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A Scheme on Indoor Tracking of Ship Dynamic Positioning Based on Distributed Multi-Sensor Data Fusion

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ABSTRACT Investigating the model ship dynamic positioning system by simulating the actual sea conditions in the laboratory can not only avoid the risks caused by the directly experiments on a true ship, but also reduce the costs. With the purpose of realizing the high accuracy control of the dynamic positioning, besides a high accuracy mathematical model of the ship, an important condition is that the position information provided by the position detection system must be accurate, reliable, and continuous. The global positioning system (GPS) signal is restricted when the model ship dynamic positioning system is set indoors. This paper describes a novel scheme for ship target tracking based on the multi-sensor data fusion techniques. To improve the accuracy of indoor positioning and ship target tracking, the characteristics of many sensors are systematically analyzed, such as radar, difference GPS, and ultrasonic sensors. Other important factors, including the indoor temperature, position, and environment, are also taken into account to further optimize the performance. Combining the Kalman filter method, the time alignment method, the coordinate transformation method, and the optimal fusion criterion method, the core algorithm of our framework employs the track correlation as the performance index of the optimal fusion. The experimental results indicate that our method outperforms the methods based on a single ultrasonic sensor. The maximum error between the estimated location and the real location is only 1.32 cm, which meets the standard for engineering applications.

INDEX TERMS Multi-sensor, data fusion, Kalman filter, optimal fusion, time registration, target track, ship model.

I. INTRODUCTION

Distributed multi-sensor data fusion (DMSDF) has been developed to solve a diverse set of problems that share some common characteristics [1]–[3]. The target tacking trajectory estimation problem has been a fruitful area of multi-sensor applications [4]–[6]. Many problems have been solved, yet new and diversified applications still challenge systems engineers [7]. Issues related to multi-sensor fusion include data association and management, sensor uncertainty, data traffic, noise filtering, making predictions and dynamic system modeling [8], [9]. They arise from the inherent uncertainties in the sensory information caused by not only device imprecision, but also noise sources within the system and the sensors [10]. In recent years, there has been increasing emphasis on using distributed multi-sensor data sources for various applications, e.g., designing distributed systems, incorporating scenario based design approaches [11], high level information fusion (HLIF), tracking, classification and situation assessment [12], [13]. Being able to deal with these uncertainties, DMSDF has become an important method to improve the performance of target tracking and detecting systems when various sensors are available [14], [15]. Moreover, compared with single sensor based methods, DMSDF combines data from multiple sensors and thus can perform inferences more efficiently and accurately [7], [14].

Due to the desired properties mentioned above, DMSDF has been found widely applicable in the area of target tracking during the past 20 years [16]. Liggins [9] proposed architectures for distributed data fusion and algorithms for target tracking. Their framework can be viewed as distributed extensions of linear and nonlinear estimation theories. The DMSDF [14], [15] is mainly used for dissimilar sensors (sensors with different observed frames), e.g., infrared and radar. For wide area surveillance applications, both the synthetic aperture radar (SAR) and the moving target indicator (MTI) types are useful for detecting the object of interest. However, while being able to detect and track an object from a long distance [14], [15], [17], the radar based systems suffer some disadvantages such as high noise, strong clutter interference and high cost for both hardware and software [17]. Moreover, the precision of the distance measurement is insufficient for applications involving indoor positioning [18]–[20]. Similarly, the ranging accuracy of a differential global positioning system (DGPS) [18], [21], [22] is up to 3-5*m*, which fails to meet the distance measurement requirement for indoor applications [23], [24]. On the other hand, systems based on the ultrasonic sensors not only are insensitive to the external light and the electromagnetic fields but also have simpler structures and relatively lower costs [19]. Furthermore, systems based on the ultrasonic sensors improve the precision that now range from decimeters to centimeters. But when a ship is at sail in the sea, it is affected by environmental factors such as winds, waves and currents. The ship has six degrees of freedom including surge, sway, heave, roll, yaw and bow [25], [26]. Each action is composed of low frequency components and high frequency components [15], [17], [18]. In order to effectively simulate the sea environment an achieve ship's real time positioning [17], [18], we propose a scheme on indoor target tracking for ship model based on distributed multi-sensor data fusion. The schematic of the DMSDF is as shown in Fig. 1.

Our aim is to improve the accuracy of indoor positioning and ship target tracking, the characteristics of multi-sensors are systematically analyzed with winds, waves, currents, and in the 26 °C.

This paper's contributions are presented as follows.

- Considering the limit of Global Position System (GPS) signal indoor for dynamic positioning ship model and the complexity of the sea conditions, environmental disturbances model (wind, wave and current), we propose a high accurate indoor location scheme based on ultrasonic.

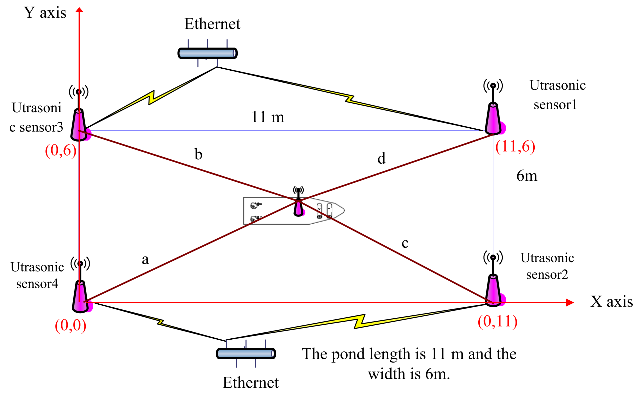

FIGURE 1. The schematic of the DMSDF.

- Considering the lack of a unified functional model and fading of indoor GPS signal, we propose a distributed fusion model to solve the problems of target track extraction, time alignment, track correlation, spatial alignment, coordinate transformation.
- To improve the signal to noise ratio and hence the accuracy of the ship indoor dynamic positioning, we propose a kind of the Kalman Filter (KF) multi-sensor signal preprocessing methods.
- This paper can achieve the weighted optimal fusion of many estimates in accordance with the principle of minimum variance.

This paper is organized as follows. Section II, III and IV introduce the related work about multi-sensor information fusion, system model and the DMSDF architecture, respectively. Section V describes the signal preprocessing of the DMSDF structure and Section VI focuses on the application of the novel data fusion approach and presents our implementation for optimized data fusion. Section VII describes a series of experiments and the related results to quantify the performance of the multi-sensor data fusion. Finally, a conclusion and future work are drawn in Section VIII.

II. RELATED WORKS

A. RELATED WORK ON DISTRIBUTED MULTI-SENSOR DATA FUSION

As the multi-sensor information fusion technology is widely applied, the number of research works have developed it aiming at many specific application fields [2]–[4]. These research works can be classified into [6]–[8]: (1) Several data fusion models of multi-sensor data fusion system [8], [9], [14]; (2) The multi-sensor data fusion (MSDF) process, fusion architectures involve centralized fusion, distributed fusion and hybrid fusion when designing a multi-sensor data fusion system [27].

1) DATA FUSION MODELS

The scholars propose some general function models of multi-sensor information fusion system from different aspects [2], [7], [8]: the Joint Directors of Laboratories (JDL) model, the waterfall fusion processes (WFFP) model, the intelligent cycle-based (IC) model, the Boyd circuit and the Omnibus model [9], [14]. The JDL model has five levels of data processing and a database. The JDL model is supported by a database-management system, which monitors, evaluates, adds, updates, and provides information for the fusion processes [2], [7], [8]. The WFFP model has six levels of processing and some similarities with the JDL model. The advantage of the WFFP model is the simplicity in understanding and applying [2], [7], [14]. The intelligence cycle-based model consists of five stages: planning and direction stage, collection stage, collation stage, evaluation stage, and dissemination stage. The IC model tries to capture some inherent processing cyclic characteristics among stages. The Boyd model represents the classis decision support mechanism in military information operations and has been widely used for multi-sensor fusion; it is considered a cyclical model. The Omnibus model is a better fusion process model that can be obtained by a combination of the Boyd and IC models. It is simple and easy to apply and follow for many non-defense DF applications.

However, there are some shortages of those models. The JDL model does not indicate the flow of the whole system. The new information after the decision of waterfall model cannot effectively used in other links. The intelligent circuit model does not contain the management requirements knowledge base and system data [8], [9], [14]. The Boyd loop and intelligence cycle realize closed loop flow control to the information respectively through the ‘‘action’’ and ‘‘spreading’’ modules when the division on fusion process is relatively rough. The Omnibus model, the practicability of which is weak, is not taken into account of the management requirements of knowledge base and system data. With the development of information processing technology, the continuous emerging of new equipment and new methods, the raising of collaborative development, big data, cloud computing, machine analytics, data sharing, resource management, other new methods and new concepts, the design model of fusion system is suffering new challenges. Consequently, the traditional information fusions JDL, WFFP, the intelligent loop fusion, the Boyd circuit and the Omnibus function model need to be revised, mainly including the revise of the division and the definition of the function level.

2) DATA FUSION ARCHITECTURES

In MSDF process, the data fusion architecture involves centralized fusion, distributed fusion, hybrid fusion [6], [14]. (1) The centralized fusion architecture used similar multi-sensor. The data fusion decisions are based on the maximum possible information gathered from the system sensor in the centralized fusion [28], [29]. (2) The distributed fusion is mainly used for dissimilar multi-sensor that sensor with observation frames [9]. This architecture has been used for smart structures and large flexible, monitoring of spacecraft health or aircraft, large sensors, huge automated plants, target tracking applications and chemical industries [14]. (3) The Hybrid fusion has both distributed and centralized fusion schemes for the disposition of the required sensor configurations. This structures is very suitable for the information fusion and processing system of a flight test range and cloud computing [14].

