



Analysis of the sensitivity and specificity of compressed sensing magnetic resonance imaging in the diagnosis of heart failure

Liguo An¹, Jianxing Qiu², Yu Zhou¹, Jin Hui¹, Jinchao Geng¹

¹Department of Radiology, Wangjing Hospital of CACMS, Beijing, China; ²Department of Imaging, Peking University First Hospital, Beijing, China

Contributions: (I) Conception and design: L An; (II) Administrative support: J Qiu; (III) Provision of study materials or patients: L An; (IV) Collection and assembly of data: L An, Y Zhou; (V) Data analysis and interpretation: J Hui, J Geng; (VI) Manuscript writing: All authors; (VII) Final approval of manuscript: All authors.

Correspondence to: Dr. Liguo An. Department of Radiology, Wangjing Hospital of CACMS, 6 South Wangjing Zhonghuan Road, Chaoyang District, Beijing 100102, China. Email: anliguo@st.btbu.edu.cn.

Background: Magnetic resonance imaging (MRI) is a powerful tool for predicting heart failure (HF) patient prognosis (including death), but it adversely affecting clinical diagnosis and work efficiency. Compressed sensing technology reconstructs and recovers signals using sampling points that are far below the requirement of traditional sampling laws, which can shorten the signal acquisition time without affecting the image quality of MRI. This study aimed to apply compressed sensing technology to the MRI images of patients with HF to evaluate its effectiveness in the diagnosis of HF. Although compressed sensing MRI technology has not yet been widely adopted in clinical practice, it has demonstrated favorable application prospects. Through continuous updating and optimization, it is expected to become a research hotspot in medical imaging, providing more valuable information for clinical work.

Methods: In this study, 66 patients with acute ischemic stroke admitted to hospital were selected for the experimental group, and 20 patients with normal cardiac function who underwent physical examinations during the same period were selected for the control group. An MRI image reconstruction algorithm based on compressed sensing was developed and used in the cardiac MRI image processing.

Results: The results showed that the e' and heart rate of the experimental group were significantly higher than those of the control group, and the E/e' ratio was significantly lower than that of the control group ($P < 0.05$). The early peak filling rate (PFR1), the PFR1/the late peak filling rate (PFR2), the early filling volume (FV1), and the FV1/the filling volume (FV) of the experimental group were significantly higher than those of the control group, and the PFR2 and the late filling volume (FV2) of the experimental group were significantly lower than those of the control group ($P < 0.05$). The diagnostic sensitivity, specificity, and the area under the curve (AUC) for the concentration-time of the PFR2 were 0.891, 0.788, and 0.904, respectively. The diagnostic sensitivity, specificity, and AUC for the FV2 were 0.902, 0.878, and 0.925, respectively. The peak signal to noise ratio and structural similarity of the images reconstructed using the orthogonal matching pursuit algorithm were significantly higher than those determined by the sensitivity coding algorithm and the orthogonal matching pursuit algorithm ($P < 0.05$).

Conclusions: The imaging algorithm based on compressed sensing had excellent processing effect on cardiac MRI and improved the image quality. Cardiac MRI imaging had good diagnostic performance for HF and had the value of clinical popularization.

Keywords: Compressed sensing; cardiac magnetic resonance imaging (cardiac MRI); heart failure (HF); acute ischemic stroke

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Introduction

Heart failure (HF) refers to a group of syndromes with the clinical manifestations of pulmonary circulation and/or systemic circulation congestion and insufficient organ and tissue blood perfusion caused by various cardiac structural or functional diseases, resulting in impaired ventricular filling and/or ejection function and the failure of cardiac output to meet the metabolic needs of body tissues. The main manifestations are dyspnea, limited physical activity, and fluid retention (1-3). The common predisposing factors of HF include infection, serious arrhythmia, anemia, pregnancy, emotional excitement, and pulmonary embolism (4). Left HF is caused by left ventricular compensatory insufficiency and is the most common in clinical settings. The main manifestations of left HF are pulmonary circulatory venous congestion and low cardiac output. The symptoms of left HF include dyspnea, cough, expectoration, hemoptysis, fatigue, and renal impairment (5,6). Simple right HF is rare, and mainly in pulmonary heart disease and some congenital heart diseases. Clinical manifestations of right HF include systemic circulation venous congestion, gastrointestinal, liver congestion, dyspnea, and malignant vomiting (7,8).

With the development of imaging technology, there are more and more ways to clinically diagnose HF, including radionuclide, multi-spiral computerized tomography (CT), left ventricular angiography, echocardiography, and cardiac magnetic resonance imaging (MRI) (9). Among these, radionuclide obtains information about both cardiac

function and myocardial perfusion, and has high reliability but low spatial resolution. The perfusion imaging defect area has a certain influence on the boundary of the heart (10,11). CT can obtain cardiac images in an anatomic direction, but its temporal resolution is low. Left ventricular angiography was previously considered the gold standard; however, it is invasive and radioactive (12). Ultrasound has been widely used in the field of cardiac detection, and has a number of advantages, including that it does not use radiation, has low costs, and is simple to operate; however, it also has low resolution and the accuracy of evaluations of cardiac structural changes in patients with HF is not reliable (13). With its high spatial and temporal resolution, cardiac MRI displays the cardiac anatomical structure, myocardial activity, and myocardial ischemia well. Its clinical use has attracted wide attention.

Compressed sensing refers to a signal reconstruction technology based on sparse signal characteristics that enable the signal sampling and compression process to proceed simultaneously, thus greatly reducing the sampling rate (14). Sun *et al.* [2019] (15) combined analysis-based blind compression sensing with other non-local low-rank constraints to obtain better MRI images with fewer measurements, and simulation results showed that the performance of the proposed method was superior to previous algorithms. Imaging speed has always been the main factor limiting the clinical use of magnetic resonance (16,17). As the down-sampling reconstruction method can be used to address the imaging speed issue, the use of the compressed sensing algorithm is of great research value (18).

