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A river velocity inversion method based on a multi-peak precise matching algorithm for acoustic tomography

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Abstract. This paper addresses signal matching challenges encountered in River Acoustic Tomography (RAT) [1] technology applications within short-distance rivers. To overcome limitations associated with significant errors in traditional maximum peak methods within such environments, a novel multi-peak accurate matching approach is proposed. This method integrates a greedy strategy [2] with the Hungarian algorithm [3], resulting in enhanced accuracy. Experimental findings demonstrate that velocity inversion errors are reduced to below 10% when compared to conventional manual flow measurement techniques, representing a substantial improvement. Furthermore, a comprehensive technical framework for RAT technology, spanning from signal processing to parameter inversion, is presented. This framework offers a viable solution for unmanned, real-time intelligent hydrological monitoring using RAT technology. This study promotes the application of acoustic tomography [4] from ocean to river, and provides a new technical paradigm for hydraulic engineering and ecological monitoring.

Keywords: river acoustic tomography; multi-peak precise matching; hydrological monitoring; velocity inversion; water temperature inversion

1. Introduction

Accurate and timely monitoring of river hydrological parameters is essential for efficient water resource management, flood forecasting, preservation of water ecosystems, and the safe operation of critical water infrastructure projects. Traditional methods for monitoring velocity and water temperature typically rely on point-contact tools such as rotor current meters and Acoustic Doppler Current Profilers [5], or remote sensing technologies. However, these methods face challenges such as limited monitoring coverage, gaps in data collection, and significant environmental interferences in complex hydrological conditions like floods and ice events. As a result, they do not meet the requirements of modern intelligent water management for comprehensive, high-resolution integrated monitoring across entire river sections with superior spatiotemporal accuracy.

Acoustic tomography technology offers a novel approach to river hydrological monitoring due to its non-invasive nature, wide coverage, and real-time multi-parameter inversion capabilities. Jin Zixin from Hiroshima University in Japan first utilized this technology in the 199s to monitor river velocity and study flow field distribution. Subsequently, the Second Institute of Oceanography and Xiamen University have also adopted river acoustic tomography technology in the 21st century to investigate tidal currents and hydrology in various regions such as the Qiantang River, island coasts, and the offshore area of Fujian. River acoustic tomography (RAT) technology deduces hydrological data across river cross-sections by measuring the time difference in acoustic signal propagation within the river. Additionally, it indirectly estimates temperature fields by leveraging the physical relationship between sound velocity and water temperature. This technology excels in overcoming challenges posed by wide, shallow, high-speed, or complex terrain river channels that are traditionally difficult to measure effectively. Nevertheless, in typical river settings characterized by short distances and shallow water depths, the minimal difference in acoustic signal propagation delays poses a challenge. This results in a notable decrease in the accuracy and reliability of

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conventional signal matching methods, such as the maximum peak method, thereby significantly impeding the practical application of this technology.

Thus, this study seeks to address the fundamental signal processing challenge encountered in the application of acoustic tomography in short-distance river scenarios. By devising a novel signal matching algorithm, the aim is to enhance the accuracy and stability of velocity and water temperature inversions in intricate hydrological settings. This research endeavors to offer essential technical advancements to facilitate the transition of acoustic tomography technology from theoretical concepts to practical hydrological monitoring applications. Furthermore, it aims to present a reliable signal matching approach to underpin the development of a sophisticated and effective next-generation river monitoring system.

2. Research data

Data were collected from six observation stations positioned along a specific river segment spanning distances of 115m to 610m, encompassing approximately 6.65 hectares. Each station is outfitted with a RAT system featuring an external transceiver transducer. Stations S1 and S4 are further equipped with temperature and depth (pressure type) sensing probes set at a deployment depth of 1m. The channel exhibits typical characteristics including low salinity, a direct relationship between water temperature and meteorological variations, and a consistent gradient of sound velocity.