B. RELATED WORK ON TARGET TRACKING FOR DYNAMIC SYSTEM

In [22], the authors survey various mathematical models of target motion/dynamics proposed for maneuvering target tracking. According to the coupling among motions along different environment, these models developed for target tracking can be classified into 1D, 2D, and 3D categories.

However, few models have been developed that are particularly suitable for ships, submarines, and ground targets [22]. In order to achieve the target tracking of direction, there are various algorithms used to realize the multi-sensor data fusion, such as the particle filter [4], [6], [18], Kalman filter method [21], [26], [31], [32], the least square method, the α filter method [7], [14], [18] and the β filter method [18]. It is well known that the so-called measurement origin uncertainty and the target motion uncertainty are two major challenges in target tracking [22]. According to the uncertain measurement sources, Sun [21] proposed a series of methods, aiming at the ascertain measurement sources, Rocker and McGillem [16] proposed the vector state and the measurement fusion. This article, in the view of the uncertain ship motion trajectory, presents a kind of average weighted fusion method to achieve the optimal fusion of N estimate values according to the minimum variance principle.

C. RELATED WORK ON INDOOR TARGET TRACKING FOR SHIP MODEL

Considering the influence of wind, wave, current, working environment (sailing speed, operational model), navigational conditions and other uncertainties, it's hard to effectively achieve the ship position on the sea [15], [18], [30]. We used a variety of sensors: wind vane and anemometer are used to measure the wind direction and speed, gyro-compass (heading sensor) is used to measure the ship's directing, the gyro-compass has a long life and a rich experience on the sea, so it completely suit for the offshore drilling ship's dynamic positioning system [24], [33]; MRU sensor is motion sensor, it can measure the ship's dynamic linear motion and attitude [34]–[36]. It can measure the ship's rolling, pitching, yawing and heaving that has a high accuracy. In order to effectively achieve the ship indoor location, we used for dissimilar sensors, i.e. Infrared, GPS, Radar, DGPS, RFID, WLAN, UWB, Time Difference of Arrival (TDOA), and Ultrasonic. The infrared sensor has following problems: the design and the development of it are complex and have a large power consumption, which means that the cost is high, the applicability is weak and the measuring distance is short. As the ultrasonic sensor exactly overcomes these shortcomings, the independent developed ultrasonic receptor is adopted to carry out the indoor ship tracking

TABLE 1. Comparison of various technologies.

Method	Signal types	Device cost	Precision	Restricting factors
GPS[14]	Electromagnetic wave	Higher	15m	Fails to meet the indoor requirement.
Radar[15]	Rlectromagnetic wave	Higher	5m	Suitable for indoor and long distance use.
DGPS[14]	Electromagnetic wave	High	3-5 m	Fails to meet the indoor requirement.
RFID[17]	Electromagnetic wave	Lower	5m	Complex model and environmental change to modeling.
WLAN[17], [18]	Electromagnetic wave	Lower	10m	Complex model and environmental change to modeling.
UWB[20]	Electromagnetic wave	Highest	1m	Devices require precise time synchronization.
TDOA[19]	Ultrasonic and Electromagnetic wave	Lower	<50cm	Suitable for indoor use with distances<50m.
HPPM[19]	Ultrasonic and Electromagnetic wave	Lower	<30cm	Suitable for indoor use with distances<24m.
Ultrasonic[19]	Ultrasonic	Lower	<10cm	Suitable for indoor use with distances<7.2m.

experiments [14], [15], [17]. In the actual measurement,the received sound waves from the ultrasonic receptor are not amplified,so for easy observation, two stage amplifier and a band-pass filter are added near the transducer. In total, the received sound waves are amplified 50 times to be observed. A comparison of these technologies [18]–[20] is shown in Table 1.

Due to the ultrasonic ranging by the echo metering distance principle, calculation of the distance from transducer to the ship center through measuring the time that the transducer sending and receiving sound waves.

However, for the environments like high temperature, high humidity, amounts of dust, steam that was not applicable. If indoor temperature is higher than 28°C, the error of the system will deviate to negative direction, and if it is lower than 20 °C, the error will deviate to positive direction. In order to improve the detecting accuracy of the ultrasonic sensor, plentiful experiments were carried out in the 26 °C laboratory via the independent designed ultrasonic sensor, effectively reduced the error caused by temperature. After plentiful trials, we found that if the humidity in 50%-60%, the ultrasonic ranging accuracy will be relatively high.

III. SYSTEM MODEL

Ships are exposed to waves, wind, and current forces in the sea [24]. The ships motion system provides reliable measurements of heading and position, collects information from the multi-sensor, such as MRU, compass, speed log, gyros, ultrasonic sensor, and accelerometers [24]. So, we independent researched a set of control version, propeller and designed a 2.8m ship model, the ship model is 0.76m wide, 1m tall is as shown in *Appendix*. Above all, we use the DMSDF model that is implemented with some multiple parallel (not in the real sense of parallelism or on parallel computers. However, this is feasible and should be implemented in this way for reducing the computation time) filters. Each filter corresponds to one of the multiple models. Due to the switching between the different models, there is an exchange of some information between the filters. During each sampling period, it is likely that all the filters of DMSDF approach are in operation. The overall state estimation is a combination of the state estimations from the individual filters [14].

According to Section II and Table 1, we use ultrasonic sensor to implement indoor target tracking for ship model. Each local ultrasonic sensor is used to process the signal that can form a local track [37]. For the local track estimations, the distributed Kalman filter method is used to preprocess the signals and thereby obtain better accuracy in determining the local track. By considering the collection of the discrete time varying linear stochastic control system with N sensors, the DMSDF model is obtained. The distributed multi-sensor single target strategy is validated using ship tracking data. The state and measurement models are given by

$$X_k(t+1) = \psi(t)X_k(t) + W_k(t) \tag{1}$$

$$Z_k(t) = H_k(t)X(t) + v_k(t), \quad t = 1, 2, \ldots, N \tag{2}$$

where $X_k(t) \in R^n$ is the t^{th} state, $W_k(t)$ is white noises, $Z_k(t)$ is the measurement of the k^{th} sensor for t^{th} time, $v_k(t)$ is the measurement noise. In order to ensure the distributed Kalman filtering is not diverging, the model in [38] is used as the Kalman filtering, that is $\hat{x}_k(0) = E[x(0)]$, $P_k(0) = \sigma[x(0)]$, $\psi(t)$ is the $N \times N$ transition matrix that propagates the state $X_k(t)$ from t to $t+1$; $H_k(t)$ is the measurement model or sensor-dynamic matrix; $\psi(t) = 0.9048I$ and $H_k(t) = 1I$ are time varying matrices with suitable dimensions [38], I is a unit matrice, $Z_k(t)$ is the measured data, the subscript k denotes the k^{th} sensors and N is the number of times. $W_k(t)$ and $v_k(t)$, $t = 1, 2, \ldots, N$ are white noise with zero mean and $E[W(t)] = 0$, $E[W(t)W^T(j)] = Q(t)\delta_{tj}$, the summary of indoor tracking variables used for ship model and distributed multi-sensor data fusion applications is shown in Table 2.

$$E[v_k(t)] = 0, \quad E[v_k(t)v_k^T(j)] = R(t)\delta_{tj} \tag{3}$$

where $Q(t)$ is the variance of $W_k(t)$, $R(t)$ is the variance of $v_k(t)$, the superscript T denotes the transpose, and δ_{tj} is the Kronecker delta function. The method is validated using experimental trajectory data and also actual tracking data as shown in Fig. 3.

IV. STRUCTURE OF THE DMSDF APPROACH

The DMSDF approach provides two significant advantages over single sensor source data: one is the statistical advantage gained by combining data from the same source and the other one is the use of multiple types of sensors to increase the accuracy of the DMSDF approach, with which a quantity can be observed and characterized. The DMSDF approach would primarily involve the following [23]: (1) the hierarchical transformations between the parameters of observation and the generation of decisions regarding the location (kinematics and even dynamics), characteristics (features and structures), and the target of an entity [25] and (2) the inference and interpretation based on the detailed analysis of the observed scene

TABLE 2. Summary of indoor tracking variables used for ship model and distributed multi-sensor data fusion applications.

