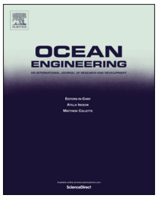
Ocean Engineering 124 (2016) 135–140

Contents lists available at ScienceDirect

Ocean Engineering

journal homepage: www.elsevier.com/locate/oceaneng



Investigating sound speed profile assimilation: An experiment in the Philippine Sea

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ARTICLE INFO

Article history:
Received 5 July 2015
Received in revised form
26 June 2016
Accepted 26 July 2016
Available online 4 August 2016

Keywords:
Sound speed profile
Assimilation radius
Multipath arrival delay
Correlation structure

ABSTRACT

In this paper, a single datum assimilation method is described for constructing the sound speed profile (SSP) in the ocean. Our method's key is assimilation radius, where various radii provide different SSPs. By means of the Bellhop acoustic model and acoustic data, we calculated the optimal SSP assimilation radius. Due to the lack of proper in-situ observations, an SSP inversion method is proposed. Inverted SSP compared to assimilated SSP indicates close correlation, showing that both methods yield reliable results. Historical data analysis indicates a stable correlation structure under certain conditions, implying the optimal assimilation radius would measure SSP effectively under similar conditions.

1. Introduction

SSP has great influence on underwater acoustic propagation, particularly sound transmission loss and multipath arrival structure. Thus, SSP greatly affects underwater activities like Anti-Submarine Warfare (Rui et al., 2012; Yan et al., 2007) and acoustic communication (Rouseff et al., 2001; Stojanovic et al., 1994). The ocean environment, particularly ocean temperature, which fluctuates continually, determines SSP. As well, when there exists ocean phenomena like internal wave or eddy, SSP can vary greatly even in a short time. Hence, it is necessary to address SSP estimation problems with data assimilation methods, called 'SSP assimilation'.

Much research has been conducted about the SSP assimilation issue with products like Modular Ocean Data Assimilation System (Fox et al., 2001) (MODAS) . Utilizing the three-dimensional variational (3D-VAR) method, the MODAS system predicts sea surface temperature via satellite data. The MODAS system has a database which contains the regression relationship between sea surface parameters and underwater parameters. Once 3-D temperature fields are calculated, corresponding salinity profiles according to a stable temperature-salinity relationship are obtained. Finally, the SSP of the area is within reach by means of an empirical formula for sound speed. Simple Ocean Data Assimilation (James et al., 2000) (SODA), on the other hand, is an ocean data assimilation product with averaged monthly 3-D temperature and salinity data. SODA starts with the Modular Ocean Model (Chen et al., 2003) (MOM), predicts dynamic ocean state, corrects the predicted field with measured data, and obtains the assimilated result. The Ocean Variational Analysis System (Jiang et al., 2007) (OVALS), developed by Zhu Jiang, brought about progress in the field of ocean data assimilation. Zhu's system uses the 3D-VAR method to perform data assimilation for each layer of the ocean. Assimilation parameters include both temperature and salinity. Researchers like Qingyu (2006) and Ying (2004) have studied the effect of mesoscale phenomena on acoustic propagation, including eddies, fronts, and internal waves. However, studies systematically applying ocean data assimilation on acoustic propagation are far from sufficient.

The key issue of SSP assimilation problem is the assimilation radius, with different radii providing different SSPs. Assimilation radius defines a range, within which the measured SSP can be used for SSP assimilation. If the assimilation radius is too small, there will be too few data available for SSP assimilation, resulting in assimilation result being easily corrupted by noisy SSP. If the assimilation radius is too large, too many data including those with low relevance to the target point will be used, leading to the assimilation result being smoothed.

An SSP assimilation experiment in the Philippine Sea was conducted, obtaining an optimal SSP assimilation radius. Data sources include SODA, Argo (Gould et al., 2004) (a daily data profile containing temperature and salinity), and acoustic data collected from an experiment conducted in the Philippine Sea in July of 2013. This paper proposes a method to obtain optimal SSP assimilation radius for SSP assimilation problems. First, we apply the Argo data to provide different SSPs with varied assimilation

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http://dx.doi.org/10.1016/j.oceaneng.2016.07.062
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radii. Since SSP affects the acoustic multipath arrival structure greatly, the measured acoustic multipath arrival data are used to find the SSP which best matches the acoustic data. The radius corresponding to this SSP is the optimal radius. Finally, by analyzing the correlation structure of that area, the optimal radius is tested for future SSP assimilation needs. An SSP inversion method was also performed. Results show that the inverted SSP and the assimilated one are in good agreement with each other, demonstrating both SSPs thus obtained are correct.