Table 1. Station latitude and longitude

Numble	Longitude	Latitude
S1	115.411408°E	32.434952°N
S2	115.411341°E	32.433988°N
S3	115.409602°E	32.434998°N
S4	115.414570°E	32.433752°N
S5	115.408108°E	32.434963°N
S6	115.406885°E	32.434136°N

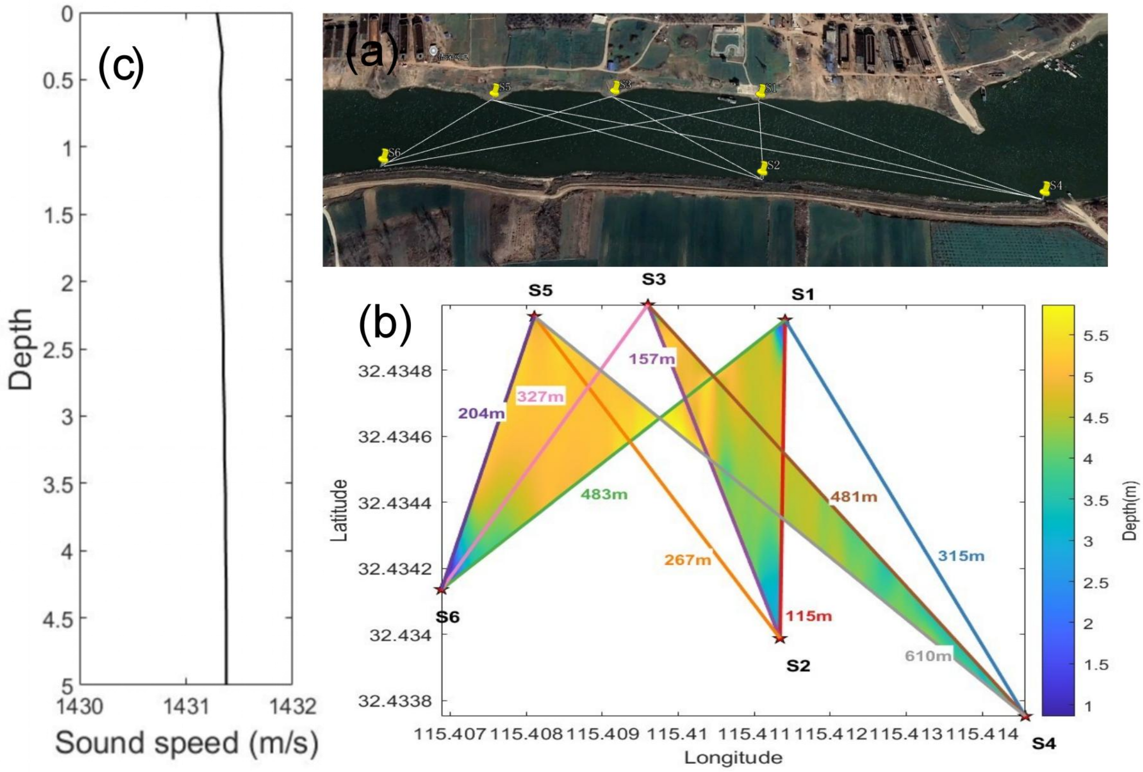

Fig. 1 Site distribution and environmental parameters

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Table 1 presents the longitude and latitude coordinates of the station, while Figure 1 illustrates the sound velocity profile of the study area. In (c) Station distribution and environmental parameters, (a) displays the actual station distribution and primary instruments, and (b) provides a schematic representation of the satellite map. The background sound velocity profile was derived from data collected along the survey line, indicating a consistent sound velocity of approximately 1431.2 m/s in the region, reflecting an isosonic gradient within the depth range. This profile aligns with the stable characteristics of the river during low water periods. The acoustic signal utilized is the M12 pseudo-random sequence code with a frequency of 30 kHz. The transducer is positioned between 0.7 and 0.8 m above the riverbed, and for practical purposes, the distance between the transducer and the temperature and depth sensors can be disregarded. The sediment in the channel is predominantly sand with a density ranging from 1.6 to 2.0 g/cm³, and an acoustic attenuation coefficient of approximately 0.1 to 0.5 dB/m.