Variable	Name	Variable	Name
N	The Number of sensor	Z_{truth}	The true value of the target location
$X_k(t)$	Thet^{th}state	$\Delta\eta$	The inherent system error in the ultrasonic
$W_k(t)$,$\nu_k(t)$	White noises	N_{ji}	The noise of sensor j which scans for the i times
$\psi(t)$,$H_k(t)$	$\psi(t)$ is state transition matrix; $H_k(t)$ is the measurement matrices.	D_{ik}	The distance between the mean value and the observed value
$Z_k(t)$	Measure data	$\hat{Z}i$	The robust estimation
k	The k^{th} sensor	R_{ii}	The variance about the target trajectory by estimating
t	The times	Z_i	The value of the sensor i measurements for n_i times
$Q(t)$	The variance of $W_k(t)$	$Z(k)$	The observed signal at k moment
$\nu_k(t)$	The variance of $\nu_k(k)$	$\hat{Z}(k\|k)$	The predictive value at k moment
T	The transpose	R	The estimation of the ultrasonic accuracy
δ_{tj}	The Kronecker delta function	R_g	The optimal fusion estimated variance
$\tilde{X}_k(t+1)$	State time propagation	W_i	The weight matrix
$\tilde{P}_k(t+1)$	Covariance time propagation	I	The identity matrix
K_kt+1	The Kalman filter gain	$\bar{Z}_i$	The true position value
P_kt+1	The prediction covariance matrix	$\tilde{Z}$	The unbiased estimation of the true position of the target
$\hat{x}(k)$	Interval estimated value for 3 points	l	The pond length
Δt	The interval time	w	The pond wide
t_{k-1}	The time of $k-1$	l_{ab}, l_{cd}	The side length of triangle
Z_{ji}	Observation value obtained by sensor	h_{ab}, h_{bc}	The height of triangle
M	The number of all the tracks	S_{ab}, S_{bc}	The area of triangle
S_{cd}, S_{ad}	The area of triangle	l_{bc}, l_{ad}	The side width of triangle
Z_{ji}	Observation value obtained by sensor	h_{cd}, h_{ad}	The height of triangle

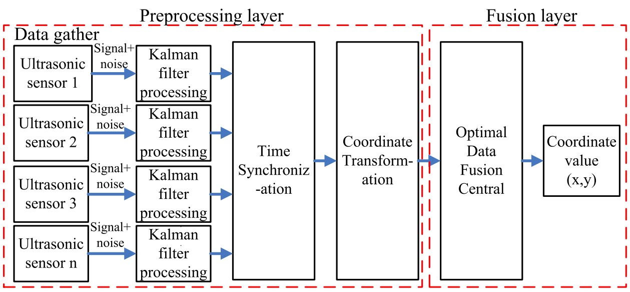

FIGURE 2. The two layer structure of the DMSDF approach.

or the entity in the context of a surrounding environment and the relationships with the other entities.

According to the stage on which the data fusion takes place, the DMSDF approach can be implemented at two different processing layers: the signal preprocessing layer and the optimal data fusion layer. In fact, the DMSDF approach has a target processing track [18], [21] shown in Fig. 2.

A. THE FIRST LAYER - THE SIGNAL PREPROCESSING LAYER

The prediction and estimation of the signal state are based on the signal layer data association (e.g., the collections of the information systems, the eliminating outliers, and the target data distribution processing). With the first step prediction

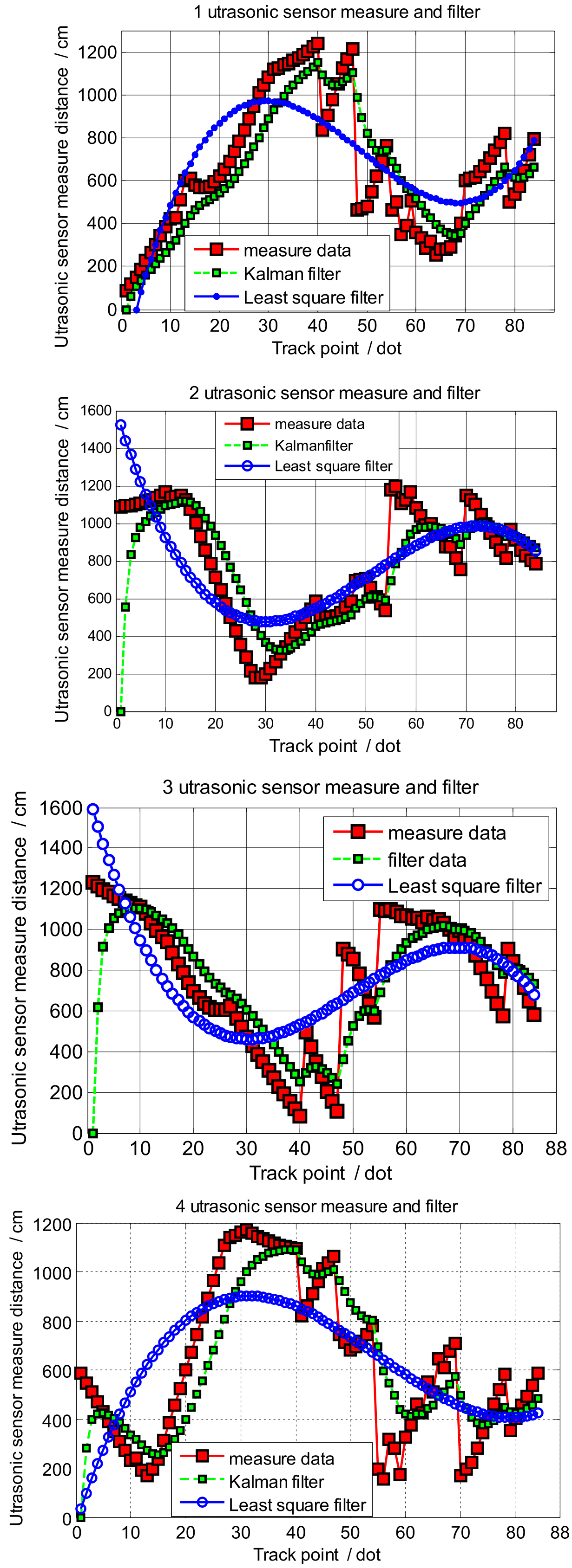

FIGURE 3. The Kalman filter process signal experiment.

and the smoothing errors between any sensors, the signal preprocessing layer has nested parallel structures. Due to the different positions of the reference system, the sampling frequency is not necessarily the same. For example,one system may get a measured value when another system has not sent a measured value at a period. As a result, each measuring system has the measured data in real time and requires a unified sampling frequency to be used in the specific algorithm [26]. Owing to the influence of the difference of the sensors' sampling period and boot time, the different delay of communication network and other factors, there may be time differences among the observation data of the same target on the air from different sensors. In order to maximize the advantages of the multi-sensor data fusion system, the temporal alignment to the multi-sensor data would be the premise of data's parallel fusion. Before data fusion, the time synchronization of the same target of the real time data must be performed. For each different reference coordinate used by the measuring system, there are many ways to define an arbitrary rotation, scale and transformation to map one coordinate frame into another. In this paper, the some state point is used to transform into the Cartesian coordinate system, as shown in Fig. 4.

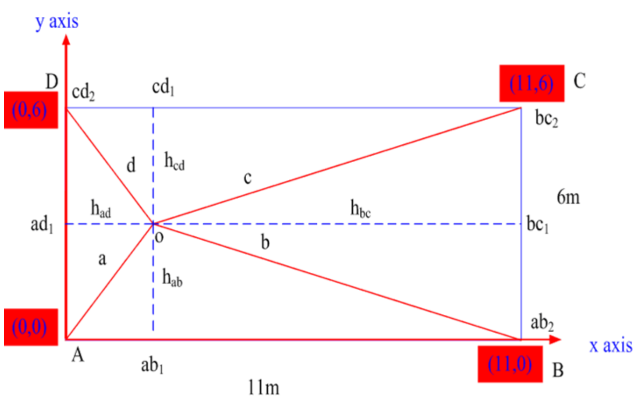

FIGURE 4. **DMSDF plot of the 4 ultrasonic sensors responses for target tracking.**

B. THE SECOND LAYER - THE OPTIMAL FUSION LAYER

The optimal fusion layer, which is mainly used for similar sensors, involves time synchronization and bias correction of the sensor data. This layer is the fusion center where data are fused to determine the optimal weights and to achieve the optimal weighted data fusion.

V. SIGNAL PREPROCESSING LAYER

A. DMSDF KALMAN FILTER

Random noise is a part of the measured data from a sensor. To weaken the effect of the noise on the signal, the sampled data are processed to eliminate outliers and are smoothed via a filter. The purpose of data filter smoothing is to eliminate the interference components and change the characteristics of the original data. The DMSDF method can be applied to the track reconstruction of the maneuvering target. In the distributed multi-sensor track environment, it is important to know how to fuse the information from multiple sensors together [28]. Commonly, all the measurement vectors are combined from the different sensors into one measurement vector, and then the centralized filter with the standard Kalman filtering [21] can be obtain. However, the centralized filter [29] will lead to a high computational burden in the fusion center due to the high-dimension computation and the large data memory required. Recently, the data fusion distributed Kalman filter was widely studied and applied in the communications and control fields because the parallel structures can increase the input data rates and enhance reliability. According to [10], [22], [39], and [40], the DMSDF Kalman filter [30], [39], [40] is given by:

(1) The state and covariance time propagation is given as:

$$\hat{X}_k(t+1) = \psi(t)\hat{X}_k(t) \tag{4}$$

(2) Covariance matrix:

$$P_k(t+1) = \psi(t)P_k(t)\psi(t)^T + R(t) \tag{5}$$

Where $P_k(t+1) = E[\tilde{X}_k(t+1)\tilde{X}_k^{\,T}(t+1)]$; $\tilde{X}_k(t+1) = X_{k+1}(t+1) - \hat{X}_k(t+1)$. (3) Kalman gain:

$$K_{k+1}(t+1) = \tilde{P}_k(t)H_k^T(t)[H_k(t)\tilde{P}_k(t)H_k^T + R(t)]^{-1} \tag{6}$$

(4) The state and covariance update equations are given as:

$$\begin{aligned}\tilde{X}_{k+1}(t+1) = \psi(t)\tilde{X}_k(t) + K_{k+1}(t+1)\\ \times [Z_k(t) - \psi(t)\tilde{X}_k(t+1)]\end{aligned} \tag{7}$$

(5) The state and covariance update equations are given as:

$$P_{k+1}(t+1) = [I - K_{k+1}(t+1)\psi(t)] + P_k(t+1) \tag{8}$$

Where $P_{k+1}(t+1) = E[\tilde{X}_{k+1}(t+1)\tilde{X}_{k+1}^T(t+1)]$; $\tilde{X}_{k+1}(t+1) = X_{k+1}(t+1) - \tilde{X}_{k+1}(t+1)$; $K_k(t+1)$ is the Kalman filter gain and $P_k(t+1)$ is the prediction covariance matrix. The same DMSDF model is involved in the distributed Kalman filters. The distributed Kalman filter process signal initializing value can be seen in *Section VII.A*.

