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Kalman filtering approach to maritime targets tracking

SUMMARY

The paper presents a solution to the maritime target tracking problem based on 2D radar data. The characteristics of ship movements in a cluttered environment imply the application of complex filtering techniques to achieve a high accuracy estimation of motion parameters. An implementation of tracking procedures based on adaptive interactive multiple model (IMM) algorithms is considered to maintain moving-target tracks. A study of the IMM procedure filter is performed and illustrated by a simulated example of maritime target tracking.

INTRODUCTION

Rapid development of sea transport makes it necessary to improve the knowledge of movements of maritime objects. Sophisticated navigating and maneuvering techniques must be applied to ensure safety of sailing in difficult conditions such as low visibility and neighborhood of other ships or harbor devices. This implies increasing demands for coastal survey and collision avoidance (ARPA) systems. Such systems work out the information on a current sea situation based on measurements (plots) supplied by radars, which are often the only sources of data.

Tracking algorithms are an important part of these systems. The tracking task mainly involves estimating real-time motion parameters of the targets observed by the radar. As certain inaccuracies in radar measurements and false plots exist, the target motion dynamics and radar data are considered under the theory of the optimal filtering of stochastic processes and therefore complex filtering techniques are applied. Many solutions were proposed for tracking targets [1]. They concern three problems : track formation, plot-track correlation (to minimize the influence of disturbances) and track updating (precise evaluation of motion parameters for maneuvering and non-maneuvering targets). Development of modern technology, especially of the computational power, enables implementation of the solutions which combine an acceptable performance with a reasonable complexity.

In this paper the main principles of tracking systems are presented. A theoretical discourse is illustrated by simulation of a tracking process in one of the test settings proposed by the International Maritime Organisation (IMO).

TRACKING ALGORITHM CHARACTERISTICS

In radar systems the data on targets is provided in the form of plots which define the target location in polar co-ordinates. Tracking algorithms are designed for an appropriate processing of plots and for maintenance of the tracks which describe a target motion trajectory.

Periodic inflow of radar data, implied by the antenna scan period and real-time processing requirements, results in a specific scheme of the tracking algorithm. An essential computational cycle of such algorithm includes the following functions [1] :

- data acquisition – assignment of the received plots and processed tracks to appropriate azimuthal sectors
- plot-to-track correlation (association) – combinatorial linking of current plots to guided tracks
- track updating (filtering) – estimation of an observed-target state vector
- track initiation – generation of new tracks that appeared in the radar coverage.

DATA ACQUISITION

The controlled airspace is divided into equal azimuthal sectors (additionally divided into semisectors, i.e. halves of sectors) which consist of segments (Fig.1) used for the plot and track processing : association, initiation and updating of tracks. This division arises from the principles of sequential radar data receiving and effective data processing. Track and plot semisectors are offset by one semisector to avoid boundary errors in a correlation procedure (Fig.2).

There are three kinds of data structures in the system, which describe the individually processed plots and tracks and enable effective data management :

- directories including identifiers for all the tracks and plots available
- distribution indices marking the assignment of tracks and plots to individual segments (according to the tracks and plots positions)
- plots and tracks databases for all the descriptions of tracks and plots.