3. The Principles And Methods Of The Research

3.1 Principles

The propagation delay of sound waves in a moving medium is modulated by the flow velocity and the speed of sound. When a sound wave propagates between two transducers separated by a distance L, the time difference between downstream and upstream propagation mainly reflects the average flow velocity along the path:

$$\Delta T = \frac{t_i^+ - t_i^-}{2} \approx -\int_{L_i} \frac{u \cdot n}{c_m^2} ds \tag{1}$$

$$\delta_t = \frac{t_i^+ + t_i^-}{2} \approx -\int_{L_i} \frac{\Delta c \cdot n}{c_m^2} ds \tag{2}$$

The direction vector n represents the sound ray path in the positive direction, while denotes the average sound velocity in the region. Given that sound velocity perturbations Δc and flow rate u are significantly smaller than the average sound velocity c_m, a linear approximation of the equation can be employed. This can be expressed as:

$$f = Ex + m \tag{3}$$

where f is the propagation delay, E is the kernel matrix of background information, and x is an unknown. Regularized solution by minimizing the objective function:

$$L = (f - Ex)^T (f - Ex) + \sigma^2 x^T x \tag{4}$$

$$\hat{x} = (E^T E + \sigma^2 I)^{-1} E^T f \tag{5}$$

Accurate time delay data of reciprocal acoustic signal propagation is crucial for velocity field inversion, directly impacting parameter estimation quality. Currently, two primary technical approaches are employed for time delay determination. The first method involves a matching technique utilizing sound ray simulation. This method utilizes background hydrological data acquired from instruments such as CTD [5] to infer sound ray arrival patterns through numerical simulation of the sound field. Subsequently, the method identifies the delay peak that aligns with theoretical expectations. The second method, known as the maximum signal-to-noise ratio peak method, involves extracting the peak with the highest signal-to-noise ratio from the received signal as the effective time delay. Subsequent identification of other correlation peaks in the time domain is based on this initial peak extraction.

Utilizing the identified time delay data and a suitable inversion algorithm enables accurate estimation of velocity and sound velocity distributions. In freshwater settings, the water temperature

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parameter can be additionally determined through an empirical relationship linking sound velocity and temperature [6], given the minimal salinity fluctuations and known water depth.

The inversion process entails iterative optimization, involving continuous adjustment of the regularization parameter to minimize the error between model output and observational data until reaching a predetermined threshold value, thereby yielding a stable solution vector. The detailed procedure of this inversion calculation is illustrated in Figure 2.