B. TIME SYNCHRONIZATION

A distributed Kalman filtering algorithm is used to estimate the optimal state and then the estimated result is sent back to the fusion center. To achieve the ultimate goal of multi-sensor fusion, the fusion center must perform real time synchronization to be sent the same goal of the data for each time point. A time alignment synchronizes the measurement information from the same target coming from the desynchronized signals of different sensors. The results of using data without time synchronization may be worse than the one of using data from a single sensor to fuse. Therefore, to maximize the superiority of the multi-sensor data fusion system, achieving the time alignment of multi-sensor data is a prerequisite for the integration in parallel, and the pros and cons of the registration method directly affects the data fusion [41].

In terms of implementing time synchronization by the nearest neighbor interpolation method, to minimize the error of the interpolation, the principle of the interpolation node selection is used to achieve time synchronization in the middle of the interpolation interval. According to the principle of the interpolation method, it is assumed that the time synchronization node is in the middle of the interval, and the interval estimated value for three points are $\hat{x}(k-1)$, $\hat{x}(k)$, $\hat{x}(k+1)$. The corresponding instants for them are t_{k-1}, t_k, t_{k+1}. As the difference between the moving distances of a target in the adjacent scan interval is small, the three moments can be considered as equal intervals (the interval is Δt). It can be assumed that t_{k-1}, t_k, t_{k+1} are equally spaced,that is $t_k - t_{k-1} = T$. Suppose the time of interpolation node is t: the measured value of t can be calculated by the Lagrange 3 point interpolation method [25], [32], [33].

$$\begin{aligned} x(t) = &\frac{(t-t_k)(t-t_{k-1})}{(t_{k-1}-t_k)(t_{k-1}-t_{k+1})}\hat{x}(k-1) \\ &+ \frac{(t-t_{k-1})(t-t_{k+1})}{(t_k-t_{k-1})(t_k-t_{k+1})}\hat{x}(k) \\ &+ \frac{(t-t_{k-1})(t-t_k)}{(t_{k+1}-t_{k-1})(t_{k+1}-t_k)}\hat{x}(k+1) \end{aligned} \tag{9}$$

Corresponding algorithm for time synchronization:

Each ultrasonic sensor station determines different trajectories after data processing; first determine the tracks that are overlapped in duration. The minimum and maximum time in these track groups are taken as the starting and ending times of the time synchronization. Through the track prediction algorithm (this paper takes the relatively simple linear prediction algorithm), the entire track can be forecasted in the missing part. One path is taken as a benchmark for the time axis for time synchronization. The other tracks are interpolated at the corresponding times through the Lagrange interpolation method in 3 points. Finally, a matrix of data that has the same time coordinates, which is used in the following track related steps, is obtained. Note that according to the corresponding algorithm of time synchronization, the following two main problems should be resolved:

1) Ensure the reference point for the time of measuring station of the sensor to be consistent.

2) The sampling measurement period for the sensors is inconsistent and not the same as the synchronized time period.

C. COORDINATE TRANSFORMATION

Ship moving targets normally maneuver on circular paths which have led to tracking filters on circular turns. In this section, this paper will transform the tracking maneuvering target problems from the ultrasonic distance to the Cartesian coordinate. The distance values can be obtained from the N ultrasonic sensors. The corresponding distance values should be transformed into the Cartesian coordinate system points. This method defines the position of a point by its perpendicular distance from two or more reference lines. Two straight lines, called the x-axis and the y-axis, form the basis of a two-dimensional Cartesian-coordinate system. The x-axis is usually horizontal and the y-axis is perpendicular to it. The intersecting point of the two axes is called the origin (O) [18], [22], [34]. Any points on this plane can be identified by an ordered pair of numbers that represents the distances to the two axes. According to this algorithm, the data observed by N ultrasonic sensors is extracted, and the resulting numbers are shown in Table 3.

TABLE 3. The experimental coordinate transformation results of the DMSDF.

The number of ultrasonic sensors	1	2	3	4	...	N-1	N
Track number extraction	1	1	3	6	...	C_{N-1}^2	C_N^2

VI. THE DMSDF OPTIMIZED FUSION

A. ULTRASONIC SENSOR TRACK CORRELATION

After time synchronization, the track groups can be determined that having the same time slot and interval. Then, the track correlation is determined by the recent field correlation algorithm. This paper first confirms the size of the tracking gate of the target track, and determines the primarily related observation. The tracking gate is a rough inspection method to assign observation echoes to target tracks whatever they have been established or not. It can be concluded from the analysis that if the chosen gate is too large, there will be many untargeted observations and noise waves that fall into the gate, negatively influencing the performance of the gate. Conversely, if the chosen gate is too small, the probability of performing the target observation out of the gate will increase. This also negatively influences the data association performance. So for the DMSDF method, the appropriate wave gate size should be identified firstly. When the tracking wave is determined, the approximation of the track and the observation point, which fell into the gate, the approximate statistical distance, and the distances between every track and all of the observed waves will be calculated. A $M*N$ statistics matrix, where M is the number of all the tracks and N is the number of all the observed waves, is finally got [41].

B. ACCURACY OF THE ESTIMATED ULTRASONIC SENSOR OBSERVATIONS

Owing to the inherent systematic errors of the ultrasonic sensor and noise caused by measurement error, which can lead to a large position error obtained by a single ultrasonic sensor scan, the results of the continuous and repeated scans should be optimized. Optimizing repeated scan is robust method which reduces the measurement error. The measurement model of ultrasonic sensor j which scans the target i times can be expressed as:

$$Z_{ji} = Z_{truth} + \Delta\eta + N_{ji} \tag{10}$$

where Z_{ji} is the observation value obtained by sensor j which scans i times. The Z_{truth} is the true value of the target location. The $\Delta\eta$ is the inherent system error in the ultrasonic sensor. N_{ji} is the noise of sensor j which scans i times. To make the method more suitable for determining the accuracy of the ultrasonic optimal data fusion, two methods are introduced (*Section VI.B.(1)* and *VI.B.(2))*.

1) ACCURACY ESTIMATE BASED ON THE OVERALL DATA

For the distributed multi-sensor data fusion measurement model, $Z_i = [Z_{i1}, Z_{i2}, ...Z_{ini}]$ is the value of the sensor i measurements for n_i times, the robust estimation $\hat{Z}_i$ and the variance R_{ii} about the target trajectory of the estimates can be obtained [35].

Let

$$\bar{Z}_i{}' = \frac{1}{n_i}\sum_{k=1}^{n_i} Z_{ik}; \tag{11}$$

and set

$$R'_{ii} = \frac{1}{n_i}\sum_{k=1}^{n_i}[Z_{ik} - \bar{Z}_i{}'][Z_{ik} - \bar{Z}_i{}']^T \tag{12}$$

The distance between the mean value and the observed value is calculated as:

$$D_{ik} = \sqrt{[Z_{ik} - \bar{Z}_i{}'][Z_{ik} - \bar{Z}_i{}']^T} \tag{13}$$

where Z_{ik} is rearranged according to ascending order of D_{ik}, and $(\frac{n_i}{2} + 1)$ is the number of observation values that are in the valid estimated basis. Taking $\hat{Z}_i$ as effective observation mean value [35], [36], that is:

$$\hat{Z}_i = \frac{1}{m_i}\sum_{k=1}^{m_i} Z_{ik} \tag{14}$$

where $m_i \leq \frac{n_i}{2} + 1$ is the maximum integer. R_{ii} is effective variance of observation values, that is:

$$R_{ii} = \frac{1}{m_i}\sum_{k=1}^{m_i}[Z_{ik} - \hat{Z}_i][Z_{ik} - \hat{Z}_i]^T \tag{15}$$

Now, the δ is taken as a smaller positive number to control the x-axis data of the robust estimate, (where $\delta = 0.3$), if $|\hat{Z}_i - \hat{Z}_i{}'| < \delta$, the estimating value is achieved. $\hat{Z}_i$ and R_{ii} are the location of the counted target estimate and robust variance estimate, respectively. If $|\hat{Z}_i - \hat{Z}_i{}'| \geq \delta, Z'_i = \hat{Z}_i, R'_{ii} = R_{ii}$ are taken as the new observation mean value and are taken back for the cycle estimation.

2) ACCURACY ESTIMATION BASED ON THE PREDICTED VALUE AND THE ESTIMATED TRAJECTORY INTERPOLATION VALUE

Since the accuracy of the ultrasonic sensor may also lead to prediction bias, which makes errors between the prediction points and the observation points become small, the prediction points and the deviation of the actual observation points can be used as a standard to measure the accuracy of the ultrasonic sensor.