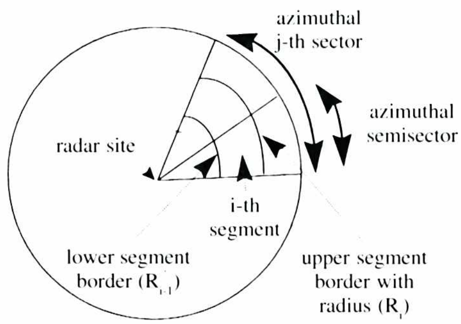

***Fig. 1.** Sector-segment division of the controlled airspace*

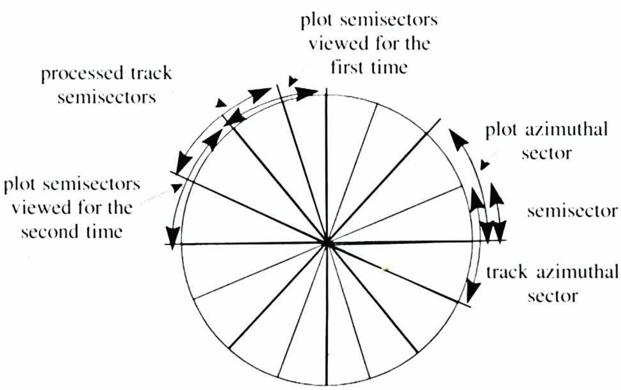

***Fig. 2.** Azimuthal sectors*

PLOT-TO-TRACK CORRELATION

A correlation procedure consists in joining the best-fitted plots to the existing tracks as a result of scanning segments for plots and tracks in an elementary cycle of data processing. As the correlation procedure concerns two track semisectors and four plot semisectors from their neighborhood (the two inner plot semisectors overlap the two track semisectors as shown in Fig.2), all the plot semisectors are explored twice. An ellipsoid area called a correlation gate, is created around each predicted track position (determined in virtue of a previous scan). The size of this gate depends on a covariance matrix of a corresponding innovation process [1] and on an evaluation of a target motion characteristics (maneuvering or non-maneuvering). All the plots located in the gate are paired with the track resulting in a set of pairs. Each pair can be characterized by a value of an association quality, or a „statistical" distance, which serves as a criterion of correlation between plots and tracks that is used for ordering the sets of preliminarily associated pairs. Such criterion makes it necessary to analyze groups of tracks and plots mutually correlated because a track can pass through a cluttered region or several targets can be located in the same neighborhood.

Most correlation techniques apply combinatorial methods of assortment that are based on a proper decomposition of data sets (lists of plots and tracks) resulting from the sector-segment division.

All the single tracks are one by one analyzed (by exploring a list of their correlated plots) until every track is associated with one plot at most.

TRACK UPDATING

A successfully finished correlation process makes a basis for performing a procedure of tracks updating which consists in calculation of current and predicted parameters of the observed targets. Estimation of target's parameters (location, velocity, acceleration) is performed by adaptive Kalman filtering based on a suitable state-space description.

The principle of optimality of a Kalman filter which produces unbiased minimum variance estimates of real motion parameters is conditioned both by the consistency of the signal object model (involved in the filter equations) with the observed target and by the knowledge of covariance characteristics of measurement noise processes.

In this study tracking of the sea targets, which have complex and generally unknown dynamics, is taken into consideration. This implies an adaptive method of state estimation, performed by processing the data relative to multiple target models which correspond to different types of motion. In practice an Interactive Multiple Model (IMM) algorithm is used [2] with two kinematics models describing non-maneuvering and maneuvering types of motion.

The basic idea behind this estimation scheme is to compose a current average value of a conditioned state estimate by a linear combination of the partial estimates obtained from individual estimation filters. The weighting coefficients in such estimation are *a posteriori* probabilities of selecting the considered estimation filters.

To determine the partial estimates and the *a posteriori* probabilities it is necessary to reduce the number of the statistical hypotheses concerning the assumption on the motion types in each estimation cycle. In the IMM method a suitably parameterized Markov process is applied that describes inter-model transitions accomplishing with given transition probabilities. The IMM algorithm guarantees mutual exchange of information, which affects the component (partial) estimates in each calculation cycle. In particular the interaction of estimators is performed by a reinitialization procedure prior to the predictive stage in the Kalman filter procedure. Both the reinitialization of the partial estimates based on the previously obtained, model-conditioned estimates and the calculation of the probabilities of the events that the particular model is valid are performed at each cycle of estimation.

For the target motion equations described in the Cartesian co-ordinates and the following state variables :

x – location co-ordinate along x-axis
y – location co-ordinate along y-axis
v_x – velocity co-ordinate along x-axis
v_y – velocity co-ordinate along y-axis
a_x – acceleration co-ordinate along x-axis
a_y – acceleration co-ordinate along y-axis

the estimated state vector can be defined at the discrete time k as :

$$\mathbf{x}(k) = [x(k)\ v_x(k)\ a_x(k)\ y(k)\ v_y(k)\ a_y(k)]^T \qquad (1)$$

With a given set of M signal models of a moving target (M=2 shall be used here), let $\hat{x}_i(k \mid k)$, i=1,2, denote an *a posteriori* partial estimate obtained in the k-th estimation cycle of the i-th filter. This estimate is an optimum measurement-conditioned state estimate: $\hat{x}_i(k \mid k) = E[\mathbf{x}(k) \mid Z(k)]$, where Z(k) denotes a set of measurements up to the k-th moment of discrete time. In the considered IMM algorithm the prediction stage is not based on the *a posteriori* (partial) estimate $\hat{x}_i(k-1 \mid k-1)$ (like in the classical KF filtering scheme [1]), but on a corrected estimate $\hat{x}_i^0(k-1 \mid k-1)$ that reinitializes the i-th filter :

$$\hat{x}_i^0(k-1 \mid k-1) = E[\mathbf{x}(k-1) \mid M_i(k), Z(k-1)] \qquad (2)$$

$$i = 1,2$$

where $M_i(k)$ denotes the event that in the normalized time range <k-1,k) the target state evolves according to the i-th signal model (i=1,2).