Presently, ultrasound is still the mainstream method used to diagnose left ventricular function in patients with HF. To date, few studies have examined the use of cardiac MRI. Therefore, the research idea of this work is as follows. (I) A total of 66 patients with acute ischemic stroke were selected as the experimental group, and 20 patients with normal cardiac function were selected as the control group; (II) cardiac MRI scans were performed on the patients and evaluated by several senior physicians; (III) based on compressed sensing, an MRI image reconstruction algorithm was constructed to reconstruct and process the patients' heart MRI images, and the traditional sensitivity encoding (SENSE) algorithm and orthogonal matching tracking (OMP) algorithm were introduced to conduct simulation experiments for comparison; (IV) the clinical data of the experimental group and the control group were compared; (V) left ventricular function parameters of patients were obtained, and the diagnostic efficacy of

Highlight box

Key findings

- MRI based on the compressed sensing algorithm had better overall quality and displayed the cardiac structure.
- The PFR2 and the FV2 had good classification ability and could be used as effective indicators for evaluating heart failure.

What is known and what is new?

- Ultrasound is still the mainstream method used to diagnose left ventricular function in patients with heart failure, but few studies have examined the use of cardiac MRI.
- We performed cardiac MRI scanning in patients with heart failure and constructed a MRI image reconstruction algorithm based on compressed sensing.

What is the implication, and what should change now?

- MRI based on the compressed sensing imaging algorithm has diagnostic value for heart failure.

each parameter on HF was analyzed by receiver operating characteristic (ROC) curves. Left ventricular functional parameters include left ventricular ejection fraction (LVEF), endothelium-dependent vasodilation (EDV), ecosystem service value (ESV), peak filling rate (PFR), and filling volume (FV), which can be used to evaluate cardiac hypertrophy or atrophy, assess cardiac contractile and pumping function, cardiac diastolic function, and blood reflux, etc. A comprehensive analysis of these cardiac MRI indicators can provide a comprehensive assessment of the function and structure of the heart, providing important references and guidance for the diagnosis and treatment of heart disease. ROC curve has important applications in medical diagnosis. When the accuracy of medical examinations needs to be evaluated, ROC curve can help physicians to evaluate the accuracy of medical examinations and improve the credibility of medical examinations. ROC is an important tool that can be applied to model comparison, model adjustment, and medical diagnosis. In this study, it was assumed that the diagnostic sensitivity and specificity of MRI images based on compressed sensing algorithm were better than those of traditional detection methods. Therefore, patients with HF were selected as the experimental group, and those with normal cardiac function were selected as the control group. All the patients were subjected to cardiac MRI scanning, and the compressed sensing reconstruction algorithm was applied to process MRI images. The objective of this study was to investigate the diagnostic value of cardiac MRI based on compressive sensing imaging algorithm for HF by analyzing cardiac MRI image parameters. We present the following article in accordance with the STARD reporting checklist (available at <https://jtd.amegroups.com/article/view/10.21037/jtd-23-190/rc>).

Methods

Study objects

Patients diagnosed with HF in Wangjing Hospital of CACMS from December 1, 2019 to October 15, 2020 were selected as the experimental group, aged between 36 and 75 years old. Meanwhile, 20 patients with normal cardiac function who underwent physical examination in this hospital at the same period were selected as the control group. The study was conducted in accordance with the Declaration of Helsinki (as revised in 2013). The study was approved by ethics committee of Wangjing Hospital of

CACMS (No. 20201578) and informed consent was taken from all the patients.

Inclusion criteria of experimental group: (I) patients having typical HF symptoms; (II) patients with no claustrophobia, and MRI examination was allowed; (III) New York Heart Association Functional Score $\geq$ level I; (IV) patients with normal left ventricular systolic function; (V) ultrasound results showed diastolic dysfunction (ie, e/e' ratio ≥ 15).

Inclusion criteria of normal group: (I) the medical test results were normal, and there was no disease affecting the experimental results; (II) patients with LVEF $> 50\%$; (III) the ultrasound index E/e' ratio was ≤ 8 .

Exclusion criteria for all subjects: (I) patients suffering from conditions including coronary heart disease, atrial fibrillation, and dilated cardiomyopathy; (II) patients suffering from chronic obstructive pulmonary disease; (III) patients having symptoms of renal failure; (IV) patients with secondary hypertension and hyperlipidemia; (V) patients suffering from combined endocrine diseases.

Ultrasonic testing

The scan was performed with the Netherlands Philips high-end heart Department iE33 four-dimensional Doppler color ultrasonic diagnostic instrument. The patient was placed in the lateral decubitus position in the resting state. The probe was placed at the apex of the heart to obtain the standard 4-chamber view of the apex. The peak diastolic blood flow velocity E and peak diastolic blood flow velocity in the late diastolic period were measured A . Tissue doppler imaging was used to record the motion velocity of the septum, lateral wall, inferior wall, and anterior wall of the mitral annulus. The e' values of the 4 regions were measured. The average value was obtained to calculate the E/e' .

MRI testing

Netherlands Philips Ingenia 3.0T full digital magnetic resonance system was employed. The patient was placed in the supine position and instructed to hold their breath, so that the heart was in a relatively fixed position during each scan, and the image collection was completed at the end of the breath holding. The scanning range was from the bottom of the heart to the apex of the heart, and multi-layer images were successively collected to obtain a cross-sectional black blood sequence, long axis 2, 3, and 4 chamber heart of the left ventricle, and a series of short

axis movie sequences. The scanning parameters were as follows: excitation frequency: 1; layer thickness: 7 mm; time of repetition: 4.1 ms; time of echo: 1.5 ms, turn angle: 45 degrees; and field of vision: 256×256.