It is assumed that $Z(k)$ is the observed signal at the t^{th} moment, $\hat{Z}(k \mid k)$ is the predictive value at t^{th} moment, then the following equation can be obtained:

$$R = \frac{1}{n}\sum_{k=2}^{n}[Z(k) - \hat{Z}(k \mid k)][Z(k) - \hat{Z}(k \mid k)]^T \tag{16}$$

The obtained value of R can be taken as an estimate of the ultrasonic accuracy [18]. If the optimal fusion is required, R should be minimized. Using the experimental results, a series of data are processed from four ultrasonic sensors by the above two methods (Section *VI.B.(1)* and *VI.B.(2)*) and the corresponding variance estimate for each ultrasonic sensor are obtained. The data obtained by the latter method is relatively (Section *VI.B.(2)*) stable, so it can be concluded that the latter method is more suitable for determining the accuracy of the ultrasonic sensors.

C. THE DMSDF OPTIMIZED FUSION RULE

After performing the time synchronization and trajectory estimation, several groups of relevant (judged to represent the same target) track data can be obtained, then it is necessary to consider which convergence criterion is required to fuse the target tracking data [35]. Here this paper uses the weighted optimal method and achieves the optimal fusion of N estimations in accordance with the principle of minimum variance [18], [36]. According to the minimum variance principle, this paper proposes a kind of weighted average fusion method that can achieve the optimal fusion of N estimate values.

Assumption 1: $W_i, i = 1, 2, ...N$ is a set of matrices with $W_1 + W_2 + ...W_N = I$, where I is a identity matrix,and the expression of optimal fusion estimation is given by

$$\tilde{Z} = W_1\bar{Z}_1 + W_2\bar{Z}_2 + ... + W_N\bar{Z}_N \tag{17}$$

where $\bar{Z}_i$ is a true position value and $\tilde{Z}$ is an unbiased estimation of the true position of the target. N is the number of ultrasonic sensors.

1) THE DMSDF OPTIMAL FUSION CRITERION

First, $\tilde{Z}$ should be an unbiased estimation of the true position of the target, which means $E(\tilde{Z}) = \bar{Z}$. Second, $\tilde{Z}$ should minimize the trace of the estimation error variance matrices,which means the optimal fusion estimated variance R_g is smaller than any other variance estimation of a single sensor.

Lemma 1: Under **Assumption 1** and **the DMSDF optimal fusion criterion**, N ultrasonic sensor signals are used in the fusion of the target tracking data, we obtain.

$$\tilde{Z}_N = \sum_{i=1}^{N} R_{ii}^{-1} Z_i / \sum_{i=1}^{N} R_{ii}^{-1}, \quad R_{g,N} = 1/\sum_{i=1}^{N} R_{ii}^{-1} \tag{18}$$

Proof: (i) Let $K = 2$. From *Eq.*(14), one has that

$$\tilde{Z}_k = W_1\bar{Z}_1 + W_2\bar{Z}_2 = \bar{Z}_1 + W_2(\bar{Z}_2 - \bar{Z}_1) \tag{19}$$

$$\begin{aligned} R_{g,k} &= E[(\tilde{Z} - \bar{Z})(\tilde{Z} - \bar{Z})^T] \\ &= (I - W_2)(I - W_2)^T R_{11} + (I - W_2)W_2^T R_{12} \\ &\quad + W_2(I - W_2)^T R_{21} + W_2 W_2^T R_{22} \end{aligned} \tag{20}$$

If it is assumed that $\bar{Z}_1$ and Z_2 are not correlated, $R_{12} = R_{21} = 0$, and $W_i = W_i^T$, the *Eq.*(17) will reduce to:

$$R_{g,k} = (1 - W_2)^2 R_{11} + W_2^2 R_{22} \tag{21}$$

Taking the derivative on both sides of the equation and setting it zero, the following equation is eventually obtained:

$$W_1 = \frac{R_{22}}{R_{11} + R_{22}}, \quad W_2 = \frac{R_{11}}{R_{11} + R_{22}} \tag{22}$$

Substituting Eq.(19) and Eq.(17) into Eq.(16) yields:

$$\tilde{Z}_k = \frac{R_{11}^{-1}\bar{Z}_1 + R_{22}^{-1}\bar{Z}_2}{R_{11}^{-1} + R_{22}^{-1}} \tag{23}$$

$$R_{g,k} = \frac{1}{R_{11}^{-1} + R_{22}^{-1}} \tag{24}$$

(ii) Let K = N − 1, from Eq.(15), one has that

$$\tilde{Z}_k = \sum_{i=1}^{N-1} R_{ii}^{-1}\bar{Z}_i / \sum_{i=1}^{N-1} R_{ii}^{-1}, \quad R_{g,k} = 1/\sum_{i=1}^{N-1} R_{ii}^{-1} \tag{25}$$

Similarly, the algorithm is promoted to N signals to the integration of the track using mathematical induction

$$\begin{aligned}\tilde{Z}_{k+1} &= W_1\bar{Z}_1 + W_2\bar{Z}_2 + \ldots + W_k\bar{Z}_k + W_{k+1}\bar{Z}_{k+1} \\ &= \tilde{Z}_k + W_{k+1}\bar{Z}_{k+1} \end{aligned} \tag{26}$$

$$\begin{aligned}\tilde{Z}_{k+1} - \bar{Z}_{k+1} &= W_1\bar{Z}_1 + W_2\bar{Z}_2 + \ldots + W_k\bar{Z}_k \\ &\quad + W_{k+1}\bar{Z}_{k+1} - \bar{Z}_{k+1} \\ &= \tilde{Z}_k + W_{k+1}\bar{Z}_{k+1} - \bar{Z}_{k+1} \end{aligned} \tag{27}$$

$$\begin{aligned} R_{g,k} &= E[(\tilde{Z}_{k+1} - \bar{Z}_{k+1})(\tilde{Z}_{k+1} - \bar{Z}_{k+1})^T] \\ &= (I - W_{k+1})(I - W_{k+1})^T R_{k,k} \\ &\quad + (I - W_{k+1})W_{k+1}^T R_{k,k+1} \\ &\quad + W_{k+1}(I - W_{k+1})^T R_{k,k+1} \\ &\quad + W_{k+1}W_{k+1}^T R_{k+1,k+1} \end{aligned} \tag{28}$$

If it is assumed that $\tilde{Z}_k$ and $\bar{Z}_{k+1}$ are not related, $R_{k,k+1} = R_{k+1,k} = 0$, and $W_i = W_i^T$, the Eq.(17) will be reduced to:

$$R_{g,k} = (1 - W_{k+1})^2 R_{k,k} + W_{k+1}^2 R_{k+1,k+1} \tag{29}$$

Taking the W_{k+1} derivative on both sides and setting it zero, we get W_k, W_{k+1}, which in addition to Eq.(24) are merged into Eq.(23) to yield:

$$\tilde{Z}_{k+1} = \sum_{i=1}^{k+1} R_{ii}^{-1}\bar{Z}_i / \sum_{i=1}^{k+1} R_{ii}^{-1} \tag{30}$$

$$R_{g,k+1} = 1/\sum_{i=1}^{k+1} R_{ii}^{-1} \tag{31}$$

From (i) and (ii), we prove Eq.(15) is true.

VII. EXPERIMENTAL RESULTS

To effectively achieve the indoor ship location, we independent researched a set of control version, propeller and designed a 2.8 m ship model, the ship model is 0.76m wide, 1m tall is as shown in *Appendix*. To effectively simulate the sea environment, we used a variety of sensors: wind vane and anemometer are used to measure the wind direction and speed, gyro-compass (heading sensor) is used to measure the ship's heading, the gyro-compass has a long life and a rich experience on the sea, so it completely suit for the offshore drilling ship's dynamic positioning system; MRU sensor is motion sensor, it can measure the ship's dynamic linear motion and attitude. It can measure the ship's rolling, pitching, yawing and heaving, and has a high accuracy. The ultrasonic used for indoor distance detection, to get ship's actual position, achieves the purpose of indoor positioning. A Personal Computer(PC) is used to realize the real-time 3D simulation of the ship. The main controller is mainly used to achieve the data collection, processing and the realization of the control algorithm. The handle work station is used to achieve the active work station, and it can achieve real-time moving.

According to the above algorithm, this section illustrates the characteristics of the DMSDF algorithms through the experiment. There are four ultrasonic sensors for measuring state around the ship. The length of the ship is $L = 2.8m$, the depth of the ship is $H = 1m$, the width of the ship is $B = 0.76m$, wind speed is $3m/s$ and the meaningful height of waves is $0.3m$. The specific physical map is shown in *Appendix*. Using the OPC technology in [26], programming under matlab 7.1, achieved reliable and high speed data communication among PC, main controller and sensors, the sampling time is $T = 1s$. The experimental figure of the DMSDF is shown in Fig. 1.

Fig. 1 shows that the length and the width of the pond are $11m$ and $6m$, respectively. It could be found that the positions of the 4 ultrasonic receivers around the pond. There is an ultrasonic sender on the ship. The 4 ultrasonic receivers detect the signal from the ultrasonic sender on the ship and send the data to a local computer (the optimal data fusion center). We gathered a set of real time data and performed filtering in Matlab 7.1. The sampling time is 1s, and the sample size is 300 times.

A. KALMAN FILTER PROCESS SIGNAL EXPERIMENT

The extended Kalman filter (EKF) was introduced in [38] and [39] for implementing target tracking in a single-sensor system. However, because the EKF only uses the first order terms of the Taylor series expansion of nonlinear functions [40], [41], it often introduces large errors in the estimated statistics of the posterior distributions of the states. So, using the distributed Kalman filter process signal in *Section V.B*, we initialize $\psi(t) = e^{-0.1} = 0.9048I$, $R(t) = 1I$, $H_k(t) = 1I$, $Q(t) = 1 - e^{-0.2} = 0.1813I$, $\hat{x}_k(0) = E[x(0)]$, $P_k(0) = \sigma[x(0)]$. In order to show the advantages of our proposal method, the results are optimum with the raw measurements and least square filter values. The Kalman filter and least square filter process signal experiment is shown in Fig. 3.

