# CoTrack: A framework for tracking dynamic features with static and mobile underwater sensors


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## ABSTRACT

Current feature tracking frameworks in sensor networks exploit advantages of either mobility, where mobile sensors can provide micro scale information of a small sensing area or numerical models that can provide macro scale information about the environment but not both. With the continual development of underwater sensor networks, mobility becomes an important feature to integrate next generation sensing systems. In addition, recent advances in environmental modeling also allow us to better understand basic behavior of the environment. In order to further improve existing sensing systems, we need a new framework that can take advantages of existing fixed sensor networks, mobile sensors and numerical models. We develop *CoTrack*, a *Collaborative Tracking* framework, that allows mobile sensors to cooperate with fixed sensors and numerical models to accurately track dynamic features in an environment. The key innovation in CoTrack is the incorporation of numerical models at different scales and sensor measurements to guide mobile sensors for tracking. The framework includes three components: a macro model for large-scale estimation, a micro model for locale estimation of specific features based on sensor measurements, and an adaptive sampling scheme that guides mobile sensors to accurately track dynamic features. We apply our framework to track salinity intrusion in the Columbia River estuary in Oregon, United States. Our framework is fast and can reduce tracking error by more than 50% compared to existing data assimilation and state-of-the-art numerical models.


## 1. INTRODUCTION

In this work, we develop CoTrack, a Collaborative Tracking framework, for estimating and tracking dynamic features in an underwater environment using fixed and mobile sensors, and numerical models. The key innovation in CoTrack is the incorporation of numerical models at different scales and sensor measurements to guide mobile sensors for tracking. We apply our framework to track salinity intrusion in the Columbia River Estuary in Oregon. Our contributions of this work are the following

- A framework for building macro models for specific features. Unlike previous approaches, we address the case where general models for environment are available. From these models and empirical data, we develop specific models for interested features. Our model reduces the estimation error by 27% and the framework for building model can be adapted for other features.
- A framework for building micro models estimating distances to a feature from sensor measurements. The model estimates the true feature location from mobile sensor measurements. This model can reduce the estimation error of the macro model by 37%.
- An adaptive sampling scheme to improve tracking performance. The idea is to use macro models to guide a mobile sensor where to take its first measurement and use micro models to iteratively refine the location of the feature. By combining these two models, we can reduce the total error by more than 50% compared to existing frameworks.



## 2. PROBLEM STATEMENT

Let $G$ be a finite set of points in space modeling the environment. For each $\omega \in G$, let $p_{\omega,i} = (p^1_{\omega,i}, p^2_{\omega,i}, .., p^j_{\omega,i} ..., p^k_{\omega,i})$ be a tuple of $k$ physical parameters such as temperature, water velocity, or salinity level associated with $\omega$ at time step $i$. $j$ is the parameter index.

DEFINITION 1. A wedge *of parameter* $p^j$ *at threshold* $u$ *at time* $i$ *is a set* $\Omega = \{\omega \in G | p^j_{\omega,i} = u\}$.

Let $d$ be the distance from the intersect of the true wedge and a transect to a landmark and $\hat{d}$ be the estimation of $d$. The subscript $i$ in $d_i$, $\hat{d}_i$ and other notations is to indicate the parameter at the corresponding time step $i$. Let $n$ be the total number of time steps and $M = \{m_1, m_2, ..., m_n\}$ is the set of known physical parameter of the environments such as atmospheric pressure, wind velocity, and time of day and sensor measurements. The tracking wedge problem can be stated as

PROBLEM 1. *Given* $M$, $\min_{\hat{d}} RMSE = \sqrt{\frac{\sum_{i=1}^{i=n}(d_i - \hat{d}_i)^2}{n}}$

For example, we want to track salinity wedge at a certain *psu* threshold along the transect shown in dashed line in Figure 1.