Because for i, j=1,2

$$\hat{x}_i^0(k-1|k-1) = \\ = \sum_j \hat{x}_i(k-1|k-1)P[M_j(k-1)|M_i(k),Z(k-1)] \tag{3}$$

the estimate $\hat{x}_i^0(k-1|k-1)$ accumulates the *a posteriori* partial estimates appropriately weighted by the conditional probabilities of the originating event $M_j(k-1)$ under the given resulting event $M_i(k)$, i=1,2. The quality of the estimate can be characterized by an appropriate covariance matrix $\hat{P}_i^0(k-1|k-1)$.

The initializing partial estimate $\hat{x}_i^0(k|k-1)$ is calculated by means of the model state transition matrix. This quantity and the resulting current value of the innovation process :

$$\hat{z}_i(k) = z(k) - h(\hat{x}_i^0(k|k-1)) \tag{4}$$
$$i = 1,2$$

where z(k) denotes a current measurement vector and h stands for an operator of projection of the state vector into the measurement space, along with its covariance matrix are applied in the next estimation stage called the measurement correction, during which the following quantities are computed : the estimate $\hat{x}_i(k|k)$, its covariance matrix $\hat{P}_i(k|k)$ and the *a posteriori* probability $P[M_i(k) | Z(k)]$, i=1,2, that at the time k the i-th model has been valid. The *a posteriori* estimates together with their probabilistic characteristics serve for calculation of the composed estimate $\hat{x}(k|k)$ of our ultimate interest :

$$\hat{x}(k|k) = \sum_i \hat{x}_i(k|k)P[M_i(k)|Z(k)] \tag{5}$$
$$i = 1,2$$

The predictive stage of the estimation process requires to evaluate the *a priori* probabilities $P[M_i(k+1)|Z(k)]$ of the given model selection at the time k+1:

$$P[M_i(k+1)|Z(k)] = \sum_j P_{ji} P[M_j(k)|Z(k)] \tag{6}$$
$$i, j = 1,2$$

where the transition probabilities

$$P_{ji} = P[M_i(k)|M_j(k-1), Z(k-1)] \tag{7}$$
$$i, j = 1,2$$

are used that define the probability of switching from the j-th model describing the target at the time k-1 to the i-th model at the time k. These probabilities are the elements of Markov process transition matrix.

With equation (3) updated to the k-th moment, the estimates $\hat{x}_i^0(k|k)$ and $\hat{x}_i^0(k+1|k)$ are computed and next the *a priori* estimate :

$$\hat{x}(k+1|k) = \sum_j \hat{x}_i^0(k+1|k)P[M_i(k+1)|Z(k)] \tag{8}$$

is evaluated for the use in the plot-to-track correlation procedure. The covariance matrices $\hat{P}_i^0(k|k)$, $\hat{P}_i^0(k+1|k)$, and $\hat{P}_i(k+1|k)$ undergo a similar updating procedure.

As all the measurements are given in polar co-ordinates, either the observation process is transformed and linearized before using the classical Kalman filtering [3] or an extended Kalman filter is implemented.

The whole filtering scheme for the two interacting models is presented in Fig.3.