The obtained images were transferred to the workstation, and the left ventricular section from the apex to the bottom of the heart was the semi-automatic contour delineation of the endocardial membrane. The program automatically generated the time-volume curve of the left ventricle and collected the cardiac function parameters of the left ventricle, including LVEF, left ventricular end-diastolic volume (LVEDV), left ventricular end-systolic volume (LVESV), the early peak filling rate (PFR1), the late peak filling rate (PFR2), the early filling volume (FV1), and the late filling volume (FV2).

MRI algorithm based on compressed sensing

Because of the sparsity of the image in the sparse domain constructed on the sparse basis, the image could be reconstructed by solving a minimum optimization issue, which was written as follows:

$$\min_f \|\Upsilon f\|_0 \quad \text{subject to } r = H_u f \quad [1]$$

where $\|\cdot\|$ represents the Euclidean norm, $\|\Upsilon f\|_0$ represents the number of non-zero elements in the matrix, f represents the image, and Υ represents the sparse basis.

Due to the influence of environment, noise, and measurement error, the signal acquired in the process of signal acquisition always had a certain error. Under the error condition, Eq. [1] was optimized as follows:

$$\min_f \|\Upsilon f\|_1 \quad \text{subject to } \frac{\|r - H_u f\|_2^2}{2} \leq \theta \quad [2]$$

where θ represents the upper bound of error. We decided to transpose the objective function and constraint term in Eq. [2], which was illustrated as follows:

$$\min_f \frac{\|r - H_u f\|_2^2}{2} \quad \text{subject to } \|\Upsilon f\|_1 \leq z \quad [3]$$

where Z represents a constant related to sparsity. By adding the constraint term to the above equation as a penalty term to the objective function, it was transformed into the following unconstrained optimization problem:

$$\min_f \frac{\|r - H_u f\|_2^2}{2} + \alpha \|\Upsilon f\|_1 \quad [4]$$

where $\alpha \|\Upsilon f\|_1$ represents the regularization term, α represents the regularization parameter, and $\min_f \frac{\|r - H_u f\|_2^2}{2}$ represents

the data fidelity term. Better reconstruction results can be obtained by balancing data fidelity terms and regularization terms. Thus, the objective function was defined as:

$$f^* = \min_f p(f) \quad [5]$$

If $p(f)$ was a convex function, Eq. [5] was a convex optimization problem. f^* represents the estimated value of the image after solution. The gradient descent method was used to solve the minimum objective function. The gradient descent iteration equation was written as follows:

$$f_{c+1} = f_c - l_c \nabla p(f_c) \quad [6]$$

where C represents the iteration ordinal, f_z represents the image data of the c^{th} , $\nabla p(f_c)$ represents the gradient value of the objective function at the point f_z , and l_c represents the step size of the c^{th} iteration. The gradient descent method in Eq. [6] showed that the search direction of each iteration had a negative gradient direction, which was the direction with the fastest decline of function value. From the direction of the negative gradient, the optimal point was gradually approached until the minimum point of the objective function was found. In the solving process, the step size was obtained by backtracking the line search method. The process of the MRI imaging oral contraceptives (OCS) algorithm based on optimized compressed sensing is shown in *Figure 1*.

Image quality evaluation methods

Mean square error (MSE), peak signal to noise ratio (PSNR), and structural similarity (SSIM) were used as indexes to evaluate the quality of the reconstructed images (19). MSE was calculated as follows:

$$MSE = \frac{\sum_{i=0}^{p-1} \sum_{j=0}^{q-1} [E_0(i, j) - E_1(i, j)]^2}{p * q} \quad [7]$$

where $p * q$ represents the original image size, E_0 represents the image, and E_1 represents the reconstructed image.

PSNR represents the relative size of the maximum possible signal power and the noise power represented by MSE, and was written as:

$$PSNR = 20 \cdot \log_{10} \left[\frac{2^b - 1}{\sqrt{MSE}} \right] \quad [8]$$

where B represents the number of image pixel gray value bits. SSIM represents image structure by combining brightness, contrast, and the attributed reflecting object structure in the image, and was expressed as:

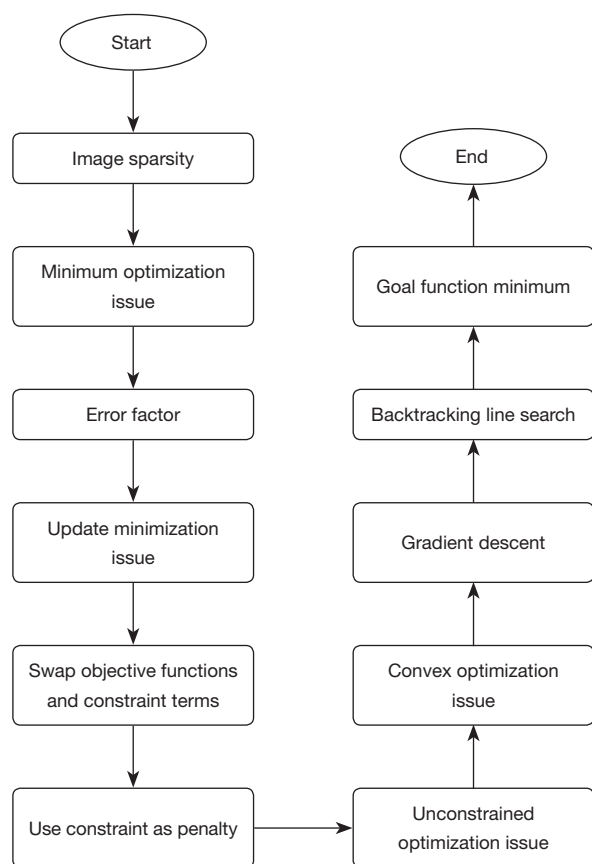


Figure 1 MRI imaging algorithm flow based on compressed sensing. MRI, magnetic resonance imaging.

$$SSIM(E_0, E_1) = \frac{(2\beta_0\beta_1 + n_0)(2\delta_0\delta_1 + n_1)}{(\beta_0^2 + \beta_1^2 + n_0)(\delta_0^2 + \delta_1^2 + n_1)} \quad [9]$$

where β_0 and β_1 represent the brightness of the E_0 and E_1 images, respectively, δ_0 and δ_1 represent the variance of the E_0 and E_1 images, respectively, and n_0 and n_1 represent the constant terms.