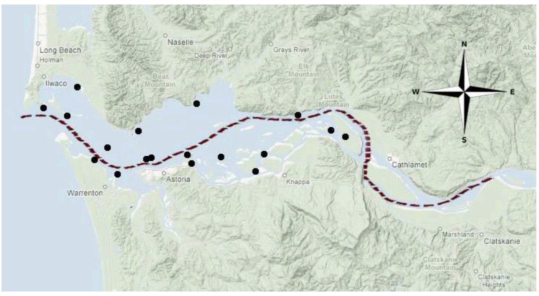

**Figure 1: Transect in the Columbia river estuary, Oregon, U.S.. The model overlays on top of the physical map of the river estuary. The dashed line is the transect. The dots are existing fixed sensor stations.**

## 3. COTRACK FRAMEWORK OVERVIEW

Figure 2 present the overview of CoTrack, which includes 3 main components: *Macro model* estimates the wedge location at a large scale from existing information such as time, environmental forcings, and fixed sensor measurements.

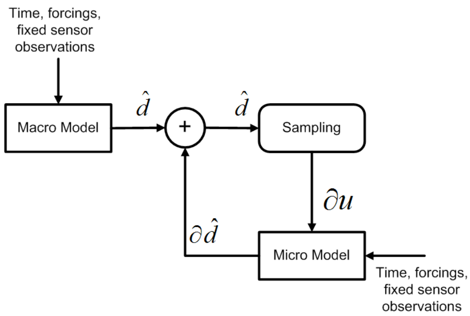


**Figure 2: CoTrack Overview**

*Micro model* estimates the distance to the true wedge from mobile locations where the measurements are taken. This model estimates wedge location at a much smaller scale compared to the macro model because it assumes that the measurements are taken at locations estimated from the macro model and hence are nearby the true wedge location.

*Adaptive sampling* scheme that incorporates macro and micro models to guide mobile sensors. Mobile sensors first go to the locations estimated by the macro model and take measurements. The mobile sensors then use the micro model to calculate the offset between their current locations and the true wedge location. The process can be iterative until the estimation is stable or the difference between the sensor measurements and the expected threshold is negligible.

## 4. CASE STUDY

As a study case, we track salinity wedge at a certain *psu* threshold along the transect shown in Figure 1.

**Error reduction using CoTrack (Table 1).** The salinity threshold is 15 psu. CoTrack can reduce the RMSE from 550m to 200m or equivalently 63% and reduce the MAE from 450m to 155m or equivalently 67% compared to the state-of-the-art data assimilation. CoTrack processing time is negligible. **Error reduction versus number of iterations.** Figure 3 shows the estimation error versus the number of iterations in CoTrack adaptive sampling. Both RMSE and MAE degrades quickly and become stable after about 6 iterations. This results suggest that only about 6 iterations in adaptive sampling are able to give good estimation of the salinity wedge.

| Metric | SELFE | Data Assimilation surrogate model | CoTrack |
|---|---|---|---|
| RMSE (m) | 6362 | 550 | 200 |
| MAE (m) | 4553 | 450 | 155 |
| Processing Time (s) | 0.02 | 25 | 0.2 |

**Table 1: Tracking performance comparison.**

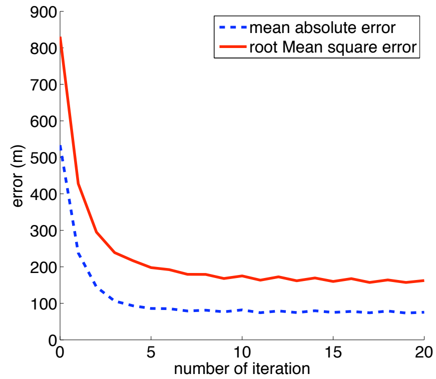


**Figure 3: Error reduction versus number of iterations.**

## 5. CONCLUSION

We have described CoTrack, a collaborative tracking framework that incorporates existing fixed sensor networks with mobile sensors and numerical models to track dynamic features in a large scale environment. The key idea is to use a macro model to quickly locate feature's vicinity and a micro model to iteratively refine the feature location. CoTrack has three main components, a macro model that estimates features' locations at a large scale, a micro model that estimates the offset between mobile sensors' locations and the features' locations, and a adaptive sampling scheme that use the two models to iteratively refines the estimation. We apply CoTrack to track salinity intrusion in the Columbia river estuary in Oregon. CoTrack is fast and can reduce the error by more than 50% compared to the state-of-the-art data assimilation framework. This improvement promises a significant contribution in understanding and improving exisiting physical models as well as the impacts of natural and human activities in the river estuary ecosystem.

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## 6. REFERENCES

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