For the following problems: the sensor faults or exceptions in the data recording or reading, the sudden change and interference of the surrounding environment, and the error of operator, some large error discontinuities values exist in the collected data. The Kalman filtering can effectively achieve the dynamic data filtering and smooth processing. Fig. 3 shows that Kalman filtered data are smoother than the measured data. In particular, the measured data change greatly, whereas the filtered data are smoother. Fig. 3 shows that the least square filter data are smoother than the Kalman filter data. But the least square filter is bad for real-time data.

B. TIME SYNCHRONIZATION AND COORDINATE TRANSFORMATION EXPERIMENT

According to *Section V.B* and *V.C*, 4 ultrasonic sensors are used for the DMSDF test, as shown in Fig. 4. After time synchronization, this paper uses the state point transformation into the Cartesian coordinate system.

1) THE a, b AND AB COMPOSITION OF THE TRIANGLE

It is assumed that the area is S_{ab}, the $\Delta abAB$ perimeter is L_{ab}, $l = 11\ m$ is the pond length, and $w = 6m$ is the pond's width. Then the following equations are obtained:

$$l_{ab} = \frac{a+b+1}{2}, \quad S_{ab} = \sqrt{l_{ab}(l_{ab}-a)(l_{ab}-b)(l_{ab}-l)}, \tag{32}$$

$$h_{ab} = \frac{2S_{ab}}{l}, \quad ab1 = \sqrt{a^2 - h_{ab}^2} = \sqrt{a^2 - \frac{4S_{ab}^2}{l^2}} \tag{33}$$

$$ab2 = \sqrt{b^2 - h_{ab}^2} = \sqrt{b^2 - \frac{4S_{ab}^2}{l^2}}$$

The coordinate value of the point O, $(ab1, h_{ab})$ or $(l - ab2, h_{ab})$, can be got.

2) THE b, c AND BC COMPOSITION OF THE TRIANGLE IS $\Delta bcBC$

Similarly, it is called that the area is S_{bc}, the $\Delta bcBC$ perimeter is I_{bc}. Then the following equations are obtained:

$$l_{bc} = \frac{b+c+w}{2}, \quad S_{bc} = \sqrt{l_{bc}(l_{bc}-b)(l_{bc}-c)(l_{bc}-w)}, \tag{34}$$

$$h_{ab} = \frac{2S_{bc}}{w}, \quad bc1 = \sqrt{b^2 - h_{bc}^2} = \sqrt{b^2 - \frac{4S_{bc}^2}{w^2}} \tag{35}$$

$$bc2 = \sqrt{c^2 - h_{ab}^2} = \sqrt{b^2 - \frac{4S_{bc}^2}{w^2}}$$

The coordinate value of the point O, $(l - h_{bc}bc1)$ or $(l - h_{bc}, w - bc2)$, can be got.

3) THE c, d AND CD COMPOSITION OF THE TRIANGLE IS $\Delta cdCD$

Similarly, it is called that the l_{cd} area is S_{cd}. The $\Delta cdCD$ perimeter is I_{cd}. Then the following equations are obtained:

$$l_{cd} = \frac{c+d+l}{2}, S_{cd} = \sqrt{l_{cd}(l_{cd}-c)(l_{cd}-d)(l_{cd}-l)}, \tag{36}$$

$$h_{cd} = \frac{2S_{cd}}{w}, cd1 = \sqrt{c^2 - h_{cd}^2} = \sqrt{c^2 - \frac{4S_{cd}^2}{l^2}} \tag{37}$$

$$cd2 = \sqrt{d^2 - h_{cd}^2} = \sqrt{b^2 - \frac{4S_{cd}^2}{l^2}}$$

The coordinate value of the point O, $(l - cd1, h_{cd})$ or $(cd2, h_{cd})$, can be got.

4) THE a, d AND AD COMPOSITION OF THE TRIANGLE IS $\Delta adAD$

Similarly, it is called that the $\Delta adAD$ area is S_{ad}, the $\Delta adAD$ perimeter is l_{ad}. Then the following equations are obtained:

$$l_{ad} = \frac{a+b+w}{2}, \quad S_{ad} = \sqrt{l_{ad}(l_{ad}-a)(l_{ad}-d)(l_{ad}-w)}, \tag{38}$$

$$h_{ad} = \frac{2S_{ad}}{w}, \quad ad1 = \sqrt{d^2 - h_{ad}^2} = \sqrt{d^2 - \frac{4S_{ad}^2}{w^2}} \tag{39}$$

$$ad2 = \sqrt{a^2 - h_{ad}^2} = \sqrt{b^2 - \frac{4S_{ad}^2}{w^2}}$$

The coordinate value of the point O,$(h_{ad}, ad2)$ or $(h_{ad}, w - ad1)$, can be got. Using time synchronization and coordinate transformation, 4 coordinate values are obtained as shown in Fig. 5, the sampling time is 1s and the sampling occurs 300 times, the coordinate transformation data and 4 track trajectories are discrete points.

Fig. 5 shows t in the case that a, d and AD composition of the trajectory has the minimum estimated error. The c, d and CD composition of trajectory has the maximum estimated error.

C. THE DMSDF TRACK FUSION EXPERIMENT

According to *Section VI* and *VI.C*, these four tracks can be fused or combined using the optimal fusion method. The algorithm is promoted to 4 signals for the integration of the track. The optimal fusion estimated variance is smaller than any other variance estimation from a single sensor. Here, it is assumed $N = 4$, the matrix W_i, i $= 1, 2, 3, 4$, and $W_1 + W_2 + W_3 + W_4 = I$, where I is a identity matrix. The optimal fusion trajectory is better than the single sensor measurement trajectory, as shown in Fig. 6.

Fig. 6 shows that the optimal fusion trajectory is smoother than the other trajectories based on single sensor data. The estimated error is small for the optimal fusion trajectory. If the signal cannot be received from an ultrasonic sensor,the optimal fusion system will know the precise location of the ship via the measured signal from the other ultrasonic sensors.

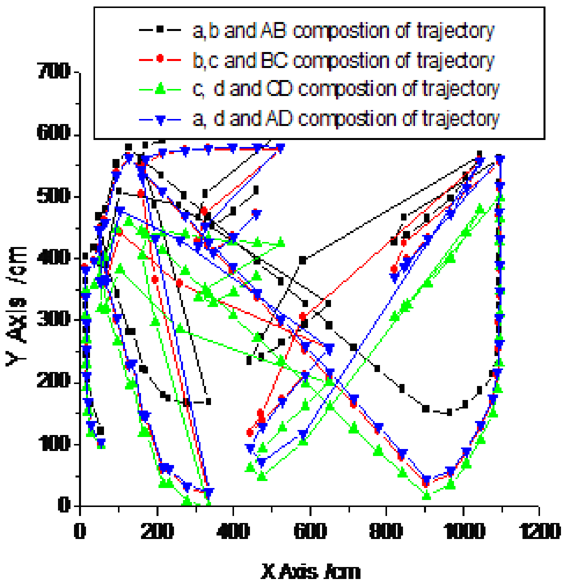

FIGURE 5. The extraction of 4 track trajectories from 4 ultrasonic sensors.

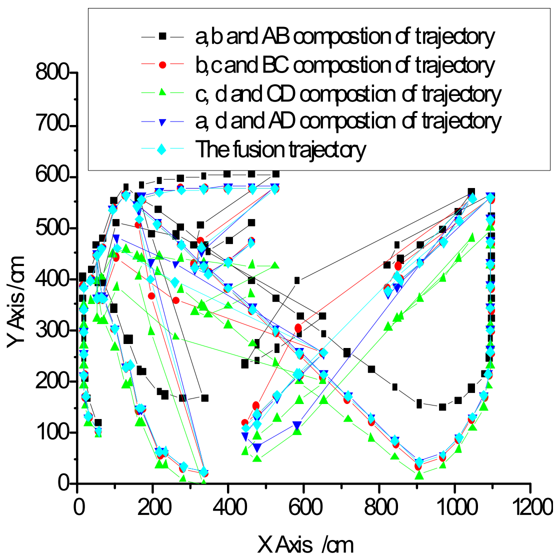

FIGURE 6. The optimal fusion trajectory.

To further demonstrate the performance of the proposed MSDF algorithm, data in 300s is sampled. The MSDF algorithm,state vector fusion [16] and truth-value are compared with experiment map, which is shown in Fig. 7.

When the ship is in the static pool and protected from the influence of wind, wave and flow, a hand-held laser ranger is used to measure distance (the accuracy is less than 1 *mm*), and the measured value is called true value. However, when the ship is influenced by wind, wave and flow conditions, the accuracy of laser ranger would be seriously affected. Usually, the laser ranger needs total reflection prism to cooperate, but the ranger used in house measures directly utilizes the reflection of smooth metope. And mainly because the distance is close, the strength of reflected signal from light is strong,

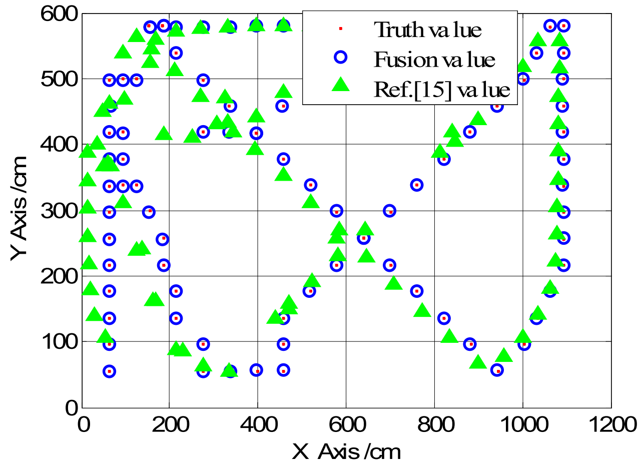

FIGURE 7. The fusion value and the truth value.

