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Underwater positioning by kernel principal component analysis based probabilistic approach

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ABSTRACT

In this paper, underwater acoustic positioning is given by kernel principal component analysis (KPCA) and maximum likelihood (ML). To reduce the impact of multi-path reflection on measured signals, we utilize location fingerprinting to implement positioning. In order to check whether the proposed positioning scheme has the ability to tolerate multi-path reflections or not, experiments are conducted in a confined towing tank with boundary walls. Different frequency components of a physical sound projector are viewed as the virtual sound projectors. Thus the required hardware is greatly reduced. Our positioning scheme is divided into two stages, which are offline training and online testing. In the training stage, underwater acoustic signals are collected at different pre-specified reference locations and then projected to the KPCA space. In the testing stage, underwater acoustic signals are collected at an unknown location and then projected to the KPCA space. Underwater positioning is given by probabilistic pattern recognition of maximum likelihood in the KPCA space. Finally, the Euclidean distance between the actual and estimated positions are calculated and taken as the positioning error. The results show that underwater positioning by KPCA based probabilistic approach is accurate and efficient.

1. Introduction

Nowadays most underwater positioning systems adopt traditional geometric measurement methods such as time of arrival (TOA) and direction-of-arrival (DOA) [1–5]. However, these methods require precise hardware to measure the arrival time difference or direction of acoustic signals during positioning. If signals encounter multi-path reflections, measured results will be affected by these reflected signals. In order to reduce the impact of reflected signals on measured results, we utilize location fingerprinting [6–8] and probabilistic pattern recognition to implement underwater acoustic positioning. The reason why it is named "location fingerprinting" is that the positioning procedures are similar to those of human fingerprint identification. By doing so, the underwater acoustic positioning scheme do not need to achieve accurate direct propagation signals. Studies [9–11] indicated that the accuracy of positioning depends on the number of signals, i.e., more signals lead to more accurate positioning. However, the increase of hardware also leads to experimental difficulties. To reduce the required hardware, we utilize different frequency components from one physical sound projector to simulate multiple underwater sound projectors. Each frequency interval from the sole physical sound projector is considered as a virtual signal source transmitted by a virtual underwater sound projector.

The study includes two stages, which are training (offline) and testing (online). During the training stage, we utilize one fish finder as the sole underwater physical sound projector and one hydrophone as the sole sound receiver. The fish finder transmits analog AM (amplitude modulation) signals and these analog signals are converted into the frequency domain through the FFT (Fast Fourier Transform). Designated components of spectra are selected, recorded and viewed as the virtual sound projectors. Note that these designated components of spectra are time-varying due to environmental fluctuations. To reduce the complexity of underwater acoustic signals and the impact of fluctuations, signals of virtual sound projectors are projected to the KPCA [12–14] space. Each projection is assumed to have a Gaussian distribution for probabilistic pattern recognition. The mean and standard deviation for features in the KPCA space are calculated and recorded to constitute the Gaussian distribution. In the testing stage, we utilize ML (maximum likelihood) [15–17] on databases of the training stage to estimate coordinates of an unknown location where underwater acoustic signals are received. Finally, the Euclidean distance between the actual and estimated positions is calculated and taken as the error of underwater positioning.

In particular, experiments of this study are conducted in a towing tank at the National Cheng-Kung University in Tainan, Taiwan.

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Obviously, there exist multi-path reflections from boundary walls of the tank. This arrangement will help us to check whether the proposed positioning scheme has the ability to tolerate multi-path reflections or not.

In Section 2, formulations of our underwater positioning scheme are first given. Experiments and results are given in Section 3. Finally, the conclusion is given in Section 4.

2. Formulations

In our treatment, there is one wideband transmitter together with one receiver. Different intervals of frequency components transmitted by a wideband transmitter are collected to simulate different sound projectors, i.e., "virtual" sound projectors. Signals measured at selected reference locations are processed and recorded as the training database. Signals measured at an unknown location are compared with the training database through location fingerprinting, i.e., probabilistic pattern recognition. Therefore, an estimate of the unknown location will be achieved.