Observation indexes

The following information from patients was collected: age, gender, body mass index (BMI), heart rate (HR), body surface area (BSA), ratio (E/e') of early diastolic blood flow velocity of mitral valve (E) to early diastolic peak velocity of mitral annulus (e'), time interval from onset of symptoms to follow-up MRI examination, medical history (related diseases such as heart disease, stroke, transient ischemic attack, atherosclerosis, etc.), National Institutes of Health Stroke Scale (NIHSS) score, and modified Rankin Scale

(mRS) score. The cardiac MRI parameters and image quality indicators were collected from two groups of participants and compared.

Evaluation parameters

To rule out the influence caused by inconsistent data volumes of various types of images, MRI images were evaluated from three aspects of sensitivity, specificity, and the area under the curve (AUC). The calculations are shown in Equations 1 and 2. AUC is the area under the curve of subject curve (ROC), and ROC is a comprehensive index reflecting the relationship between sensitivity and specificity. The larger AUC indicated that the diagnosis was correct.

$$Sensitivity = \frac{TP}{TP + FN} \quad [10]$$

$$Specificity = \frac{TN}{TN + FP} \quad [11]$$

True positive (TP): the number of samples where the model predicts positive and the true value is positive.

False negative (FN): the number of samples where the model predicts negative but the true value is positive.

False positive (FP): the number of samples where the model predicts positive but the true value is negative.

True negative (TN): the number of samples where the model predicts negative and the true value is negative.

The AUC was calculated using the trapezoidal rule. The area of the trapezoid was calculated as (upper base + lower base) * height / 2, which is equal to $(x_2 - x_1) * (y_1 + y_2) / 2$.

Statistical methods

SPSS 19.0 statistical software was used for the data processing in this study. The mean $\pm$ standard deviation was used for the measurement data, and the percentage (%) was used for the counting data. Pairwise comparisons were performed by a one-way analysis of variance. The diagnostic effect of diffusion-weighted imaging, SWItch, 3D TOF MRA, and MR scale-PWI sequences on the ischemic penumbra was analyzed by ROC curves. The differences were considered statistically significant if the P values were <0.05 .

Results

Comparison of the clinical data between the 2 groups

Figure 2 shows the results of comparisons of the clinical data

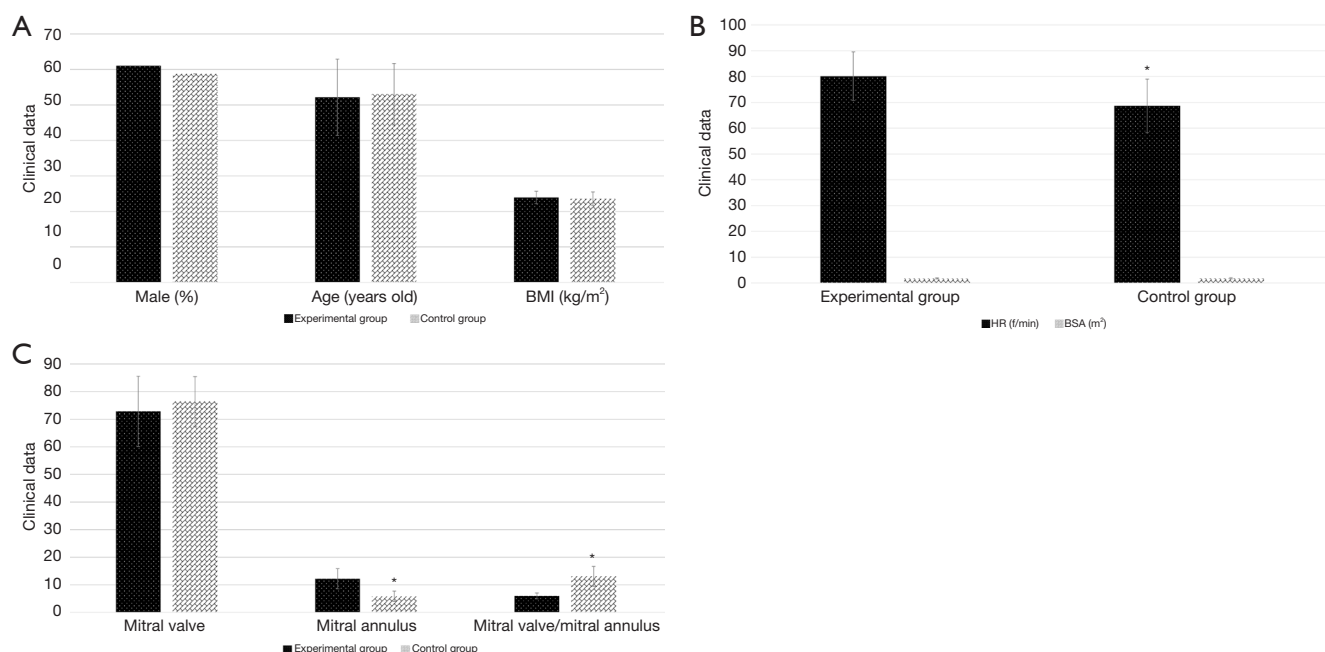


Figure 2 Comparison of the clinical data between the 2 groups. (A) Proportion of males, age, and BMI; (B) HR and BSA; (C) the ratio of E, e' and E/e'. *, the differences between the control group and the experimental group were statistically significant ($P < 0.05$). E, mitral value; e', mitral annulus; MRI, magnetic resonance imaging; HR, heart rate; BSA, body surface area; BMI, body mass index.