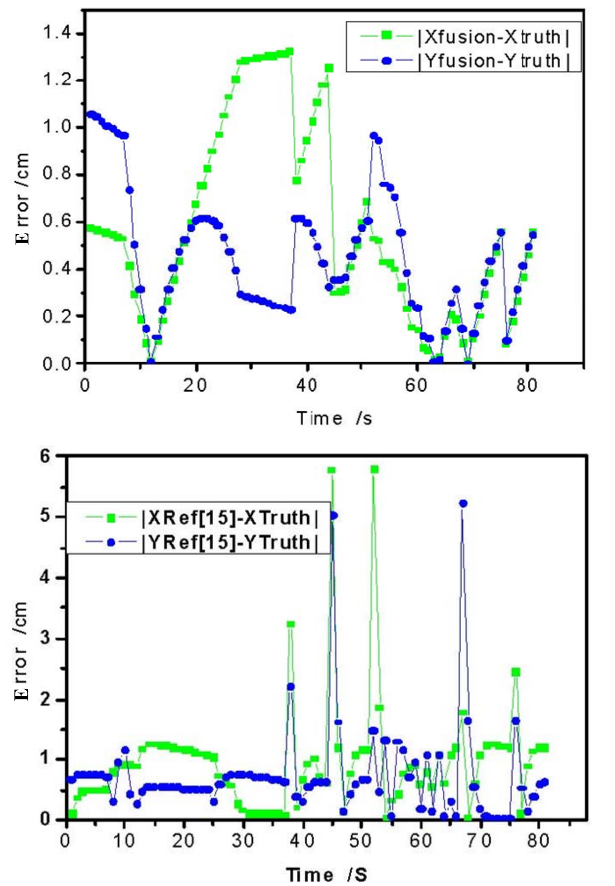

FIGURE 8. The x- and y-axis estimated error values for the optimal fusion trajectory.

meanwhile, it should be vertical. Otherwise, the return signal would be too weak to get the accurate distance [3], [42].

Fig. 7 shows that the MSDF fusion values are close to the truth values. The MSDF fusion algorithm is more accurate than the state vector fusion in [16] and [43]. According to *Section VI*, the result shows that the MSDF fusion algorithm is able to improve the precision of the data, as shown in Fig. 8.

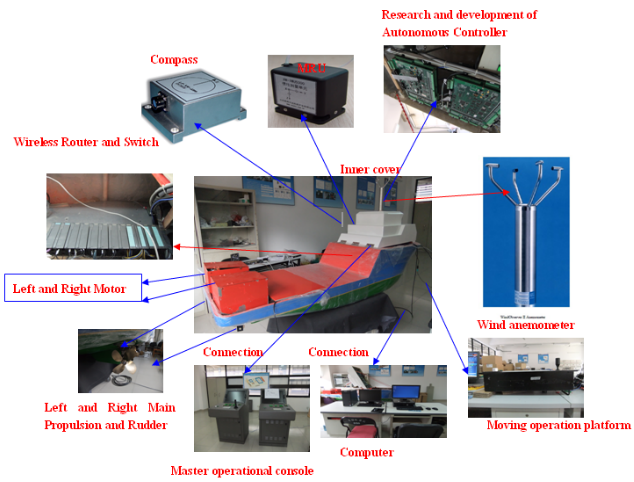

FIGURE 9. 2.8 m ship model.

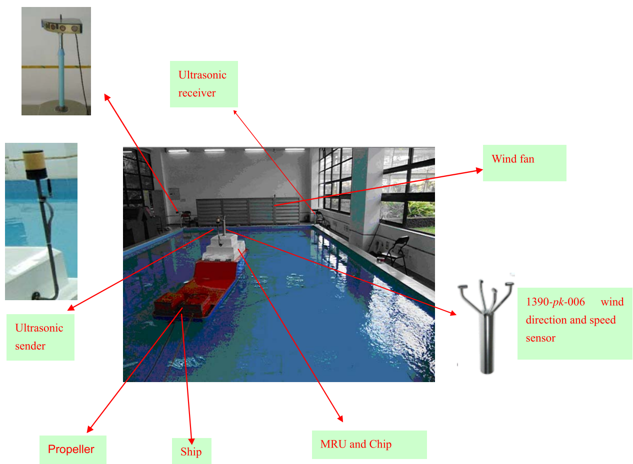

FIGURE 10. Ship's real-time positioning.

Fig. 8 shows the x- and y-axis estimated error values for the MSDF fusion trajectory. The maximum error is 1.32*cm* between the true value and the MSDF fusion value. After data fusion, the precision of the data is effectively improved. But the state vector fusion value [16] of the maximum error is 5.78*cm*.

In summary, several experiments indicate that the proposed DMSDF track fusion approach has greatly improved the target-tracking performance. Note that the performance of the data fusion is significantly affected by the dynamic positioning of the ship being tracked [2], [44], [47].

VIII. CONCLUSIONS AND FUTURE WORK

We have introduced a proposed data fusion scheme in the distributed multi-sensor environment using the optimized fusion theory. The data fusion algorithm is used to track a ship's location based on the input signals from ultrasonic sensors. The method is used to predict a ship's moving path and can be fused to provide improved track performance. It is suitable to single object indoor ships tracking with multi-sensor. The DMSDF optimized fusion theory yields the combination of information fusion theory and Kalman filtering theory in the applied indoor ships tracking. The practicality picture of ship control system is shown in *Appendix*. The DMSDF can be performed at two different processing layers. The optimized fusion trajectory x and y axis estimated maximum error value is 1.32*cm* which is between the true value and fusion value [2], [45], [47]. The DMSDF model is robust and accurate. The results imply that the DMSDF model is suitable for dealing with ultrasonic sensors systems that are suitable for indoor track ships. It has the following insights of the research work [45], [46], [48]:

- The novel scheme of target tracking with the DMSDF can be further exploited and widely applied in communication and control fields since the parallel structures can increase the input data rates and have reliability.
- The novel scheme of target tracking with the DMSDF has better accuracy than any local measurement does.
- According to the experimental condition limit, it is not necessary to consider the presence of the multi-target tracking.
- It is not considered that the centralized fusion will bring a large computational burden in the fusion center due to the high dimension computation and large data memory.

APPENDIX

2.8 m SHIP MODEL

The project of Ship Dynamic Positioning System Experiment uses scale ratio of 26: 1. And the real ship is a work ship with 75 meters electric DP2. In the laboratory, the ship model is total length of 2.8m. It's total width of 0.762 m (symmetrical, half-width 0.381 m) and the total height 0.492m (0.24m deep main influenza). It draft of 0.167m, this is the specific kind as shown in Fig.9. In order to effectively simulate the sea environment and achieve ship's real-time positioning as shown in Fig. 10. We made an indoor pool, the pool is 11m long, 6m wide, 1m deep. The ultrasonic receptor was independent developed. After plentiful experiments, we have found that we can effectively improve the positioning accuracy using multiple ultrasonic receptors. But if too many receptors were used, it would lead to much more cost. Therefore, we installed a 1m tall receptor in each angle of the pool.

REFERENCES

[1] L. Shu, J. Xiong, L. Wang, J. Niu, and Q. Wang, "Poster abstract: Studied wind sensor nodes deployment towards accurate data fusion for ship movement controlling," in *Proc. IPSN*, 2013, pp. 339–340.

[2] Y. Leunga, N.-N. Ji, and J.-H. Ma, "An integrated information fusion approach based on the theory of evidence and group decision-making," *Inf. Fusion*, vol. 14, no. 4, pp. 410–422, 2013.

[3] D. Musicki and T. L. Song, "Track initialization: Prior target velocity and acceleration moments," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 49, no. 1, pp. 665–670, Jan. 2013.

[4] I. Szottka and M. Butenuth, "Advanced particle filtering for airborne vehicle tracking in urban areas," *IEEE Geosci. Remote Sens. Lett.*, vol. 11, no. 3, pp. 686–690, Mar. 2014.

[5] S. Jabbar, A. A. Minhas, T. Rashid, and S. Rho, "Heuristic approach for stagnation free energy aware routing in wireless sensor networks," *Ad Hoc Sensor Wireless Netw.*, vol. 31, nos. 1–4, pp. 21–45, 2016.

[6] A. Mohammadi and A. Asif, "Distributed particle filter implementation with intermittent/irregular consensus convergence," *IEEE Trans. Signal Process.*, vol. 61, no. 10, pp. 2572–2587, May 2013.

[7] C.-B. Chang and J. Tabaczynski, "Application of state estimation to target tracking," *IEEE Trans. Autom. Control*, vol. 29, no. 2, pp. 98–109, Feb. 1984.

[8] E. Blasch *et al.*, "Revisiting the JDL model for information exploitation," in *Proc. 16th Int. Conf. Inf. Fusion*, Jul. 2013, pp. 129–136.

