Underwater Motion and Activity Recognition using Acoustic Wireless Networks

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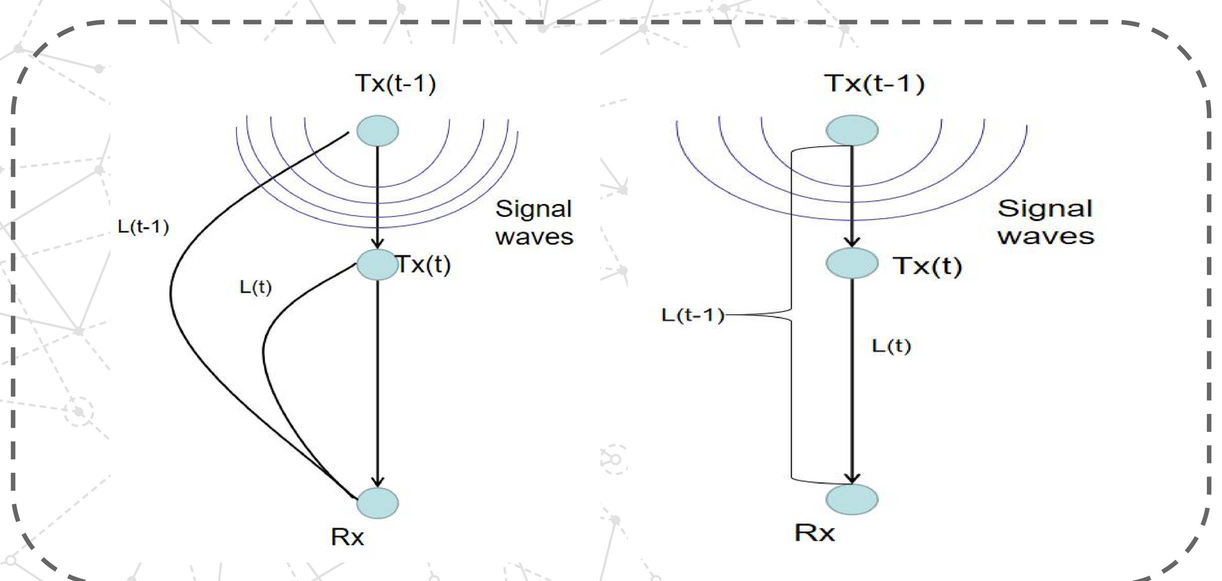
Introduction

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 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



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

$$\kappa = \frac{d\theta}{dl} = \frac{sin\theta \cdot dc}{c \cdot dz} = \frac{sin\theta \cdot g}{c} \quad R = \kappa^{-1} = \left|\frac{c(z_T)}{sin\theta_T \cdot g}\right| = \left|\frac{c(z_R)}{sin\theta_R \cdot g}\right|$$

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

$$\varphi = arccos(\frac{2R^2 - D^2}{2R^2}) \quad = arctan(\frac{k_{TO} - k_{RO}}{1 + k_{RO}k_{TO}})$$

$$\varphi = 2\phi_{TR} = 2arctan(\frac{g\sqrt{(x_T - x_R)^2 + (y_T - y_R)^2}}{2v_{suf} + gz_T + gz_R})$$

Transmission length between transmitter and receiver:

$$l_{TR} = R \cdot \varphi = \frac{c(z_T)}{sin\theta_T \cdot g} \cdot 2arctan(\frac{g\sqrt{(x_T - x_R)^2 + (y_T - y_R)^2}}{2v_{suf} + gz_T + gz_R})$$

DFS in ISSP Environment

Time of flight:

$$\tau = \left|\int \frac{dl}{c(z)}\right| = \left|\int_{\theta_T}^{\theta_R} \frac{d\theta}{sin\theta \cdot g}\right| = \frac{1}{g}\left|ln(\frac{sec\theta_R + tan\theta_R}{sec\theta_T + tan\theta_T})\right|$$