The proposed positioning scheme is divided into two stages, which are training (offline) and testing (online). We utilize one fish finder as the sole underwater physical sound projector and one hydrophone as the sole sound receiver. The fish finder transmits analog AM (amplitude modulation) signals and these analog signals are converted into the frequency domain through the FFT (Fast Fourier Transform). Designated components of spectra are selected, recorded and viewed as the virtual sound projectors. Assume $\bar{x} = [X_1, X_2, \ldots, X_M]^T$ contains the selected M spectral components from the physical sound projector at a given position. These M components of collected signals will be utilized for positioning. Note that the magnitude for each of the M spectral components is time-varying due to environmental fluctuations. To reduce the signal's complexity and the impact of random fluctuations, signals of virtual sound projectors are projected to the KPCA [12–14] space. Each projection is assumed to have a Gaussian distribution for probabilistic pattern recognition. The mean and standard deviation for features in the KPCA space are calculated and recorded to constitute the Gaussian distribution. In positioning, we utilize ML (maximum likelihood) [15–17] on existing databases to estimate coordinates of the unknown location, where the underwater acoustic signal occurs. Finally, the Euclidean distance between the actual and estimated positions is calculated and taken as the error of underwater positioning.

In the training stage, L planar reference locations (with coordinates denoted as $\bar{r}_1, \ldots, \bar{r}_l, \ldots, \bar{r}_L$) are first selected, as shown in Fig. 1. At each reference location, n sequential time-sampling measurements of underwater acoustic signals are collected for each virtual acoustic source (i.e., one frequency interval of physical projector). Therefore, the measurements will constitute a signal matrix with dimension $M \times N$, where N is defined as $N = n \times L$, as shown in Fig. 2a.

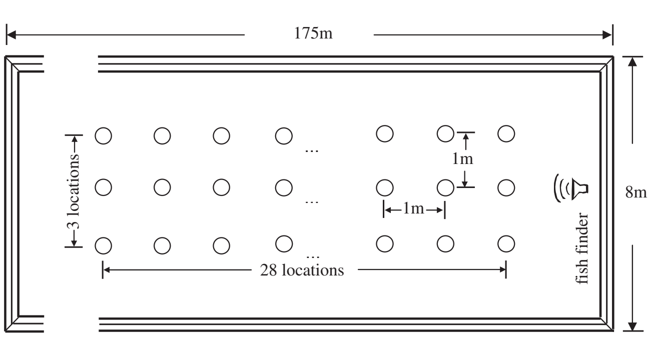

Fig. 1. The distribution of 3 × 28 = 84 planar reference locations in the towing tank.

The next step is to project the signal matrix of Fig. 2a to the eigenspace of KPCA. Assume $\bar{x}_1, \bar{x}_2, \ldots, \bar{x}_N$ denote the N column vectors of Fig. 2a. These N column vectors serve as the training data in the original space and will be mapped to high-dimensional feature space F through mapping function $\overline{\Phi}(\cdot)$, i.e.,

$$\bar{x}_j \rightarrow \overline{\Phi}(\bar{x}_j) \in F, \quad j = 1, 2, \ldots, N. \tag{1}$$

Fig. 3 gives an example of (1). In the left part of Fig. 3, a nonlinear elliptic curve separates two classes of data (i.e., circles and crosses) in the original two-dimensional space. As the original data are suitably mapped to a three-dimensional space, the projected data can be easily separated by a simple plane (right part of Fig. 3). By using this mapping function $\overline{\Phi}(\cdot)$, the training data is converted to be $(\overline{\Phi}(\bar{x}_1), \overline{\Phi}(\bar{x}_2), \ldots, \overline{\Phi}(\bar{x}_N))$. Initially, the mean of features in space F is assumed to be zero, i.e.,

$$\sum_{j=1}^{N} \overline{\Phi}(\bar{x}_j) = 0 \tag{2}$$

The covariance matrix $\overline{\overline{\sum}}$ in the feature space F is defined as