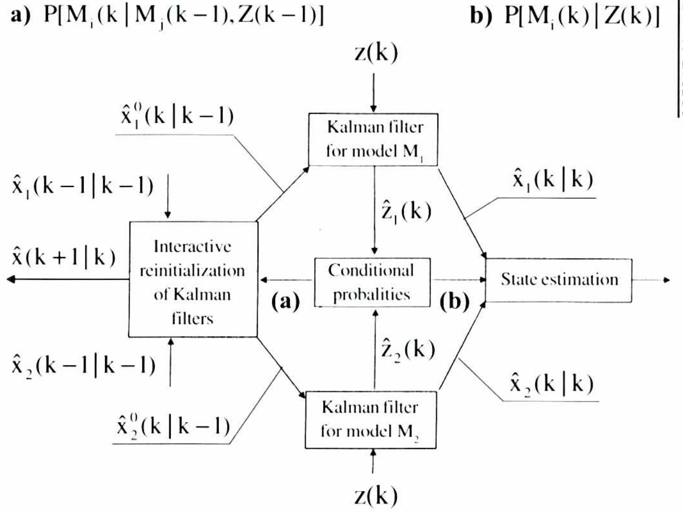

Fig.3. Interactive Multiple Model state estimation scheme

TRACK INITIATION

The appearance of new targets in the radar coverage is followed by an automatic procedure of track initiation in which the unassociated plots (from several consecutive scans) are processed that were left after the correlation procedure. It is clear that a new track should be initiated shortly after a true target has entered the area of radar observation. Such procedure, however, should not initiate false tracks due to false plots invoked by clutter or interference. The character of maritime target's motion (low velocities), a relatively short antenna revolution period, and measurement uncertainties make it difficult to detect an assumed constant velocity motion even though the target moves along a straight line.

There are certain complex solutions [4] but in this paper only a simple initiation logic is considered that creates a new track if the plots from the last three scans adhere to the constant movement hypothesis. This approach minimizes the system response time defined as the time between the instant at which a target appears in the radar coverage and the instant at which a track for that target is initiated.

Another fundamental problem concerns a method of exploring the unassociated plots. It is assumed that for each new plot an initialization criterion is verified sequentially until the first success as it is necessary to limit the number of possible plot-to-track correlations to gain the greatest effectiveness of the testing process. Thus the initiation logic does not consider any global optimization effect.

The formed track represents the simplest model referring to a straight-line motion at a constant velocity.

SIMULATION RESULTS

The results of the performance of the presented tracking algorithms are referred to certain IMO requirements related to the ARPA systems, installed on sea-going vessels to enable the avoidance of collisions. In this preliminary study the condition of tracking from a moving ship has not been considered. Nevertheless, all required standard quantities have been taken into account in spite of the fact that steady point of radar location has been simulated.

A plot generating procedure has performed a quasi-radar observation of a target moving along a given trajectory. This has been practically simulated by appropriate sampling of the accurate trajectory and disturbing it with a gaussian white sequence.

There are four scenarios (for a single target moving at a constant velocity along straight lines of different courses and velocities) defined in the IMO resolution. The presented IMM-based tracking system has been examined for those scenarios, the second one of which is illustrated in Fig.4.

