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Mobile Robot Localization Based on Multi-Sensor Model for Assistance to Displacement of People with Reduce Mobility

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***Abstract* —This paper deals multi-sensor data fusion problem for mobile robot localization. In this context, we have used data fusion sensors: encoders and ultrasonic sensor. To improve the robustness of localization and to reduce the estimation error we have proposed a Kalman Particle Kernel Filter (KPKF) approach, which is based on a hybrid Bayesian filter, combining both extended Kalman and particle filters. The KPKF filter using a Gaussian mixture in which each component has a small covariance matrix. The Kalman correction updates the weights in order to bring particles back into the most probable space area. This method can be applied for non-linear and multimodal environment and can improve localization performances and reduced estimation error. The proposed approach is implemented on a LIASD-Wheelchair experimental platform.**

Keywords—Localization; multi-sensor; data fusion; mobile robotics; Kalman filter; particle filter; smart wheelchair.

I. INTRODUCTION

Several works have been undertaken to assists and help the handicapped and elderly people to gain mobility and lead to independent life and particularly those concerning the development of services related to automated wheelchairs. Make a wheelchair intelligent and autonomous, allows us to develop new methodologies taking into account the type of handicap, environment dynamics, new communication technologies such as sensor networks and wireless mesh networks and so on. In this direction, localization process is one of the main services that have been prospected in order to ensure assisted people a better mobility and assistance in their life [1], [2]. It constitutes a key problem in mobile robotics and it consists of estimating the robot's pose (position, orientation) with respect to its environment from sensor data, and the simplest way is integrating of odometric data which, however, is associated with unbounded errors, resulting from uneven floors, wheel slippage, limited resolution of encoders, etc [3], [4]. However, such a technique is not reliable due to cumulative errors occurring over longer runs. Therefore, a mobile robot must be able to localize or estimate its parameters also with respect to an internal world model by using the information obtained with its exteroceptive sensing system [5].

The use of sensory data from a range of disparate multiple sensors, is to automatically extract the maximum amount of information possible about the sensed environment under all operating conditions [6], [7]. The main idea of data fusion methods is to provide a reliable estimation of robot's pose, taking into account the advantages of the different sensors [8].

This paper focuses on robust pose estimation for mobile robot localization. A new hybrid Particle filter method called Kalman-Particle Kernel Filter (KPKF) is proposed to minimize the system estimation error and increase the localization robustness. It's organized as follows: In section II we present and discuss some multi-sensor data fusion methods. In section III, a proposed KPKF is presented. In section IV, an example of a localization process applied on the LIASD-Wheelchair is illustrated. Finally, in section V, conclusion and some perspectives are addressed.

II. RELATED WORKS

The Kalman Filter (KF) is the best known and most widely applied parameter and state estimation algorithm in data fusion methods [9], [10]. It can be considered as a prediction-update formulation. The algorithm uses a predefined linear model of the system to predict the state at the next time step [11], [12]. The prediction and update are combined using the Kalman gain, which is computed to minimize the mean square error of the state estimate. The KF diagram is illustrated in Fig.1.

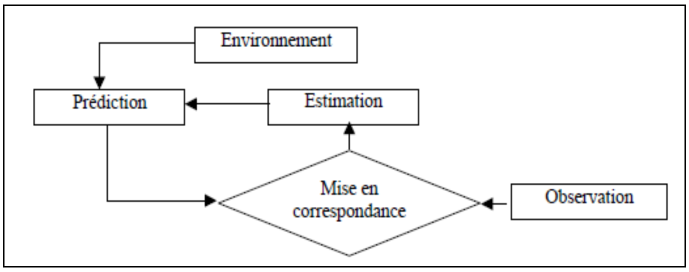

Fig. 1. Kalman filter diagram (KF).

Extended Kalman Filter (EKF) is a new version of KF that can handle non-linear measurement equations. Various EKF based-approaches have been developed. These approaches work well as long as the used information can be described by simple statistics well enough. The lack of relevant information is compensated by the use of various processes models [13]. However, they require assumptions about parameters, which might be very difficult to determine. Assumptions that guarantee optimum convergence are often violated and, therefore, the process is not optimal or it can even converge. The Kalman filter techniques rely on approximated filter, which requires tuning of modelling parameters, such as covariance matrices, in order to deal with model approximations and bias on the predicted pose. In order to compensate such error sources, local iterations, adaptive models and covariance intersection filtering have been proposed [14]. An interesting approach solution was proposed in [15], where observation of the pose corrections is used for updating of the covariance matrices. However, this approach seems to be vulnerable to significant geometric inconsistencies of the world models, since inconsistent information can influence the estimated covariance matrices.