between the 2 groups. There were no statistically significant differences in terms of the proportion of males, average age, BMI, bovine serum albumin level, and E between the experimental group and the control group ($P > 0.05$). The e' and HR levels of the experimental group were significantly higher than those of the control group ($P < 0.05$). The E/e' ratio of the experimental group was significantly lower than that of the control group ($P < 0.05$).

Comparison of cardiac MRI parameters between the 2 groups

Figure 3 shows the results of the comparison of the cardiac MRI parameters between the 2 groups. There were no statistically significant differences in LVEF, EDV, ESV, and FV between the experimental group and the control group ($P > 0.05$). The PFR1, PFR1/PFR2, FV1, and FV1/FV of the experimental group were significantly higher than those of the control group ($P < 0.05$). The PFR2 and FV2 of the experimental group were significantly lower than those of the control group ($P < 0.05$).

Analysis of cardiac MRI images

Figure 4 shows the MRI images of the heart of a 65-year-old

man with symptoms of progressive HF, who later underwent an endocardial biopsy that revealed thyroxine-carrying protein amyloidosis. Figure 5 shows MRI images of the heart of a 57-year-old man with progressive exertive dyspnea and lower limb edema.

Diagnostic performance of MRI parameters in left ventricular function

Figure 6 shows the diagnostic performance of the MRI parameters on left ventricular function. The diagnostic indexes of the PFR2 and FV2 were relatively high. The diagnostic sensitivity, specificity, and AUC for the concentration-time of the PFR2 were 0.891, 0.788, and 0.904, respectively. The diagnostic sensitivity, specificity, and AUC for the concentration-time of the FV2 were 0.902, 0.878, and 0.925, respectively. The diagnostic indexes of the other parameters (i.e., the PFR1, PFR1/PFR2, FV1, and FV1/FV) were all low.

Quality evaluation of image reconstruction algorithm

In this study, the traditional SENSE algorithm (20) and OMP algorithm (21) were used to analyze the OCS

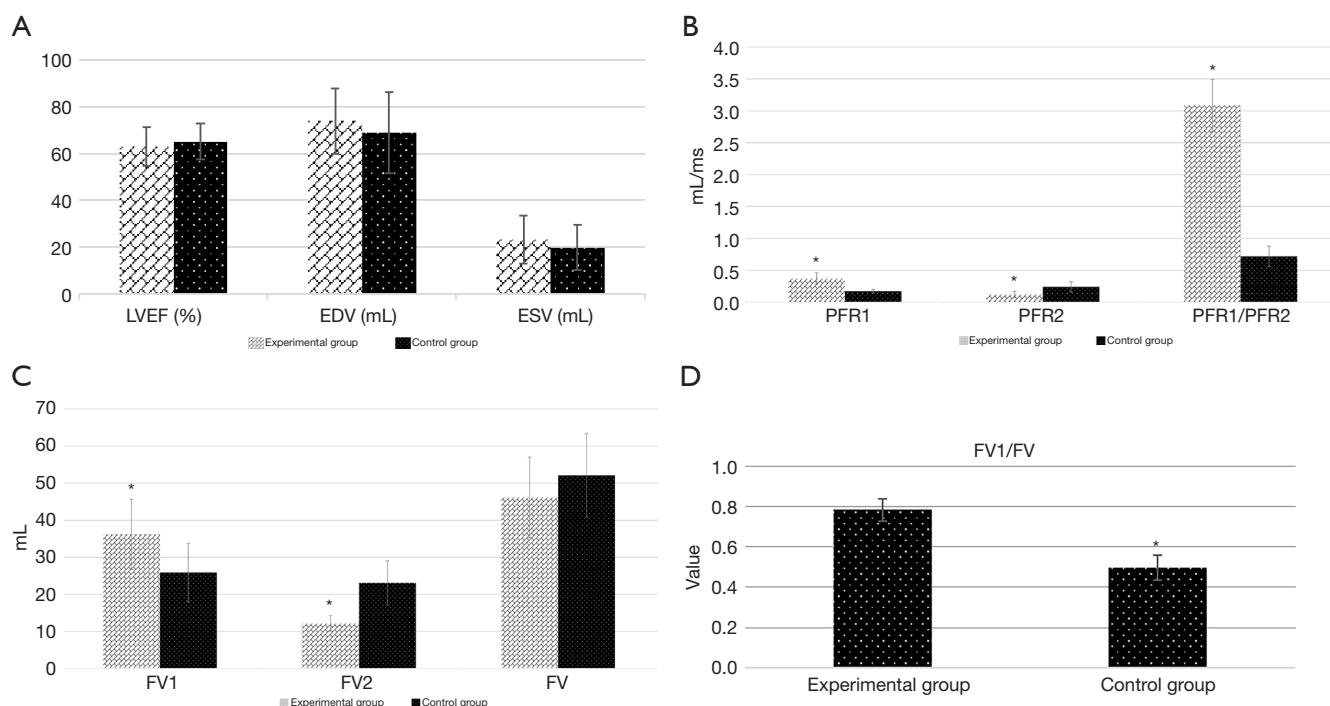


Figure 3 Comparison of the cardiac MRI parameters between the 2 groups. (A) LVEF, EDV, and ESV; (B) PFR1, PFR2, and PFR1/PFR2; (C) FV1, FV2, and FV; (D) FV1/FV. *, the differences between the control group and the experimental group were statistically significant ($P<0.05$). MRI, magnetic resonance imaging; LVEF, left ventricular ejection fraction; EDV, enddiastolic volume; ESV, end-systolic volume; PFR1, early peak filling rate; PFR2, late peak filling rate; FV1, early filling volume; FV, filling volume; FV2, late filling volume.