2. SSP profile assimilation

Sound speed C (m/s) is a function of temperature T (°C), salinity S (‰) and the static pressure P (kg/cm²) of the immediate ocean water column. By incorporating the pressure gradient dependencies of the Anderson equation into the Del Grosso equation and the Del Grosso–Mader dataset (Lovett, 1978), the equation is derived as follows.

$$C = 1449.22 + \Delta C_T + \Delta C_S + \Delta C_P + \Delta C_{STP}. \tag{1}$$

Here,

$$\Delta C_T = 4.6233T - 5.4585(10)^{-2}T^2 + 2.822(10)^{-4}T^3 - 5.07(10)^{-7}T^4$$

$$\Delta C_P = 1.60518(10)^{-1}P + 1.0279(10)^{-5}P^2 + 3.451(10)^{-9}P^3 \\ - 3.503(10)^{-12}P^4$$

$$\Delta C_S = 1.391(S - 35) - 7.8(10)^{-2}(S - 35)^2$$

$$\begin{aligned}\Delta C_{STP} = (S - 35)\Big[& -1.197(10)^{-3}T + 2.61(10)^{-4}P - 1.96(10)^{-1}P^2 \\ & - 2.09(10)^{-6}PT\Big] \\ & + P\Big[-2.796(10)^{-4}T + 1.3302(10)^{-5}T^2 - 6.644(10)^{-8}T^3\Big] \\ & + P^2\Big[-2.391(10)^{-1}T + 9.286(10)^{-10}T^2\Big] \\ & - 1.745(10)^{-10}P^3T\end{aligned}$$

From the above, it is shown that sound speed fluctuation depends mainly on temperature change. Sound speed fluctuation with temperature change is 4 m/s over 1 °C. Sound speed fluctuation with salinity is 1.14 m/s over 1‰. In the Philippine Sea area, based on the historical dataset, it is known that salinity fluctuates little, so we assume that it can be treated as a constant here due to its negligible effect. The SSP assimilation issue is thus reduced to an ocean temperature assimilation issue.

Since ocean environment is always in flux, and ocean data are sparsely sampled, it is difficult to obtain *in-situ*-measured data for all specified points we call targets. Temperature assimilation method is an effective way to estimate temperature profiles. The reason lies in this method's mechanism which employs all points near the target both in time and space, based on their correlation. Closer points are given greater weight according to their higher correlation.

Argo data close to the target profile both in time and in space within a specific range served as our source for assimilation. We then calculate the assimilated temperature profile.

$$T_{DA} = \sum_{i=1}^{P} T_i \times \alpha_i \times W_i, \tag{2}$$

$$W_i = \exp[-(l_x/L_x)^2 - (l_y/L_y)^2 - (l_t/L_t)^2], \tag{3}$$

$$\alpha_i = W_i / \sum_{i=1}^{P} W_i, \tag{4}$$

where T_{DA} is the assimilated temperature profile. T_i is the temperature profile of Argo data. Within the specific range, there are a total of P available temperature profiles. Weighted coefficients are symbolized as α_i. W_i stands for correlation coefficients between Argo points and the target. The longitudinal distance between Argo points and the target is represented by l_x. l_y is the latitudinal distance. l_t is the time lag between Argo points and the target. L_x is the longitudinal correlation distance. L_y is the latitudinal correlation distance. L_t is the timescale to define correlation in time domain.

Both for convenience and in response to the character of ocean phenomena (Fox et al., 2001), one month is the selected timescale here. Represented by assimilation radius, the spatial range requires careful study. Since the ocean variation in the latitudinal direction is much larger than that in the longitudinal direction and to simplify the study of assimilation radius, we assume that the longitudinal correlation distance is two times of the latitudinal correlation distance for convenience. Thus, the issue of assimilation radius is reduced to the issue of latitudinal radius. We describe later our search for optimal radius through Argo data and *in-situ*-measured acoustic data.

3. Philippine Sea experiment and discussion

3.1. Philippine Sea assimilation experiment

Collected in Philippine Sea in July of 2013, our data come from Argo and the measured acoustic data. Here, the Argo data are selected from June and July of 2013, at a site near the location where the acoustic experiment was conducted. The vertical water column data range is from surface to a depth of 2000 m. Since temperature variation is very weak in deep water layers, we assume a constant SSP gradient below 2000 m depth here. Temperature profiles near the target location are almost constant below 1100 m, but vary largely above that depth, as shown in Fig. 1. Hence, by averaging all the temperature profiles of this area, we obtain an estimated profile for depths from 1100 m to 2000 m. But when the averaged profile is connected with the assimilated profile at shallower depths, a discontinuity may occur. Two weighting coefficients $k_A(z)$ and $k_W(z)$ are introduced to merge the two profiles smoothly. The profile merging formula is (5)–(7).

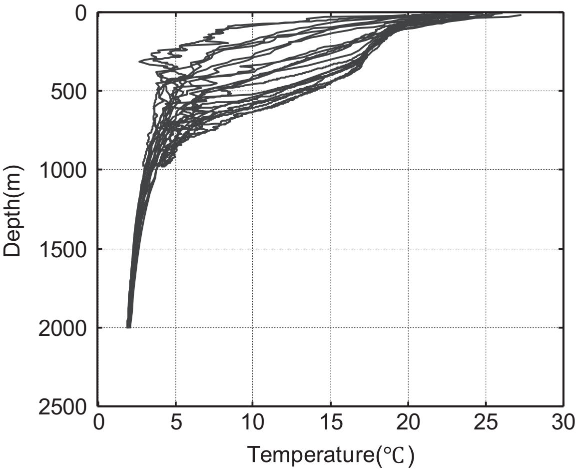

Fig. 1. Argo temperature profiles. The temperature profiles are of the same day, and their locations spread near the target point.