DFS expersion when sound speed changes with different depth:

$$f_d(t) = f \cdot \frac{v_{path}}{c(z)} = f \cdot \frac{dL(t)}{dt \cdot c(t)}$$

DFS linearly combination of velocities:

$$f_d = \frac{f}{c(t)}\frac{dL(t)}{dt} = \frac{a_x v_x + a_y v_y + a_z v_z}{\lambda(t)}$$

$$a_x = \frac{x_B(t) - x_R}{\sqrt{(x_B(t) - x_R)^2 + (y_B(t) - y_R)^2}} + \frac{x_B(t) - x_T}{\sqrt{(x_B(t) - x_T)^2 + (y_B(t) - y_T)^2}} \quad a_y = \frac{y_B(t) - y_R}{\sqrt{(x_B(t) - x_R)^2 + (y_B(t) - y_R)^2}} + \frac{y_B(t) - y_T}{\sqrt{(x_B(t) - x_T)^2 + (y_B(t) - y_T)^2}}$$

$$a_z = \frac{\frac{g[(x_B(t)-x_R)^2+(y_B(t)-y_R)^2]+[2v_{suf}+g(z_B(t)+z_R)]\cdot(z_B(t)-z_R)}{(2v_{suf}+2gz_R)\cdot\sqrt{(x_B(t)-x_R)^2+(y_B(t)-y_R)^2}}}{\sqrt{1+(\frac{g[(x_B(t)-x_R)^2+(y_B(t)-y_R)^2]+[2v_{suf}+g(z_B(t)+z_R)]\cdot(z_B(t)-z_R)}{(2v_{suf}+2gz_R)\cdot\sqrt{(x_B(t)-x_R)^2+(y_B(t)-y_R)^2}})^2}} + \frac{\frac{g[(x_B(t)-x_T)^2+(y_B(t)-y_T)^2]+[2v_{suf}+g(z_B(t)+z_T)]\cdot(z_B(t)-z_T)}{(2v_{suf}+2gz_T)\cdot\sqrt{(x_B(t)-x_T)^2+(y_B(t)-y_T)^2}}}{\sqrt{1+(\frac{g[(x_B(t)-x_T)^2+(y_B(t)-y_T)^2]+[2v_{suf}+g(z_B(t)+z_T)]\cdot(z_B(t)-z_T)}{(2v_{suf}+2gz_T)\cdot\sqrt{(x_B(t)-x_T)^2+(y_B(t)-y_T)^2}})^2}}$$

Estimation of Velocities of Target Body

- **Metal Material based synchronization**

$$\Delta f_{c,j} = \frac{\hat{f}_{s,1,j} - f_{s,j}}{k} = (\bar{b}_j - 1)f_{c,1} + \frac{\epsilon_{s,j}}{k}$$

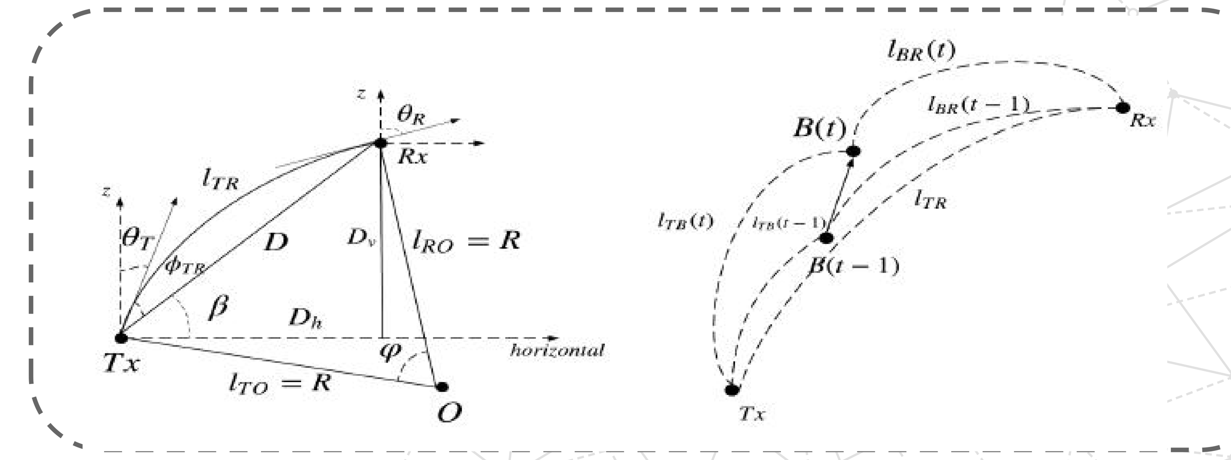
$$\epsilon_{j,t} = \epsilon_{j,f}[\frac{P_{1,j}}{B} + \frac{d_{1,j}}{v} + \sum_{i=j+1}^{J}(\frac{P_{1,i} + P_{i,1}}{B} + 2\frac{d_{1,i}}{v})]$$