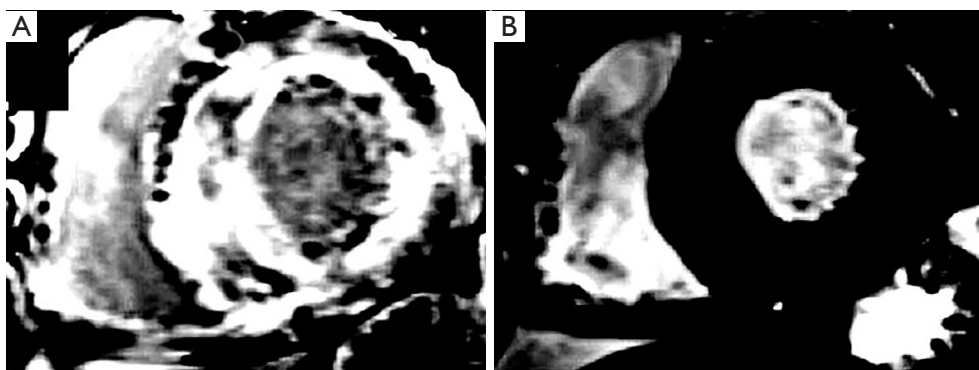


Figure 4 MRI images of the heart of a 65-year-old man. (A) Diffuse, subendocardial, and blotchy atypical myocardial enhancement at the base of the left ventricle; (B) centripetal left ventricular wall thickening. MRI, magnetic resonance imaging.

algorithm. SENSE sensitivity coding reconstruction is a parallel imaging reconstruction technology based on image domain. Its core is recovering the complete image without artifact from the image with artifact acquired by multiple coils from the under-sampled image with artifact, and realizing the reconstruction based on artifact image

by using sensitivity coding. OMP is one of the classical algorithms in the field of Compressed Sensing, which is the basis of many commonly used efficient algorithms and has the characteristics of simple and efficient. As the results in *Figure 7* show, the MSE of the images reconstructed using the OCS algorithm was significantly smaller than

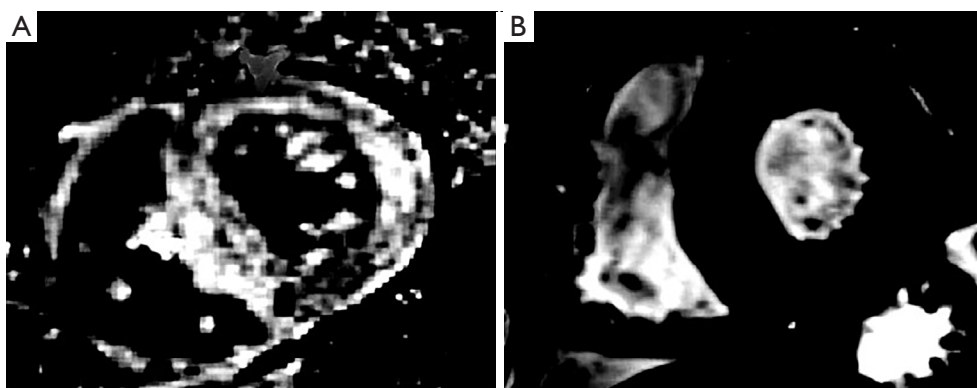


Figure 5 MRI of the heart of a 65-year-old man. (A) Left ventricular myocardial diffusion, transmural, and subendocardial enhancement; (B) the signal intensity of the blood pool was low without contrast agent. MRI, magnetic resonance imaging.