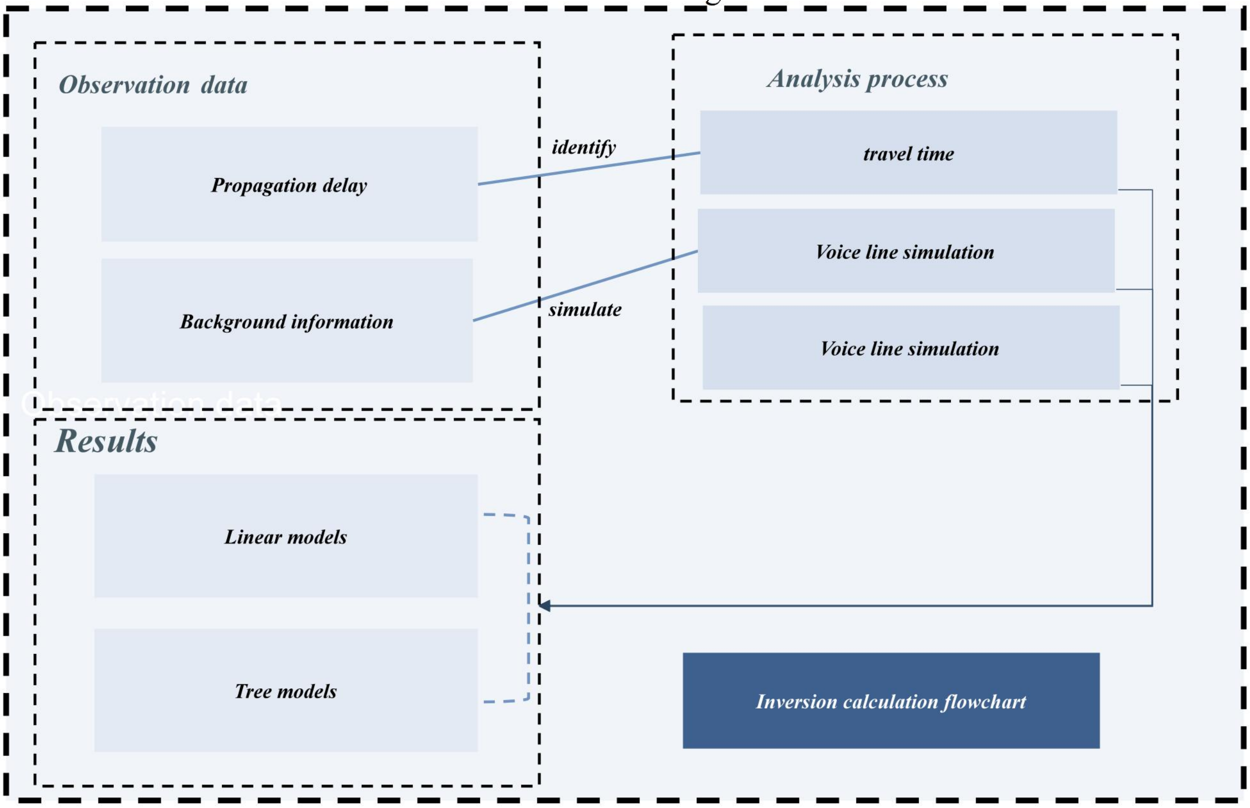

Fig. 2 RAT data inversion process

3.2 Methods

First, during the signal propagation process, select the moments where the signal-to-noise ratio is greater than the threshold. Let the set of all detected peaks be denoted as P. Each peak p ∈ P corresponds to a signal-to-noise ratio SNR(p) and a position (such as a time point) l(p). Given the signal-to-noise ratio threshold θ, the filtered peak set S is:

$$\mathcal{S}=\{p\in\mathcal{P}\mid\mathrm{SNR}(p)>\theta\} \tag{6}$$

Express the peaks by time index. Let ti be the peak time and SNRi be the corresponding signal-to-noise ratio. Then the filtered set of time points is:

$$T=\{t_i\mid\mathrm{SNR}_i>\theta\} \tag{7}$$

Suppose there are n groups of filtered peaks, denoted as S1, S2, ..., Sn, where Sk = {pk,i | i = 1, 2, ..., mk}, and mk is the number of peaks in the kth group. Each peak pk,i has a position l(pk,i). The goal is to align or assign the peaks in these peak sets. Consider the binary matching problem (for example, matching two sets of peaks Sa and Sb), define the distance function d: Sa × Sb → R+ (it can use Euclidean distance, time difference, etc.), and the elements of the cost matrix C are:

$$C_{ij}=d(l(p_{a,i}),l(p_{b,j})) \tag{8}$$

Introduce the greedy strategy for the initial candidate screening: Set the distance threshold δ, and the candidate matching pair set is:

$$\text{Pairs}=\{(p_{a,i},p_{b,j})\mid C_{ij}<\delta\} \tag{9}$$

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Then, the Hungarian algorithm (Kuhn-Munkres [7] algorithm) is applied to solve the minimum matching. Let M be the matching matrix, where Mij = 1 indicates that peak pa,i matches peak pb,j, and otherwise it is 0. The optimization problem is:

$$\min \sum_{i=1}^{m_a} \sum_{j=1}^{m_b} C_{ij} C_{ij} M_{ij} \tag{10}$$

To sum up, the process of the multi-peak precise matching method can be expressed as:

$$\mathcal{S} = \{ p \in \mathcal{P} \mid \mathrm{SNR}(p) > \theta \}$$

$$\text{For } k = 1 \text{ to } n: \quad \mathcal{S}_k = \text{ filteredpeaksfromsource } k$$

$$\text{Forpairs } (a, b): \quad C_{ij} = d(l(p_{a,i}), l(p_{b,j}))$$

$$\text{Greedyselection:Pairs } \subseteq \mathcal{S}_a \times \mathcal{S}_b$$

$$\text{Hungarianalgorithm: } M^* = \text{argmin} \sum_{i,j} C_{ij} M_{ij}$$

For multiple sets of peaks, the Hungarian algorithm can be iterated or extended for matching. The decision output is the matching result M*. Based on the identified delay data and combined with the inversion algorithm in the basic principle, the flow velocity data can be estimated more accurately. The entire inversion process is an iterative optimization calculation: by continuously adjusting the regularization parameters, the error of the model output is gradually reduced to within the preset threshold, thereby obtaining a stable solution vector.

