Underwater Motion and Activity Recognition using Acoustic Wireless Networks

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Introduction

Acoustic wireless networks have a great potential to perform passive diver activity recognition and aquatic animal classification such as regalecus glesne and jellyfish in the deep sea water environment. However, terrestrial based wireless sensing techniques cannot be directly utilized for underwater motion recognition due to the complicated influences of curve propagation path of signals in underwater. In this paper, we propose an underwater target motion recognition mechanism using acoustic wireless networks, which is able to estimate the velocities of target body components as features by dynamic self-refining optimization algorithm and underwater DFS coefficients.

Signal Propagation Model

![Signal Propagation Model Diagram]

According to snell's law, the sound propagation in isogradient SSP meets following equations:

\[
\frac{dt}{dx} \cdot \sin \theta = \frac{dt}{dy} \cdot \sin \theta = \frac{c(y)}{c(x)} \quad c(y) = c(x) \frac{\sin \theta}{\sin \theta_y} = \frac{c(x)}{\sin \theta_x} 
\]

The propagation path of sound is curve and actually an arc of a circle, we can calculate the center angle:

\[
\varphi = \arccos \left( \frac{2R - D^2}{2R} \right) = \arctan \left( \frac{c(y \cdot y) - k_0 \cdot k_0}{1 + k_0 \cdot k_0} \right)
\]

\[
\varphi = 2\pi \cdot R = 2\pi \cdot \arctan \left( \frac{\sqrt{(x \cdot x) + (y \cdot y)}}{2\cdot\text{vx} + 2\cdot\text{vy} + 2\cdot\text{vz}} \right)
\]

Transmission length between transmitter and receiver:

\[
l_{TR} = R \cdot \varphi = \frac{c(y)}{\sin \theta \cdot \sin \theta_y} = c(y) \cdot \arctan \left( \frac{\sqrt{(x \cdot x) + (y \cdot y)}}{2\cdot\text{vx} + 2\cdot\text{vy} + 2\cdot\text{vz}} \right)
\]

DFS in ISSP Environment

Time of flight:

\[
\tau = \int \frac{dt}{c(x)} = \int \frac{dt}{c(y)} = \frac{1}{2} \int \frac{dt}{c(x)} = -\frac{c(y)}{c(x)}
\]

DFS expression when sound speed changes with different depth:

\[
f_d(t) = f \cdot \frac{c(y)}{c(x)}
\]

DFS linearly combination of velocities:

\[
f_d(t) = f \cdot \frac{dL(t)}{dt} = a_1 \cdot v_1 + a_2 \cdot v_2 + \cdots + a_n \cdot v_n
\]

Estimation of Velocities of Target Body

- Metal Material based synchronization

\[
\Delta f_{d,j} = f_{d,j} - \frac{f_{d,j}}{k} = (\frac{f_{d,j}}{k} - 1) \cdot \frac{f_{d,j}}{k}
\]

\[
e_{d,j} = s_j \cdot \frac{P_{d,j}}{B} + \text{v}_j \cdot \sum_{j=1}^{n} \frac{P_{d,j} + P_{d,j} \cdot B + \text{v}_j \cdot \text{v}_j}{B}
\]

Dynamic self-refining optimization

\[
\min y \sum_{m=1}^{n} \sum_{j=1}^{J} \left[ \left| A_k \cdot V_j / \left| V_j \cdot \text{v}_j \right| \right| - D_m \right]^2
\]

Numerical Results and Analysis

![Numerical Results and Analysis Diagram]

1. Our proposed dynamic self-refining optimization frame work could significantly reduce the outliers.
2. VTB features calculated from our proposed mechanism outperforms features calculated from unsynchronized and no DSR optimization situations with respect to machine learning classification.