$$\overline{\overline{\sum}} = \frac{1}{N} \overline{\overline{\Psi}}\, \overline{\overline{\Psi}}^T, \tag{3}$$

where $\overline{\overline{\Psi}} = (\overline{\Phi}(\bar{x}_1), \overline{\Phi}(\bar{x}_2), \ldots, \overline{\Phi}(\bar{x}_N))$ and T denotes the transposition. Note that the above covariance matrix $\overline{\overline{\sum}}$ cannot be calculated directly because the mapping function $\overline{\Phi}(\cdot)$ is unknown. Instead, we utilize kernel functions to solve the eigenvalue and eigenvector. If symmetrical function $\overline{\overline{K}}$ matches Mercer's theorem [12], we could use a kernel function to describe properties of data in high dimension space. Thus, we have an $N \times N$ kernel-function matrix $\overline{\overline{K}}$, which is given as [12]

$$\overline{\overline{K}} = \begin{bmatrix} < \overline{\Phi}(\bar{x}_1), \overline{\Phi}(\bar{x}_1) > & \cdots & < \overline{\Phi}(\bar{x}_1), \overline{\Phi}(\bar{x}_N) > \\ \vdots & \ddots & \vdots \\ < \overline{\Phi}(\bar{x}_N), \overline{\Phi}(\bar{x}_1) > & \cdots & < \overline{\Phi}(\bar{x}_N), \overline{\Phi}(\bar{x}_N) > \end{bmatrix} = \overline{\overline{\Psi}}^T \overline{\overline{\Psi}}. \tag{4}$$

We utilize the above kernel function matrix $\overline{\overline{K}}$ to calculate the positive eigenvalues (denoted as $\lambda_1, \lambda_2, \ldots$) and their orthogonal eigenvectors (denoted as $\bar{\phi}_1, \bar{\phi}_2, \ldots$). The eigenvalues are ranked as $\lambda_1 \leqslant \lambda_2 \leqslant \ldots$. By applying the singular value decomposition (SVD) [16], we can easily prove that λ_i and $\overline{\overline{\Psi}} \cdot \bar{\phi}_i$ ($i = 1, 2, \ldots$) are the eigenvalues and eigenvectors of covariance matrix $\overline{\overline{\sum}}$. In KPCA, we select the top N_{KPCA} positive eigenvalues together with their eigenvectors to implement pattern recognition. For convenience, the eigenvectors are normalized as

$$\bar{u}_i = \frac{1}{\sqrt{\lambda_i}} \overline{\overline{\Psi}} \cdot \bar{\varphi}_i, \quad i = 1, 2, \ldots, N_{KPCA}. \tag{5}$$

Therefore, an N_{KPCA} dimensional eigenspace is spanned by eigenvectors of (5). Let $\bar{x}$ denote an original measurement, e.g., a column vector of matrix $\overline{\overline{\Psi}}$. Its projection on KPCA space can be given as $\overline{Q} = (q_1, \ldots, q_i, \ldots, q_{N_{KPCA}})^T$, where

$$q_i = \bar{u}_i^T \cdot \bar{x}, \quad i = 1, 2, \ldots, N_{KPCA}. \tag{6}$$

From the above formulations, we found that one only need to know the results of dot products $< \Phi(\bar{x}_i), \Phi(\bar{x}_j) >$, where $1 \leqslant i, j \leqslant N$. Details of the nonlinear function $\overline{\Phi}(\cdot)$ are not required. In this study, we utilize polynomial kernel functions to define the nonlinear transformation. The polynomial kernel for the (i,j)-element of $\overline{\overline{K}}$ is given as

$$\kappa_{ij} = < \Phi(\bar{x}_i), \Phi(\bar{x}_j) > = (\bar{x}_i \cdot \bar{x}_j)^d, \quad 1 \leqslant i, j \leqslant N, \tag{7}$$

where d is the polynomial degree.