4. Results And Analysis

4.1 Bellhop [8] Signal Propagation Simulation Results

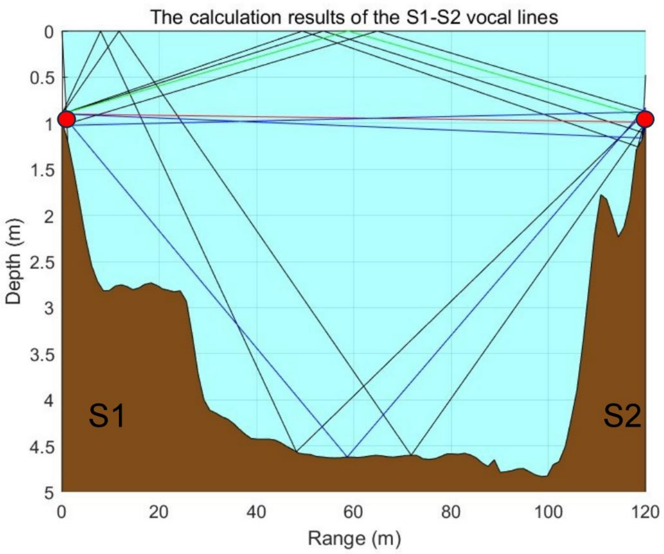

Fig. 3 The calculation results of the S1-S2 vocal lines

Utilizing the environmental input depicted in Figure 1(c) as the background profile, the Bellhop model was employed to compute the eigensound ray. Figure 3 illustrates the reciprocal propagation sound ray trajectories between stations S1 and S2, encompassing direct sound rays, water surface-reflected sound rays, and river bed bottom-reflected sound rays. The simulation delineates the signal propagation pathways. By assessing the composition of these pathways and the transmitted signal intensity (190 dB), the validity of experimental parameters such as station design and transducer placement depth is effectively confirmed. The simulation outcomes for other stations exhibit a similar pattern, comprising three sound path categories, with calculated propagation losses ranging from 30 to 60 dB.

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4.2 Reciprocal Propagation and Matching Results of Acoustic Signals

