

Tire Force Estimation for a Passenger Vehicle with the Unscented Kalman Filter

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Abstract—A robust method to estimate tire forces for a passenger vehicle with the Unscented Kalman Filter (UKF) is provided. Only standard vehicle sensors were used and no a priori knowledge of tire and road properties was required. The estimator uses the bicycle model and a random walk tire force model. The tire force estimates were compared to a CarSim reference model for combined slip maneuvers. The results showed a good overall tracking performance of the estimator. In addition, the UKF-estimator demonstrated a high convergence rate and good stability properties. The performed robustness studies showed that the estimator performs well even in the presence of disturbances such as changes in tire-road friction. This method enables a cost-effective and robust implementation for future real time vehicle applications.

I. INTRODUCTION

A. Motivation

The motion of a vehicle is primarily affected by the friction forces transmitted from the road through four small contact areas, the tire footprints. A lot of vehicle control systems rely on the knowledge of these tire forces such as classical ABS (Anti-lock Braking System) and ESP (Electronic Stability Program) systems but also in more recent applications like collision avoidance systems [1].

Tire forces depend on a lot of different variables such as slip ratios and normal loads but also on road and tire properties like the tire-road friction, road profile, tire pressure and wear. When using physical or empirical tire force models all of these influences must be known in advance. This requires extensive testing and calibrating and has to be done for each different vehicle equipped with a specific set of tires [2, p.40].

On the other hand, tire forces can be measured by using special tire sensors. This approach requires a complicated installment and these sensors are not cheap [3, p.1813].

As a consequence a practical solution is necessary which does not rely on prior knowledge of road and tire properties and uses cost-effective sensors. Some estimation algorithms treat road and tires as a black box and do not require any prior knowledge of these properties [4, p.117]. Nonlinear Kalman Filters have shown high potential in estimating vehicle states and tire forces with good accuracy even in the presence of sensor noise.

An overview of State-of-the-Art methods in estimating tire forces will be given in the following.

B. State-of-the-Art

RAY developed a method for nonlinear state and per-axle tire force estimation with a five degree-of-freedom bicycle model in the estimator and a third order random walk tire force model using an Extended Kalman Filter (EKF) [4]. This results in a 17th-order estimation model. It was assumed that the steering angle at the wheel and the applied braking torque were known inputs. The measurement vector consisted of yaw rate, front and rear wheel angular velocities and longitudinal and lateral accelerations. The tire force estimation results showed a good accuracy. RAY developed a similar method in [5]. An EKF estimated lateral tire forces per-axle and longitudinal forces for all four wheels but only during braking.

SAMADI developed a Square-Root EKF using a four wheel vehicle model with seven degrees-of-freedom and a stochastic Gauss-Markov tire force model [6]. Inputs were the braking torques at each wheel, acceleration signals and wheel angular velocities. Longitudinal forces were estimated per wheel and lateral forces were estimated per-axle.

BAFFET developed an EKF with a bicycle model and a Burckhardt/Kiencke adaptive lateral tire force model for estimating per-axle tire forces [7]. Only commonly available standard sensors were used and the knowledge of wheel torques was not necessary. The rear longitudinal force was neglected. The results showed a good tracking performance of the EKF compared to simulations from the dynamic simulator Callas with a Magic Formula tire model. BAFFET developed a similar method which uses a sliding-mode observer instead of an EKF. Appropriate observer gains were chosen with the help of several tests. Chattering effects were avoided by using a linear function [8]. The tire force estimation results showed a good estimation accuracy compared to experimental data.

DAKHLALLAH developed an EKF for tire force estimation at each wheel of a four wheel model with a Dugoff tire force model [9]. Only commonly available sensors were used. Inputs to the model were the steering angle signal, all four angular wheel velocities as well as acceleration signals and yaw rate.

DOUMIATI developed a method for the estimation of individual lateral and per-axle longitudinal tire forces neglecting rear longitudinal forces [10]. In a first block normal tire forces were estimated with suspension deflection measurements and acceleration signals. The resulting normal forces were then used as inputs to the tire force estimator along with measurements like yaw rate, accelerations, steering angle and wheel angular velocities. A four wheel vehicle model was used with a Dugoff tire force model and a relaxation tire force model for the time derivative of the force. The estimation process was conducted using an EKF as well as an Unscented Kalman Filter (UKF). The estimates followed the experimental data closely. The UKF showed superior performance compared to the EKF in terms of convergence rate and tracking performance.

NUTHONG developed an EKF and an UKF including adaptive versions for tire force estimation with a stochastic first-order Gauss-Markov tire force model [11]. The estimation results were compared to the behavior of a reference vehicle model with a LuGre friction model whereas this friction model was validated with the Magic Formula tire model. The input signals steering angle and torques at each wheel were assumed to be known. NUTHONG finally validated the tire force estimates with experimental data and tire force sensors. His results showed a very good tire force estimation accuracy especially with the UKF.

C. Contributions of this work

The main contribution of this work is to estimate tire forces with the UKF with an acceptable accuracy using only commonly available standard sensors. Most of the researchers have focussed on tire force estimation with an EKF as stated in Section I-B. The UKF has a better estimation accuracy at similar computation times and has therefore been chosen by the author.

