig. 2 (a) shows the BTP frame and its subclass TCH frame. As aforementioned, chemical InP and physical NiP have diverse attributes like unit, scale, value-range, describing method, and storage method, frames can incorporate sets of attribute descriptions using slots. As illustrated in bottom of Fig. 2 (a), a frame representing the TCH class might have slots for those different attributes, which proves that the frame-based KHR is adaptable flexibly for representing such complex and diversified data.

Another advantage by applying frame-based KHR lies in its expandability. For instance, the confirmation of some

diseases may refer to other new CP such as CK, or other relevant parameters such as BWP, ultrasound parameters, and lung-heart parameters etc. Once the symptom-disease mapping relationship (SDMR) between the physical BWP with CVDs established, the new BWP frame can be created easily by only automatically inheriting all attributes of the above parent NiP frame.

2) Architecture of KHR for Disease Set (DS)

The designed architecture of KHR for DS is illustrated in Fig. 3, in which three-layer categories are concerned, namely, grand-parent, parent, and child. The child diseases unstable angina (UAA) and ST-segment elevation myocardial

infarction (STE) are categorized under the parent disease CHD. When a new disease called as LCH meets the CHD diagnostic criteria, it will also be categorized under CHD shown as the dash arrow and blocks.

In practical frame realization, a frame inherits the attributes of all parent class frames to which it links. For

example, as illustrated in bottom of Fig. 2 (b), the frame LCH would acquire coincidentally three slots *Name*, *Clinical manifestations*, and *Suggestion* from the above parent CHD frame apart from creating its own *slots*. Hereby, this frame-based KHR shows good reusability and adaptable to new disease variants.

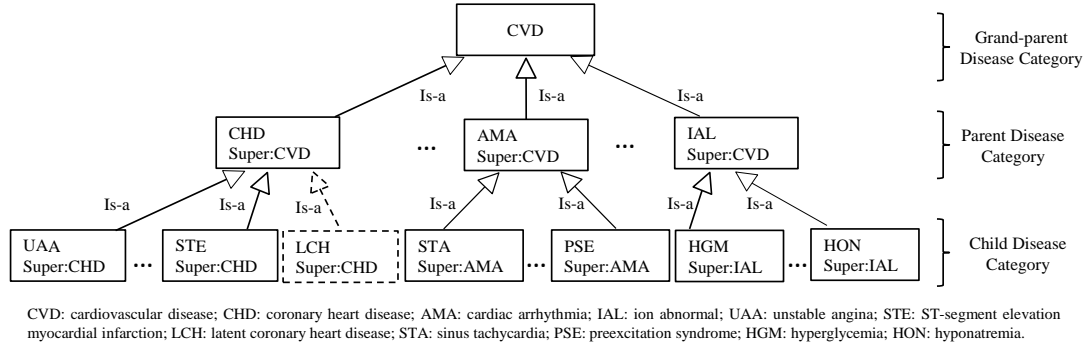


Fig. 3. Architecture of KHR for DS.

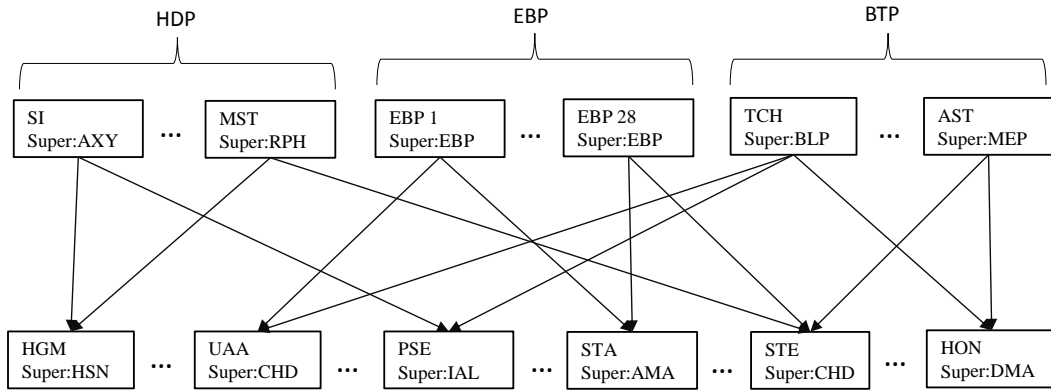


Fig. 4. Architecture of KHR for realizing SDMR.

3) Architecture of KHR for realizing the symptom-disease mapping relationship

The designed architecture of KHR for realizing SDMR is illustrated in Fig. 4. Actually, some diseases may relate only with HDP, ECG behavior parameter (EBP), or BTP. For instance, deduce the category hyperglycemia (HGM) needs only utilizing physical HDP. However, diagnosing some diseases like STE may refer to all the physical HDP, EBP and the chemical BTP.

The corresponding design of the SDMR_CHD frame and its subclass SDMR_STE are shown in Fig. 2 (c).

B. Inference Mechanism

A versatile KHR-IM is originated to verify this KHR. Patients' CPs are operated through a clinical inference function $F(x)$ to determine whether the reflected cardiovascular status is normal or abnormal.