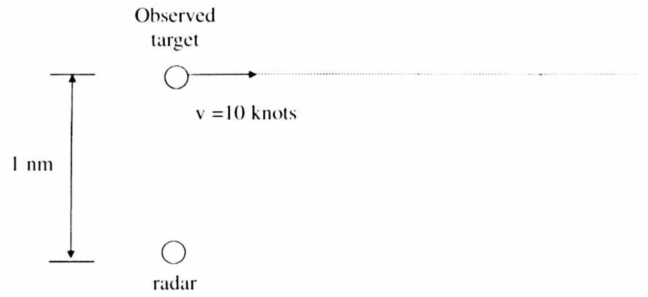

Fig.4. The second IMO scenario

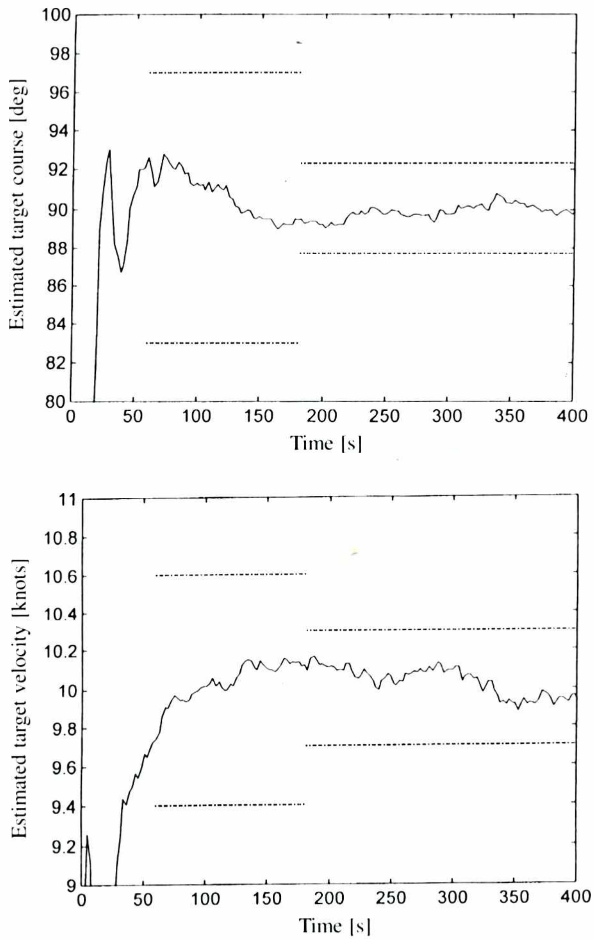

Fig.5. Estimation of target course and velocity

The IMO resolution states the accuracy of the movement parameters (the target's course and velocity) that the tracking system has to gain after the first and the third minute from the time of track formation. The values of these parameters are, in general, determined relative to the course and velocity of the monitoring ship. Thus in our experiment with the steady point of the radar location all of the movement parameters are given in absolute terms.

Some results of the target tracking procedure at the sampling period τ=2s during the IMO scenario are presented in Fig.5, where the measurement errors were modeled by a Gaussian white sequence of zero mean value and the following variances: $(33m)^2$ in range and $(0.16^{o})^2$ in azimuth. The two charts show the estimated course and velocity of the target. Both quantities were computed by means of the estimates of v_x and v_y of the state vector (1). The horizontal lines denote the admissible error ranges (defined by IMO) for course and velocity estimates.

In order to present other capabilities of the tracking algorithm, an estimated trajectory of a maritime target maneuvering at a linear velocity of 12 knots and centripetal acceleration of 0.05g turning right by 90 degrees angle has also been experimented, as shown in Fig.6.

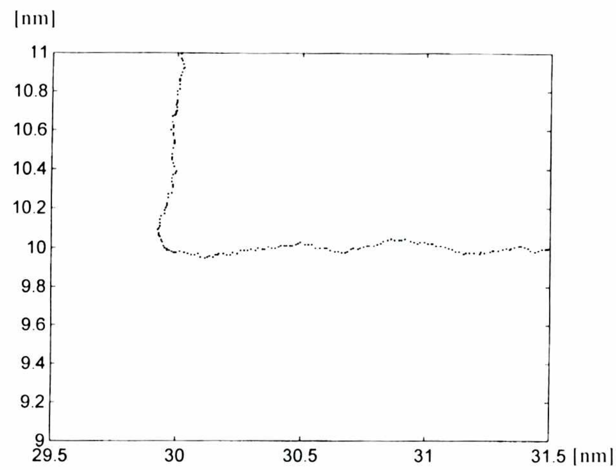

Fig.6. Estimated trajectory of a maritime target maneuvering

Another kind of correctness test consists in comparing the internal Kalman filter estimation errors and the „true" root-mean-square errors computed from the estimated state co-ordinates x, y, v_x, v_y obtained during N=10 runs :

$$\mathrm{rmse}(x_l) = \sqrt{\frac{1}{N}\sum_{k=1}^{N}\left(x_l(k) - \hat{x}_l(k)\right)^2} \tag{9}$$

where x_l is the exact value of l-th co-ordinate of **x** (x, y, v_x and v_y). Each respective theoretical dispersion of x_l is calculated as root of the corresponding element P_{ll} of the *a posteriori* covariance matrix **P** of the state vector estimated within the Kalman filter. Results of the correctness test are presented in Table.

Tab. Evaluation of IMM filter credibility for 10 different trajectories, where x_e=rmse(x), etc.

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
x_e	0.0042	0.0062	0.0037	0.0037	0.0047	0.0050	0.0061	0.0055	0.0060	0.0073
$\sqrt{P_{11}}$	0.0079	0.0079	0.0079	0.0079	0.0079	0.0079	0.0079	0.0079	0.0079	0.0079
y_e	0.0032	0.0047	0.0033	0.0033	0.0049	0.0034	0.0037	0.0028	0.0033	0.0030
$\sqrt{P_{44}}$	0.0079	0.0079	0.0079	0.0079	0.0079	0.0079	0.0079	0.0079	0.0079	0.0079
v_{xe}	0.1165	0.1510	0.1061	0.1061	0.1098	0.1458	0.1791	0.1659	0.1456	0.1706
$\sqrt{P_{22}}$	0.3729	0.3729	0.3729	0.3729	0.3729	0.3729	0.3729	0.3729	0.3729	0.3729
v_{ye}	0.0819	0.1347	0.1044	0.1044	0.1116	0.1053	0.1114	0.0975	0.1004	0.0856
$\sqrt{P_{55}}$	0.4348	0.4348	0.4348	0.4348	0.4349	0.4348	0.4348	0.4348	0.4348	0.4347