In the localization problem is often formulated by using a unique model, from both state and observation processes point of view. Such an approach, introduces inevitably modelling errors, which degrade filtering performances, particularly, when signal-to-noise ratio is low and noise variances have been poor estimated. Moreover, to optimize the observation process, it is important to characterize each external sensor not only from statistic parameters estimation point of view but also from robustness of observation process point of view [16]. It is then interesting to introduce an adequate model for each observation area in order to reject unreliable readings. In the same manner, a wrong observation leads to a wrong estimation of the state vector and consequently degrades localization algorithm performance.

Particle Filter (PF) based-methods are considered as a sequential version of the Monte Carlo methods [17]. They represent the most effective methods for nonlinear localization of mobile systems. These methods have the ability to manage a set of particles in order to determine positions, and orientations. The principle of PF is to make the particles evolving in the same way as the robot to determine new positions and then comparing its perceptions to those of the particles. We retrieve the model values odometry (prediction) between two successive moments then transmitted to the filter function for correction by the observation model. After a small number of iterations, this process converges into a position where a population of particles is very dense. The PF method is illustrated in Fig. 2.

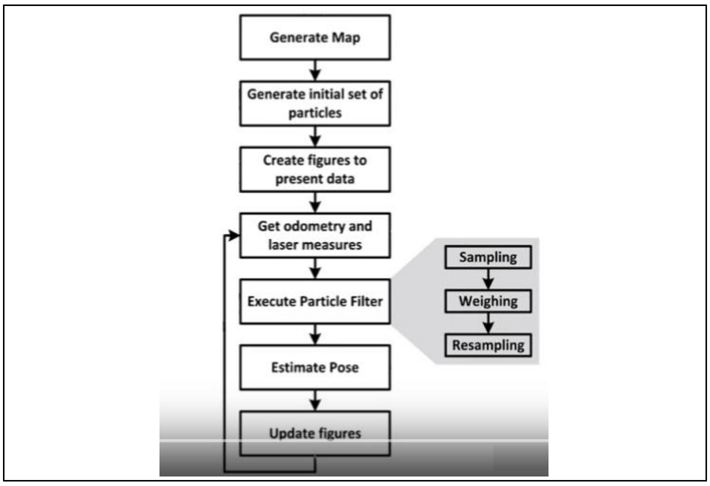

Fig. 2. Particle filter diagram (PF).

However, this filter can be very costly to implement, as a very large number of particles is usually needed, especially in high dimensional system. In case of low dynamical noise, we observe that in multiplying the high weighted particles, the prediction step will explore poorly the state space. The particle clouds will concentrate on few points of the state space. This phenomenon is called particle degeneracy, and causes the divergence of the filter.

Despite the research efforts to improve filters performance for data fusion, their behaviors remain unstable for some applications such as navigation and localization

III. PROPOSED KPKF FOR MULTI-SENSOR DATA FUSION

The Kalman-Particle Kernel Filter (KPKF) combines both an EKF and a PF for a robust localization system by adjusting the state of mobile system and reducing the estimation error. This new filter is a kind of hybrid particle filter. It is based on the representation of the kernel of conditional density and on a local linearization as a Gaussian mixture [18]. The KPKF filter method can be implemened according to three steps, as it is shown in Figure 3:

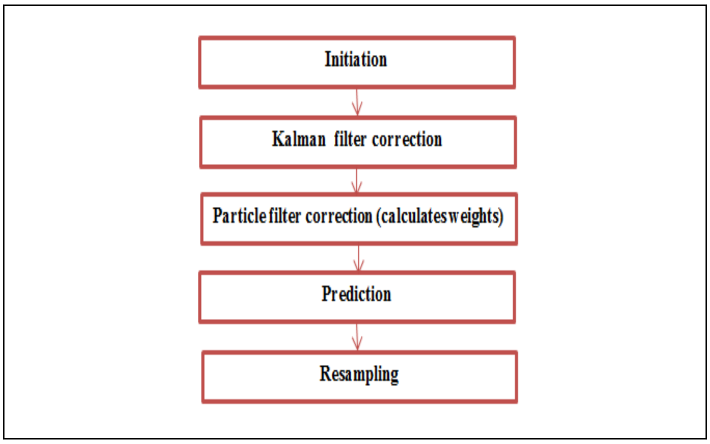

Fig. 3. Kalman-Particle Kernel Filter diagram.

- **Correction step**: is divided into two steps: a Kalman correction and a particle correction. The correction step ensures a mixture of Gaussian distribution of the filter density in order to increase the probability of the presence of the particles in the state space.
- **Prediction step:** therefore, this step is still a mixture of Gaussian distribution. In fact, the predicted density is modeled in the same way as the corrected density.
- **Resampling step**: is introduced to further reduce the divergence of the particulate filter (Monte Carlo).