Dynamic self-refining optimization

$$min_V \sum_{n=1}^{i}\sum_{j=1}^{J} \|A_n^j V_n I/\lambda(z_n^k) - D_n^j\|_F^2$$

$$V_i = \begin{vmatrix} v_x^1 & \ldots & v_x^K \\ v_y^1 & \ldots & v_y^K \\ v_z^1 & \ldots & v_z^K \end{vmatrix}$$

$$A_i^j = \begin{vmatrix} a_x^1 & a_y^1 & a_z^1 \\ \ldots & \ldots & \ldots \\ a_x^K & a_y^K & a_z^K \end{vmatrix}$$

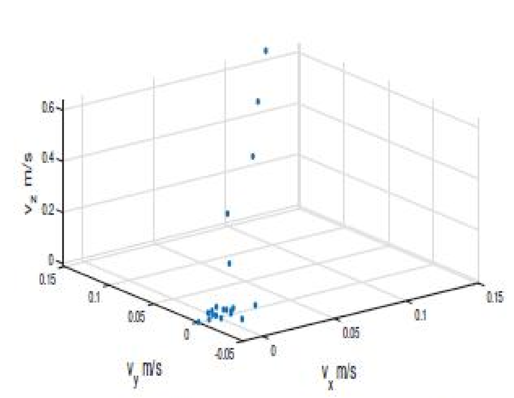


Algorithm 1 Dynamic Self-Refining VTB Optimization

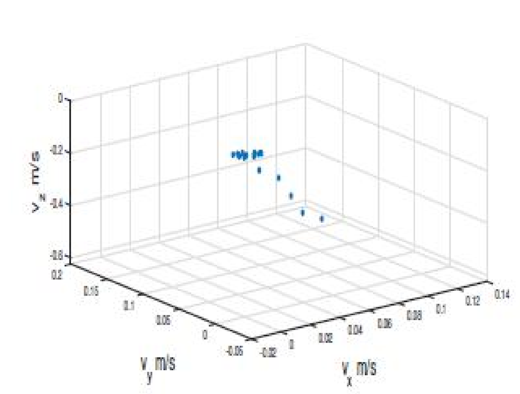
Input: Doppler frequency shift profile $D = \{D_1, D_2, ..., D_{N_t}\}$
Output: $V = \{V_1, V_2, ..., V_{N_t}\}$ velocity profile of human body components

initialize the linear coefficients profile $A_1^1, ..., A_1^J$
for i = 1 to N_t **do**
  perform $min_V \sum_{n=1}^{i}\sum_{j=1}^{J} \|A_n^j V_n I/\lambda(z_n^k) - D_n^j\|_F^2$
  for m = 2 to i+1 **do**
    for j = 1 to J **do**
      for k = 1 to K **do**
        $A_m^{jk} = [f_1^j(x_m^k, y_m^k), f_2^j(x_m^k, y_m^k), f_3^j(x_m^k, y_m^k, z_m^k)]$
        $[x_m^k, y_m^k, z_m^k] = [x_{m-1}^k + \Delta t \cdot v_x^{mk}, y_{m-1}^k + \Delta t \cdot v_y^{mk}, z_{m-1}^k + \Delta t \cdot v_z^{mk}]$ where $\Delta t = \frac{T}{N_t - 1}$
      end for
    end for
  end for
end for