CONCLUSIONS

- The results obtained by the IMM algorithm (Fig.5) apparently comply with the IMO requirements.
- The estimates (Tab.) obtained by means of the two interacting Kalman filters (FK) are even more precise than one could expect from their FK estimations. It confirms an appropriateness of the filtering method though one could expect a better consistency of the velocity error estimates. This effect can be justified by the contribution of the filter (matched with the maneuvering target model) to the estimated compound state vector (1) during the constant-velocity, straight line motion. In such case to utilize a single Kalman filter would be optimum. Due to the IMM approach, by combining the results of the two FK one obtains the observed ability of tracking a maneuvering ship (Fig.6) at the cost of slightly worse quality of the estimates.
- The simulation results approve at least a prospective usability of the described IMM-based estimation algorithms though a more reliable evaluation of the presented solution for the maritime targets tracking can only be achieved with the use of real radar data.

Appraised by Józef Lisowski, Prof.,D.Sc.

NOMENCLATURE

ARPA	-	Automatic Radar Plotting Aids
E	-	operator of probabilistic expectation
h (k)	-	operation of projection of the state vector into the measurement space
M	-	number of models
M_i	-	i-th model of vessel's movement
N	-	number of runs used in a simulation experiment
P	-	a-posteriori covariance matrix of the estimated vector x
P[A|B]	-	probality of event A conditioned by event B
rmse	-	root mean square error
x	-	state vector
$\hat{x}$	-	estimated value of quantity x
z (k)	-	current measurement vector
Z (k)	-	set of measurements up to the current time

Indices

e	-	indicator of taking rmse
i, j	-	model indices
k	-	time index
° (upper)	-	initial value of a vector
^ (upper)	-	symbol of an estimated value

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Conference

NAV 2000

From 19 to 22 September 2000 the International Conference on Ship and Shipping Research was held in Venice (Italy).

During the session on **Safety and Hydroelasticity** the paper titled :

Assessment of safety in damage condition for a ship with novel arrangement of internal spaces

was presented by Mirosław Gerigk, D.Sc. from Technical University of Gdańsk

Conferences

STAB 2000

From 7 to 11February 2000 Launceston in Tasmania hosted

7th International Conference on the Stability of Ships and Ocean Vehickles

In the conference Polish scientific circles were represented by two researchers from Technical University of Gdańsk who read the following papers during the session on **Stability Standards** :

- *Stability standards - future outlook* - by Lech Kobyliński, Prof., D.Sc.
- *An integrated method for ship safety estimation for design computation model* - by Mirosław Gerigk, D.Sc.

SAFETY AT SEA

From 6 to 8 September this year II International Conference on SAFE NAVIGATION BEYOND 2000 was held within the scope of the BALTEXPO 2000 maritime fair, which was organized by Navigation Faculty, Gdynia Maritime Academy.

Experts from 3 Italian, 2 Russian, 1 Australian , 1 Kroatian universities and 1 Kroatian shipyard as well as from Bureau Veritas participated in the conference, apart from representatives of 7 Polish universities and scientific research centres inclusive of the host, Gdynia Maritime Academy.

The conference was started with 2 papers presented during the plenary session :

- *A Safety Management System for the Ports* – by A.M. Chauvel (Bureau Veritas)
- *Shipping Safety Strategies and Management in the European Union* – by J. Kubicki (Gdynia Maritime Academy)

The remaining 24 papers presented within the scope of 7 topic sessions were devoted to the following problems :

- Economic and legal aspects of the shipping and marine technologies
- Application of the new mathematical tools to improvement of navigation and ship operation
- Design and rules of classification of the seagoing vessels and marine equipment
- Port management and marine environment protection
- Marine communications
- Risk-based approach to safe ship operation
- Lifesaving appliances.

In preparation of the conference papers 22 Polish authors and 11 from abroad were engaged.

Worth mentioning is very efficient organization of the conference, opportunity of visiting the BALTEXPO 2000 in Gdańsk and taking part in a social party ending the conference.