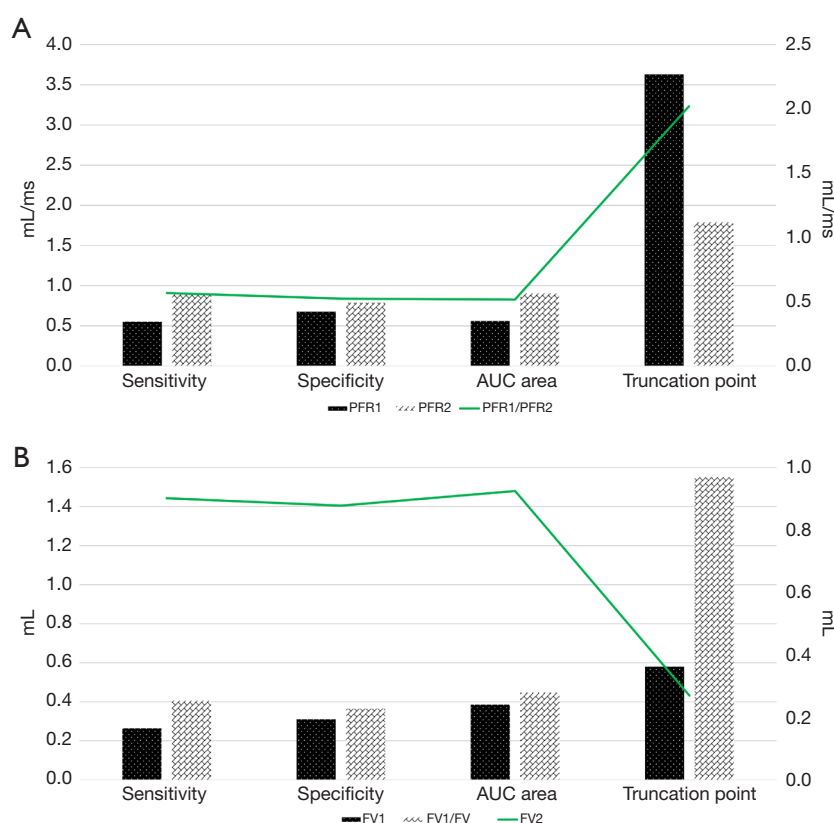


Figure 6 Diagnostic performance of the MRI parameters on left ventricular function. (A) PFR1, PFR2, and PFR1/PFR2; (B) FV1, FV1/FV, and FV2. AUC, area under the curve; MRI, magnetic resonance imaging; PFR1, early peak filling rate; PFR2, late peak filling rate; FV1, early filling volume; FV, filling volume; FV2, late filling volume.

those reconstructed using the SENSE algorithm and the OMP algorithm ($P < 0.05$). The PSNR and SSIM of the images reconstructed using the OCS algorithm were significantly higher than those reconstructed using the

SENSE algorithm and OMP algorithm ($P < 0.05$). *Figure 8* shows the MRI images reconstructed by each algorithm. The MRI image reconstructed using the OCS algorithm had better display clarity and better overall quality than

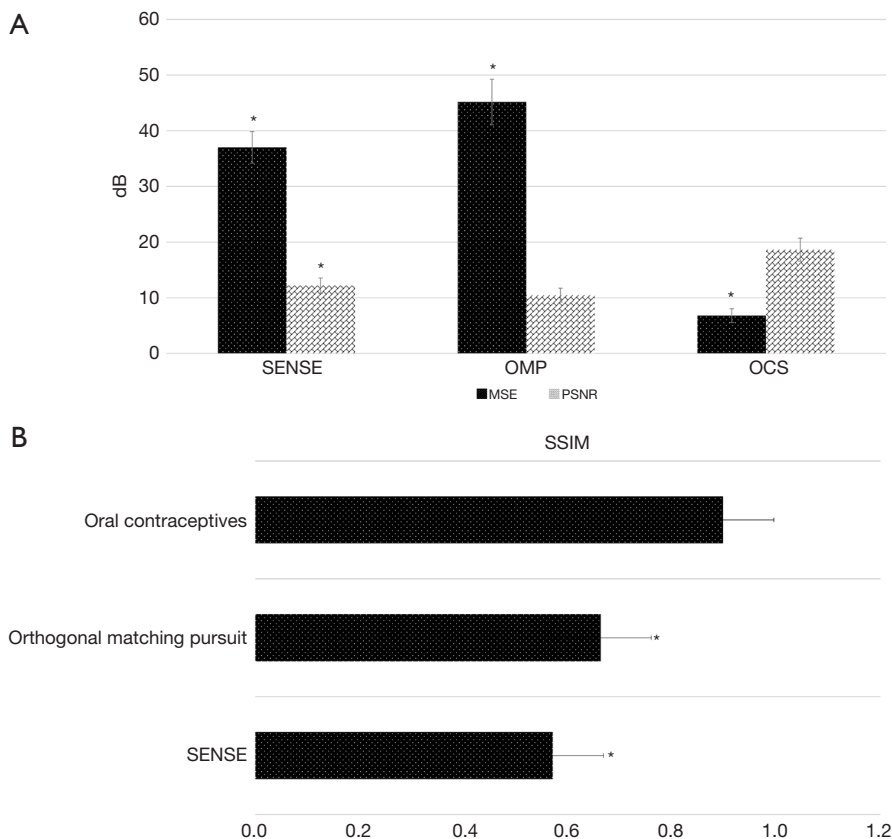


Figure 7 Image reconstruction quality evaluation of the algorithms. (A) MSE and PSNR; (B) SSIM. *, the differences between the other 2 algorithms and the OCS algorithm were statistically significant ($P < 0.05$). MSE, mean square error; PSNR, peak signal to noise ratio; SSIM, structural similarity; OMP, orthogonal matching pursuit; OCS, oral contraceptives.

those reconstructed using the SENSE algorithm and OMP algorithm.

Discussion

Preserved LVEF is defined as a symptom and sign of HF. A syndrome with roughly normal LVEF and diastolic dysfunction. It is characterized by high morbidity and high mortality, and it is difficult to treat (22). Cardiac magnetic resonance is a unique technique that can measure ventricular volume and function with high accuracy and good repetition and is considered the gold standard for quantifying cardiac function (23).

In this study, 66 patients with acute ischemic stroke were selected for the experimental group and 20 patients with normal cardiac function who underwent physical examinations during the same period were selected for the control group. All of the patients underwent cardiac MRI scanning. An MRI image reconstruction algorithm based on

compressed sensing was developed and used in the cardiac MRI image processing. First, the clinical data of the 2 groups of patients were compared, and we found that the e' and HR levels of the experimental group were significantly higher than those of the control group, and the E/e' ratio was significantly lower than that of the control group ($P < 0.05$). This is similar to the research results of Lundorff *et al.* [2021] (24), which indicated that the diastolic blood flow and HR of the left atrioventricular valve orificium in patients with HF in the experimental group differed to those in the normal group. The PFR1, PFR1/PFR2, FV1, and FV1/FV of the experimental group were significantly higher than those of the control group. Consistent with the findings of previous study (25), the PFR2 and FV2 of the experimental group were significantly lower than those of the control group ($P < 0.05$), which indicates that the left ventricular diastolic function of patients might have been impaired.