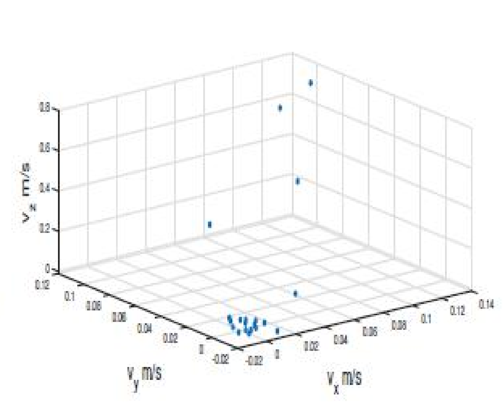
Numerical Results and Analysis



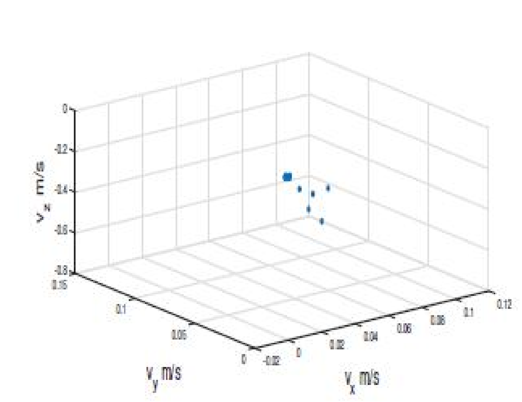
(a) lifting arm upward



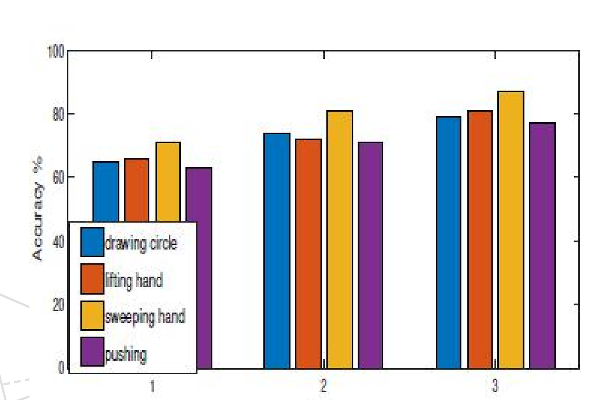
(b) putting arm downward



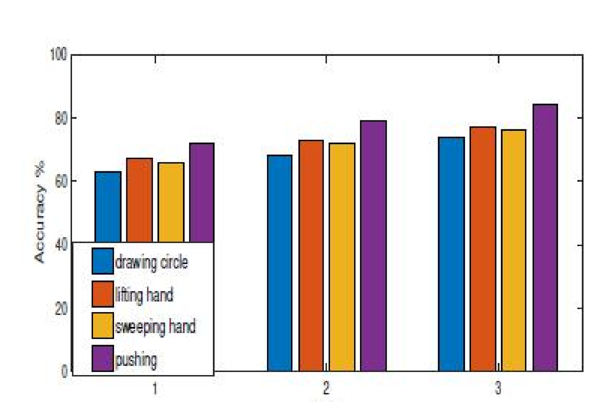
(a) lifting arm upward



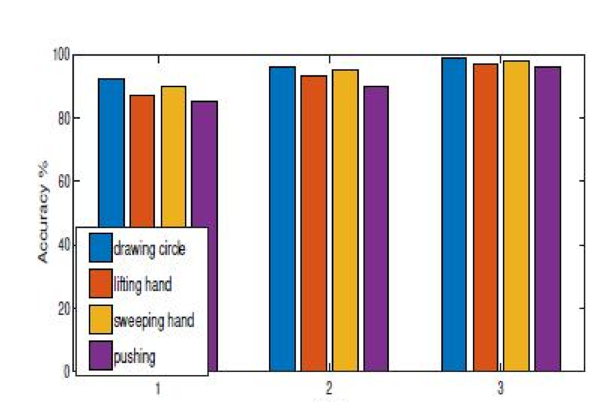
(b) putting arm downward



(a) Receivers are unsynchronized



(b) Using wrong DFS coefficients and one time optimization



(c) Using underwater DFS coefficients and DSR optimization

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