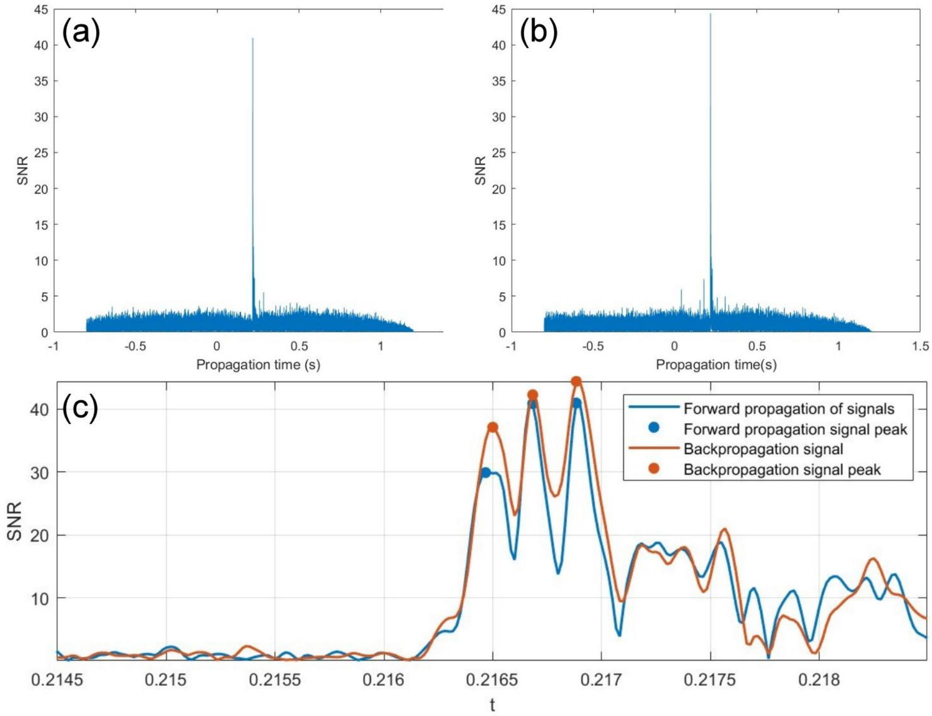

Fig. 4 The reciprocity analysis results of signals S1 to S4

Matching signal peak values in underwater acoustic tomography poses a persistent challenge due to the diverse and intricate nature of acoustic signal characteristics across different environments. For instance, in deep-sea tomography studies, sound wave simulations based on Bellhop are commonly utilized to align signals according to their arrival structures. Given the extensive distances involved, with paths spanning tens of kilometers and potential acoustic signal path differences and mapping time variances on the order of tens of meters and 10^{-2} to 10^{-1} seconds, respectively, this approach proves effective. Conversely, in river acoustic tomography investigations, station intervals typically fall below 3 km, sometimes as short as a few hundred meters, resulting in mapped time disparities of only 10^{-5} to 10^{-4} seconds. The substantial discrepancy in time resolution necessitates enhanced hardware design considerations. Consequently, the efficacy of acoustic ray matching techniques in river tomography is limited without fundamental revisions to conventional hardware design paradigms. Prior studies have employed the maximum peak method to align river signals, wherein peaks with the highest signal-to-noise ratios are identified as primary signals, with secondary peaks matched subsequent to the primary peak. This methodology is suited for addressing a subset of short-distance transmission challenges encountered in river environments.

In practical applications, the maximum peak method exhibits reduced robustness under conditions of short river distance, small river depth, and low river velocity. The reciprocal propagation results of signals S1-S4 are illustrated in Figure 3, with the complete signal propagation process depicted in panels (a) and (b) of Figure 4, revealing prominent signal peaks near the .2s timeline. Panel (c) displays a set of peak matching outcomes for bi-directional propagation signals where the maximum peak method is unsuitable, necessitating the utilization of a multi-peak accurate matching approach. This method involves screening out peak groups with signal-to-noise ratio (SNR) exceeding a specified threshold, precisely locating these peaks, and employing a combination of greedy strategy and the Hungarian algorithm for decision-making. Such a matching algorithm is well-suited for scenarios characterized by short distances, shallow depths, and low velocities in river environments.

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4.3 Inversion Results

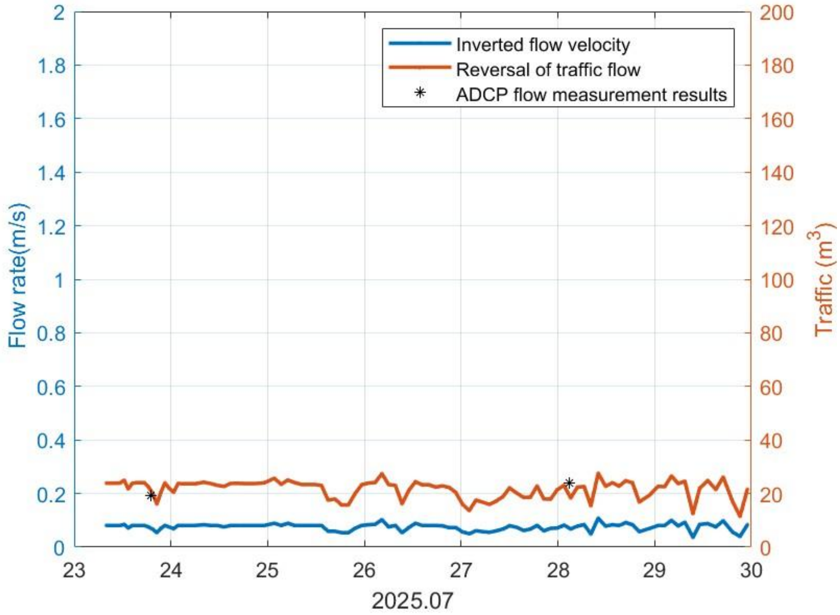

Fig. 5 Reconstruction results of flow rate and volume

Figure 5 shows the velocity and flow inversion results of the multi-peak precision matching method and gives a comparison of the results of manual flow measurement using ADCP during this period. The inversion results show that during the period from 23 to 30 days, the overall flow velocity and discharge change smoothly, the flow velocity varies from 0 to 0.2 m/s, the average flow velocity is 0.075 m/s, and the average discharge is 21.7 m³/s.