Ventricular diastolic dysfunction often precedes systolic

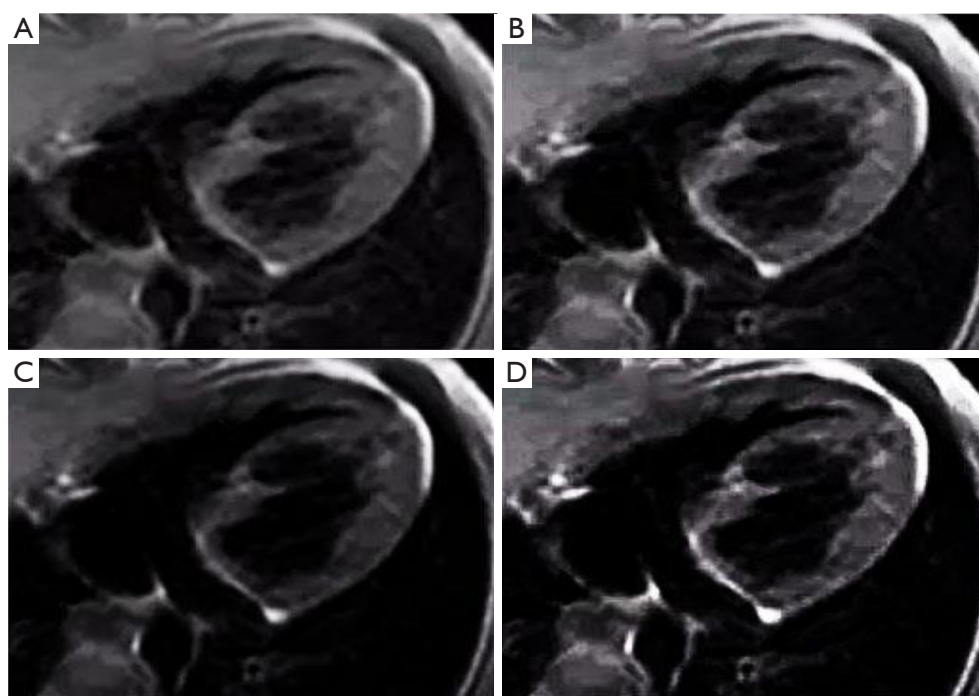


Figure 8 Image reconstruction quality evaluation of the algorithms. (A) The original image; (B,C) the SENSE algorithm, OMP algorithm, and OCS algorithm images, respectively. SENSE, sensitivity encoding; OMP, orthogonal matching pursuit; OCS, oral contraceptives.

dysfunction. Thus, even in asymptomatic patients, the evaluation of diastolic function is of great significance for patient prognosis and treatment strategies (26). There were no significant differences in the LVEF, EDV, ESV, and FV between the experimental group and the control group ($P>0.05$), indicating that there were no differences in left ventricular systolic function between the patients with HF and the normal controls.

The diagnostic performance of each MRI parameter on left ventricular function was calculated, and the diagnostic indexes of the PFR2 and FV2 were high. The diagnostic sensitivity, specificity, and AUC for the concentration-time of the of the PFR2 were 0.891, 0.788, and 0.904, respectively. The diagnostic sensitivity, specificity, and AUC for the concentration-time of the of the FV2 were 0.902, 0.878, and 0.925, respectively. The cardiac MRI image parameters PFR2 and FV2 have been shown to be effective indicators in evaluating HF (27).

The traditional SENSE algorithm and OMP algorithm were compared to the OCS algorithm. The MSE of the images reconstructed using the OCS algorithm was significantly lower than those reconstructed using the SENSE algorithm and OMP algorithm. The PSNR and SSIM of the images reconstructed using the OCS algorithm

were significantly higher than those reconstructed using the SENSE algorithm and OMP algorithm ($P<0.05$). Cardiac MRI image reconstruction using the OCS algorithm had the best effect, and thus may be used to assist doctors to make objective evaluations (28). The MRI image structure reconstructed using the OCS algorithm was clearer than those reconstructed using the SENSE algorithm and OMP algorithm, and the overall quality was better, which was consistent with the results of the quantitative data. This study still has several limitations. First, some clinical data on our patient, including hypertension, hyperlipidemia, and smoking history, were not collected. These data could have been used to assess the risk of cardiovascular disease. Second, since traditional invasive hemodynamics was not practical, ultrasonic diastolic function indices were used for grouping rather than invasive hemodynamic data. In the future, the experimental method will be further improved and a deeper exploration will be carried out in the direction of this subject.

Conclusions

In this study, 66 patients with acute ischemic stroke were selected for the experimental group, and 20 patients with

normal cardiac function were selected for the control group. All the patients underwent cardiac MRI scanning. An MRI image reconstruction algorithm based on compressed sensing was then developed and used in the cardiac MRI image processing. The imaging algorithm based on compressed sensing had excellent processing effect on cardiac MRI and improves the image quality. Cardiac MRI imaging had good diagnostic performance for HF and had the value of clinical popularization.

The findings of this study provide theoretical support for the use of MRI imaging technology in evaluating HF.

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Footnote

Reporting Checklist: The authors have completed the STARD reporting checklist. Available at <https://jtd.amegroups.com/article/view/10.21037/jtd-23-190/rc>

Data Sharing Statement: Available at <https://jtd.amegroups.com/article/view/10.21037/jtd-23-190/dss>

Peer Review File: Available at <https://jtd.amegroups.com/article/view/10.21037/jtd-23-190/prf>

Conflicts of Interest: All authors have completed the ICMJE uniform disclosure form (available at <https://jtd.amegroups.com/article/view/10.21037/jtd-23-190/coif>). The authors have no conflicts of interest to declare.

Ethical Statement: The authors are accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved. The study was conducted in accordance with the Declaration of Helsinki (as revised in 2013). The study was approved by ethics committee of Wangjing Hospital of CACMS (No.20201578) and informed consent was taken from all the patients.

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