IV. Implementation

We present an application of the Kalman-Particle Kernel Filter (KPKF) approach for a robust localization adapted to disabled and elderly people. Our approach is implemented and tested on a prototype called LIASD-Smart Wheelchair, developed in our laboratory (Informatics and Artificial Intelligence) [19]. The LIASD-Smart Wheelchair is equipped with data fusion sensors: ultrasonic sensor and, encoders.

LIASD-Wheelchair is an adjustable adults' powered wheelchair (Fig. 4). It is suitable for indoor or outdoor use and implements wired and wireless networks for communication. The wireless communication is based on two standards: IEEE 802.11 and IEEE 802.15.4. A wireless router is integrated to ensure communication between remote computer (server) and wheelchair devices (camera, embedded computer, etc.).

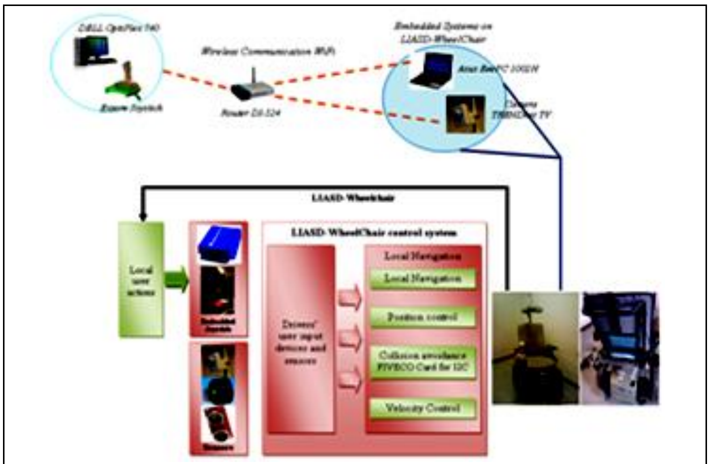

Fig. 4. Global structure of LIASD-WheelChair.

A. *Hardware Architecture*

The hardware architecture of LIASD-Wheelchair consists of sensory block, control architecture, and communication networks. The presented system includes two optical incremental encoders mounted to a motor, with resolution of 500 Counts per Revolution. Four ultrasonic sensors (US SFR08) are used to localize the wheelchair in the environment. They have a resolution of 3cm and can identify obstacles between 3cm and 6m. The US sensors interact with the computer via TCP/IP server board *FMod-TCP DB* using an I2C interface. In order to ensure navigation and anti-collision objectives a Wireless Internet Camera Server is mounted on the wheelchair headrest.

B. *Control Architecture*

The LIASD-WheelChair control architecture is divided into three levels: a basic control level, a tactical level and strategy level, as shown in Fig. 5. The strategy level concerns the way the wheelchair system can achieve the main goal. Algorithms such as planning trajectories, localization, etc. are implemented to fulfill the desired task. Elementary actions are, then generated in tactical level aiming to satisfy reached goals specified previously. Basic control level implements PID controller in the PWM/encoders boards with specific parameters for positions and speeds control.

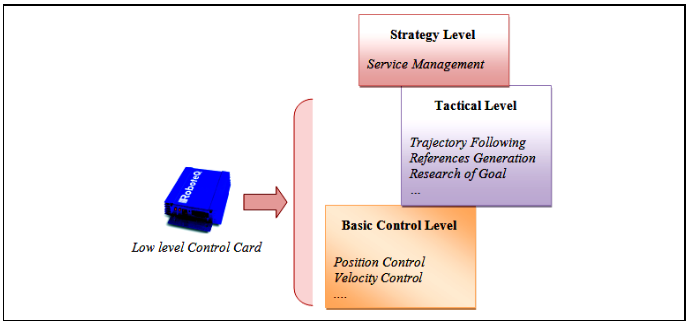

Fig. 5. LIASD-WheelChair control architecture.

Using its measurements and the characteristics of the geometrical model of the dynamic system, we determine at each moment the position and the orientation of the smart wheelchair. The odometry model introduces a major fault of the slipping of the rounds (noise of measurement) An unreliable location. To correct the odometry error, we use the data fusion theoretical method by adding the measurement of the ultrasonic sensor (observation model).

V. Conclusion and Future Works

The localization system is a complex multi-sensor process. To solve the problem of multimodality and non-linearity, we have proposed a new adaptation filter for data fusion, called Kalman-Particle Kernel Filter. The KPKF is a mixture of extended Kalman filter and particulate filter combining the advantages of both filters. Our approach is implemented on a mobile platform developed in our laboratory called LIASD Smart Wheelchair. The aim is to improve the quality of service in terms of mobility and assistance to displacement of persons with disabilities. A full test of our system is still in progress to demonstrate that our filtering approach is very effective for the robustness of system localization. Therefore, this method could use the research work that deals with the issue of the localization and navigation of stand-alone vehicles.

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