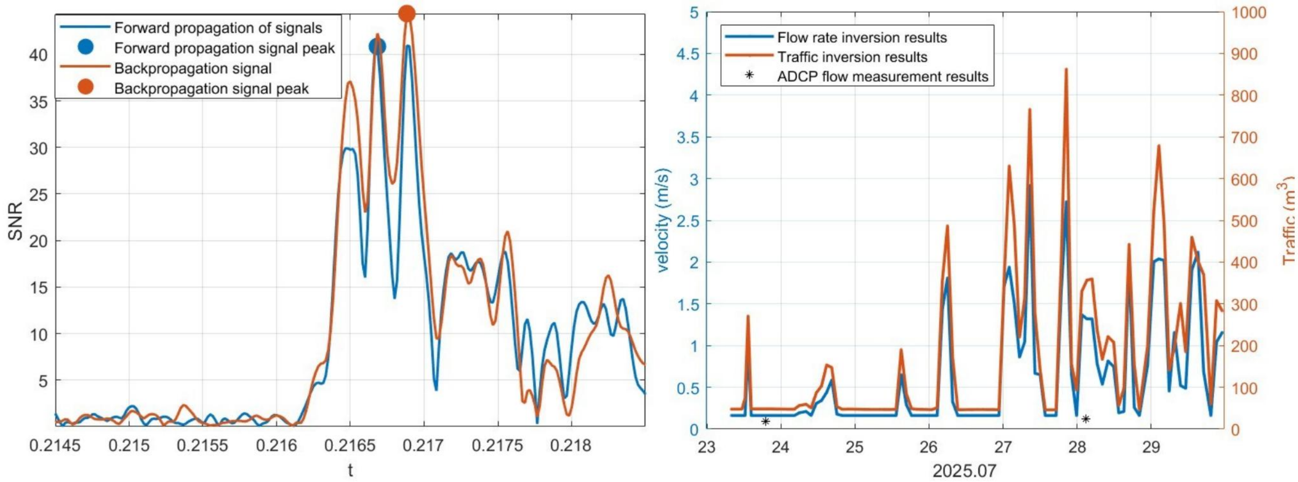

Fig. 6 The maximum peak method matching and inversion results

Figure 6 shows the signal matching results and inversion results using the maximum peak method. It can be seen that the error introduced by the matching error to the inversion results is catastrophic due to the large mismatch of the signals. Table 2 shows the inversion results of the two methods and the specific values of the comparison of the ADCP flow measurement results at two times. According to the specific numerical results, the flow measurement errors of the multi-peak accurate matching method are 8.8% and 6.59%, respectively, while the error of the maximum peak method is far more than 100%.

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Table 2. Comparison between inversion results and ADCP flow measurement results

	Time 1 Flow (m^3/s)	Time 2 Flow (m^3/s)
maximum peak method	48.25	351
multi-peak precise matching method	20.89	25.37
ADCP Current Measurement Results	19.2	23.8

5. Conclusions

Previous studies have validated the flow measurement accuracy of River Acoustic Tomography (RAT). However, the conventional signal matching approach using the maximum peak method is inadequate for short-distance river environments. The development of a reliable automated algorithm for river hydrological monitoring is essential for the sustained application of RAT technology in hydrological monitoring. This study introduces a novel multi-peak precise matching method that incorporates a greedy strategy and the Hungarian algorithm. By establishing a signal-to-noise ratio threshold, this method effectively addresses the robustness challenges associated with signal matching in short-distance river settings. Experimental validation and comparison with Acoustic Doppler Current Profilers (ADCP) confirm the efficacy and robustness of the proposed matching algorithm. The findings support the feasibility of employing this algorithm in short-distance river scenarios, thereby enhancing the potential of RAT for unmanned online monitoring applications in the field of water resource management.

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