In detailed, the operation of $F(x)$ can be summarized in the following three steps:

Firstly, h CPs are acquired which include a physiological parameters (PLPs), b BTPs, c EBPs along with d HDPs, where h, a, b, c, d denote numbers. The CPs are filled into the CPs record matrix $\mathbf{P}_{k \times h}$ as:

$$\mathbf{P} = \begin{bmatrix} p_{1,1} & p_{1,2} & \cdots & p_{1,h} \\ p_{2,1} & p_{2,2} & \cdots & p_{2,h} \\ \vdots & \vdots & \ddots & \vdots \\ p_{k,1} & p_{k,2} & \cdots & p_{k,h} \end{bmatrix}_{k \times h} \quad (1)$$

where k is the total number of patients to be diagnosed. Thus each row in $\mathbf{P}_{k \times h}$ is one CPs record for a patient and specifically $p_{x,q}$ is the x^{th} patient's q^{th} CP.

Secondly, $\mathbf{P}_{k \times h}$ is mapped to parent disease canonical matrix $\mathbf{C}_{h \times w}$ such that the reflected parent disease could be recognized. The $\mathbf{C}_{h \times w}$ is expressed as:

$$\mathbf{C} = \begin{bmatrix} c_{1,1} & c_{1,2} & \cdots & c_{1,w} \\ c_{2,1} & c_{2,2} & \cdots & c_{2,w} \\ \vdots & \vdots & \ddots & \vdots \\ c_{h,1} & c_{h,2} & \cdots & c_{h,w} \end{bmatrix}_{h \times w} \quad (2)$$

where w is the total number of parent disease categories. The parent disease diagnostic results matrix $\mathbf{ID}_{k \times w}$ is illustrated in:

$$\mathbf{ID} = \mathbf{P} \times \mathbf{C} = \begin{bmatrix} id_{1,1} & id_{1,2} & \cdots & id_{1,w} \\ id_{2,1} & id_{2,2} & \cdots & id_{2,w} \\ \vdots & \vdots & \ddots & \vdots \\ id_{k,1} & id_{k,2} & \cdots & id_{k,w} \end{bmatrix}_{k \times w} \quad (3)$$

where $id_{y,s}$ ($id_{y,s} = 0$ or $id_{y,s} = 1$) is diagnostic result of the s^{th} parent disease for the y^{th} patient. $id_{y,s} = 0$ represents the y^{th} patient does not have the s^{th} parent disease, $id_{y,s} = 1$ means the y^{th} patient has s^{th} parent disease.

Finally, $\mathbf{ID}_{k \times w}$ is mapped to child disease canonical matrix $\mathbf{DC}_{w \times n}$ such that the final disease is indicated. The matrix

$DC_{w \times n}$ is expressed as:

$$DC = \begin{bmatrix} dc_{1,1} & dc_{1,2} & \dots & dc_{1,n} \\ dc_{2,1} & dc_{2,2} & \dots & dc_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ dc_{w,1} & dc_{w,2} & \dots & dc_{w,n} \end{bmatrix}_{w \times n} \quad (4)$$

where n is the total number of child disease categories. The child disease diagnostic result matrix $D_k \times n$ is shown in:

$$D = ID \times DC = \begin{bmatrix} d_{1,1} & d_{1,2} & \dots & d_{1,n} \\ d_{2,1} & d_{2,2} & \dots & d_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ d_{k,1} & d_{k,2} & \dots & d_{k,n} \end{bmatrix}_{k \times n} \quad (5)$$

where $d_{z,t}$ ($d_{z,t} = 0$ or $d_{z,t} = 1$) is the final diagnostic result of the t^{th} child disease for the z^{th} patient.

In summary, by applying such versatile KHR-IM, the KHR which represents the CPs, relevant CVDs and their pathological relationships can be verified.

III. EXPERIMENTAL RESULTS

For the traditional inference mechanism (T-IM), the entire n rules for a specific patient are checked one by one. Thus the computation complexity is $O(n)$.

By contrast, the KHR-IM employs hierarchical diagnosis strategy by checking parent diseases firstly and then going to the corresponding child diseases if parent disease is positive. Therefore, the computation complexity is $O(w + n/w)$.

To evaluate diagnostic performance of KHR-IM, here the improved computation complexity (ICC) is defined as:

$$ICC = \left(1 - \frac{O(w + \frac{n}{w})}{O(n)}\right) \times 100\% \quad (6)$$

where w is the total number of parent diseases, and n is the total number of child diseases, as depicted in (2) and (4) respectively.

In this work, totally 103 CPs including 7 PLPs, 36 BTPs, 28 EBPs along with 32 HDPs are employed to diagnose 5 most common types of parent diseases and 30 types of child diseases; thus $h = 103$, $a = 7$, $b = 36$, $c = 28$, $d = 32$, $w = 5$ and $n = 30$. The testing results show that ICC of the proposed KHR-IM is 63.33% compared with T-IM by (6).

Higher ICC indicates better performance in terms of the resource and memory reduction.

IV. CONCLUSION

A frame-based KHR is pioneered to perform noninvasive and invasive comprehensive CVDs diagnosis in e-home healthcare efficiently. KHR represents the complex and diversified data include CPs, disease categories and their pathological relationships hierarchically. It is noteworthy that such a KHR is suitable to knowledge changes with the reusable shell design structure. In addition, a versatile KHR-IM is introduced and verified that KHR has good performance in decreasing the amount of resource and memory.

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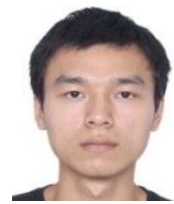
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