[9] M. E. Liggins *et al.*, "Distributed fusion architectures and Algorithms for target tracking," *Proc. IEEE*, vol. 85, no. 1, pp. 95–107, Jan. 1997.

[10] R. C. Luo, Y. C. Chou, and C. Ogst, "Multisensor fusion and integration: Theories, applications, and its perspectives," in *Proc. IEEE Int. Conf. Mechatronics Autom.*, Harbin, China, Aug. 2007, pp. 5–8.

[11] E. Pollard, B. Pannetier, and M. Rombaut, "Performances in multitarget tracking for convoy detection over real GMTI data," in *Proc. 13th Conf. Inf. Fusion*, Edinburgh, Scotland, Jul. 2010, pp. 26–29.

[12] J. Bleiholder and F. Naumann, "Data fusion," *ACM Comput. Surv.*, vol. 41, no. 1, 2008, Art. no. 1.

[13] M. G. Schooley and D. Thompson, "Ethernet-based integrated surveillance system for homeland security and homeland defense," *Proc. SPIE*, vol. 5403, p. 792, Sep. 2004.

[14] J. R. Raol, *Multi-Sensor Data Fusion With MATLAB*. Boca Raton, FL, USA: CRC Press, 2010.

[15] G. Girija, J. R. Raol, R. A. Raj, and S. Kashyap, "Tracking filter and multi-sensor data fusion," *Sadhana*, vol. 25, no. 2, pp. 159–167, 2000.

[16] J. A. Roecker and C. D. McGillem, "Comparison of two-sensor tracking methods based on state vector fusion and measurement fusion," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 24, no. 4, pp. 447–449, Jul. 1988.

[17] B. R. Abidi, N. R. Aragam, Y. Yao, and M. A. Abidi, "Survey and analysis of multimodal sensor planning and integration for wide area surveillance," *ACM Comput. Surv.*, vol. 41, no. 1, 2008, Art. no. 7.

[18] X. Q. Bian, M. Y. Fu, and Y. H. Wang, *Ship Dynamic Positioning*. Beijing, China: Science Press, 2011.

[19] L. J. Kang, M. Li, and J. H. Yang, "A high-precision positioning method for wireless sensor networks based on ultrasonic and TDOA," *Control Autom. Pub. Group*, vol. 4, no. 1, pp. 79–81, 2010.

[20] T.-H. S. Li, Y.-C. Yeh, J.-D. Wu, M.-Y. Hsiao, and C.-Y. Chen, "Multi-functional intelligent Autonomous parking controllers for carlike mobile robots," *IEEE Trans. Ind. Electron.*, vol. 57, no. 5, pp. 1687–1700, May 2010.

[21] S.-L. Sun, "Multi-sensor optimal fusion fixed-interval Kalman smoothers," *Inf. Fusion*, vol. 9, no. 2, pp. 293–299, 2008.

[22] X. R. Li and V. P. Jilkov, "Survey of maneuvering target tracking. Part I. Dynamic models," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 39, no. 4, pp. 1333–1364, Oct. 2003.

[23] M. Abdel-Aleem, C. C. Chibelushi, and M. Moniri, "Multisensor data fusion for the simultaneous location and condition assessment of underground water pipelines," in *Proc. Int. Conf. Netw., Sens. Control*, Delft, The Netherlands, Apr. 2011, pp. 416–421.

[24] T. I. Fossen and T. Perez, "Kalman filtering for positioning and heading control of ships and offshore rigs," *IEEE Control Syst.*, vol. 29, no. 6, pp. 32–46, Dec. 2009.

[25] X. Y. Li and J. Zhou, "Real time register of data time," *Electron. Eng. China*, vol. 33, no. 11, pp. 1–4, 2007.

[26] J.-B. Xiong, Q.-R. Wang, W.-C. Xu, B.-Y. Ye, J.-H. Zhang, and Z.-K. Li, "Online real-time data collection and filter of DPS multi-sensors based on OPC technology," *Comput. Eng. Sci.*, vol. 34, no. 11, pp. 135–140, 2012.

[27] R. C. Luo, C. C. Chang, and C. C. Lai, "Multisensor fusion and integration: Theories, applications, and its perspectives," *IEEE Sensors J.*, vol. 11, no. 12, pp. 3122–3138, Dec. 2011.

[28] W.-P. Chen, J. C. Hou, and L. Sha, "Dynamic clustering for acoustic target tracking in wireless sensor networks," *IEEE Trans. Mobile Comput.*, vol. 3, no. 3, pp. 258–271, Jul./Aug. 2004.

[29] E. F. Nakamura, A. A. F. Loureiro, and A. C. Frery, "Information fusion for wireless sensor networks: Methods, Models, and Classifications," *ACM Comput. Surv.*, vol. 39, no. 3, 2007, Art. no. 9.

[30] X. L. Jia and Y. S. Yang, *Ship Motion Mathematical Model*. Dalian, China: Dalian Maritime Univ. Press, 1997.

[31] B. Chen, W.-A. Zhang, and L. Yu, "Distributed finite-horizon fusion Kalman filtering for bandwidth and energy constrained wireless sensor networks," *IEEE Trans. Signal Process.*, vol. 62, no. 4, pp. 797–812, Feb. 2013.

[32] W. Koch, "Fixed-interval retrodiction approach to Bayesian IMM-MHT for maneuvering multiple targets," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 36, no. 1, pp. 2–14, Jan. 2000.

[33] T. L. Song, "Observability of target tracking with bearings-only measurements," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 32, no. 4, pp. 1468–1472, Oct. 1996.

[34] W. Zhang and G. Cao, "DCTC: Dynamic convoy tree-based collaboration for target tracking in sensor networks," *IEEE Trans. Wireless Commun.*, vol. 3, no. 5, pp. 1689–1701, Sep. 2004.

[35] S. S. Blackman, "Multiple hypothesis tracking for multiple target tracking," *IEEE Aerosp. Electron. Syst. Mag.*, vol. 19, no. 1, pp. 5–18, Jan. 2004.

[36] K. C. Chang, R. K. Saha, and Y. Bar-Shalom, "On optimal track-to-track fusion," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 33, no. 4, pp. 1271–1276, Oct. 1997.

[37] E. Mazor, A. Averbuch, Y. Bar-Shalom, and J. Dayan, "Interacting multiple model methods in target tracking: A survey," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 34, no. 1, pp. 103–123, Jan. 1998.

[38] Q. R. Wang, J.-B. Xiong, B.-Y. Ye, J.-Y. Deng, and N. Yang, "Blend algorithm based on adaptive Kalman filtering," *Comput. Eng. Design*, vol. 33, no. 8, pp. 3244–3250, 2012.

[39] X. J. Sun, Z. L. Deng, C. Li, and J. W. Wang, "Multi-model information fusion Kalman filtering and white noise disconsolation," *Inf. Fusion*, vol. 11, no. 2, pp. 163–173, 2010.

[40] J.-B. Xiong, Q.-R. Wang, S.-T. Cai, W.-C. Xu, B. Ye, and J. Wan, "Wind direction and speed forecasting optimization algorithm for ship based on time series and Kalman filter," *J. Converg. Inf. Technol.*, vol. 7, no. 8, pp. 424–432, 2012.

[41] J. B. Xiong, "Intelligence data fusion and its applications in ship dynamic positioning," Ph.D. dissertation, Guangdong Univ. Technol., Guangzhou, China, 2012, pp. 93–109.

[42] M. Liu, L. Wang, and R. Siegwart, "DP-fusion: A generic framework for online multi sensor recognition," in *Proc. IEEE Int. Conf. Multisensor Fusion Inf. Integr. (MFI)*, Sep. 2012, pp. 7–12.

[43] F. Pomerleau, S. Magnenat, F. Colas, M. Liu, and R. Siegwart, "Tracking a depth camera: Parameter exploration for fast ICP," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst. (IROS)*, Sep. 2011, pp. 3824–3829.

[44] G. Dogan, "A survey of provenance in wireless sensor networks," *Ad Hoc Sensor Wireless Netw.*, vol. 31, nos. 1–4, pp. 173–197, 2016.

[45] M. Isard and A. Blake, "CONDENSATION—Conditional density propagation for visual tracking," *Int. J. Comput. Vis.*, vol. 29, no. 1, pp. 5–28, 1998.

[46] D. Tao, L. Jin, Y. Wang, and X. Li, "Rank preserving discriminant analysis for human behavior recognition on wireless sensor networks," *IEEE Trans. Ind. Informat.*, vol. 10, no. 1, pp. 813–823, Feb. 2014.

[47] M.-Y. Chen and J.-S. Lu, "High-precision motion control for a linear permanent magnet iron core synchronous motor drive in position platform," *IEEE Trans. Ind. Informat.*, vol. 10, no. 1, pp. 99–108, Feb. 2014.

[48] N. Marchenko, T. Andre, G. Brandner, W. Masood, and C. Bettstetter, "An experimental study of selective cooperative relaying in industrial wireless sensor networks," *IEEE Trans. Ind. Informat.*, vol. 10, no. 3, pp. 1806–1816, Aug. 2014.

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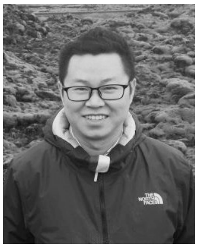

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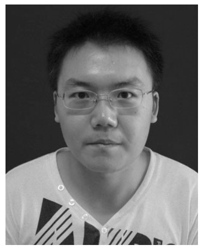

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