For future implementation in a real vehicle the computation time plays also an important role. That is why the vehicle model in the estimator shall have a reduced complexity. The stochastic tire force model used in this paper has a reduced complexity and is more efficient in simulation compared to higher order tire force models chosen in I-B.

In addition, a stochastic tire force model which does not rely on road or tire properties is chosen in contrast to some of the analytic tire models in I-B which require tire parameters.

Most of the tire force estimators mentioned in I-B work only when the vehicle is braking. The approach presented here works also when the vehicle is accelerating because the engine torque is measured and a driveline model is used.

Instead of assuming the torque at the wheel to be directly available, the author not only uses a driveline model for estimating accelerating forces but also a simple model of the braking system of the vehicle.

Several studies in I-B compare the tire force estimates to higher degree-of-freedom reference models. These models still have serious modeling uncertainties which puts the quality of reference tire forces into question. The author in this paper

compares the tire force estimation results to a sophisticated vehicle model from the vehicle dynamics simulator CarSim which includes also effects such as ABS braking. The resulting reference tire forces are therefore more realistic.

Sensor noise is added to the virtual measurements and inputs in order to get more realistic conditions. The scaling of the sensor noise terms is based on data sheets of commercially available sensors [12]. Zero-mean, white Gaussian noise is added to the virtual measurements and inputs.

Finally, the author focusses not only on estimation accuracy but also on robustness properties of the estimator when the vehicle is subject to disturbances such as changes in tire-road friction or a different vehicle mass.

A sophisticated CarSim vehicle model in conjunction with a Magic Formula Tire Model is introduced in Section II-A for generating reference tire forces. Section II-B gives an overview about the estimation process and will show the inputs, virtual measurements and outputs. The UKF-estimator model consisting of an bicycle vehicle model and a simple random walk tire force model is introduced in Section II-C. The simulation setup is described in Section III-A. Tire force estimation results are shown for a combined slip maneuver in Section III-B.

II. TIRE FORCE ESTIMATION METHOD WITH THE UKF

A. Reference Model

The CarSim commercial simulation suite [13] models and simulates the dynamic behavior of vehicles. There is a big database available and a lot of different vehicle maneuvers to choose from. The implemented vehicle models in CarSim are sophisticated. They include wind and aerodynamic effects, 3D road geometries, nonlinear suspension systems, steering systems, braking systems with ABS, different powertrains, and so on. The behavior of these vehicle models will be much more alike a real vehicle. In this paper a mid-sized sedan was chosen with a nonlinear Magic Formula tire model, suspension system, powertrain with automatic transmission and torque converter, a braking system with ABS and several other functionalities. The Magic Formula tire model was chosen because it generates horizontal tire forces with high accuracy and is efficient in simulation.

B. Estimation Process Overview

The inputs, virtual measurements and outputs for the estimation process of the UKF are shown in Fig. 1. The inputs to the reference model are the steering wheel angle δ , engine torque T_{eng} and braking pressures of the brake cylinders at the front p_{brf} and rear p_{brr} . According to the motion of the reference vehicle some virtual measurements are made. These include the longitudinal velocity v_x , longitudinal acceleration a_x , lateral acceleration a_y , yaw rate $\dot{\psi}$ and the angular wheel velocities w_f at the front and at the rear w_r .

A prediction is made based on the dynamic model equations implemented in the filter (bicycle model and random walk tire force model). This prediction is then corrected by the innovation available through the virtual measurements. The outputs

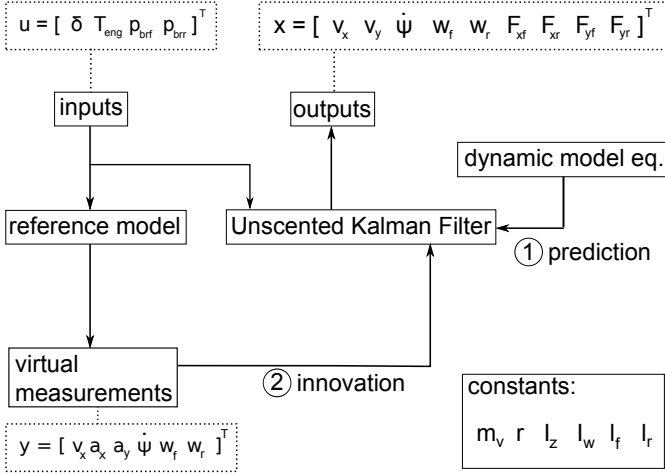


Fig. 1. Estimation process block diagram - Inputs, Virtual Measurements, Outputs

are the state estimates. The state vector includes longitudinal and lateral velocities v_x and v_y , the yaw rate $\dot{\psi}$, the angular wheel velocities w_f and w_r and of course the unknown per-axle tire forces: namely the longitudinal tire forces at the front and rear axle F_{xf} , F_{xr} and the lateral per-axle forces F_{yf} , F_{yr} . Please note that some vehicle parameters were assumed to be constant: the vehicle mass m_v , the dynamic tire radius r , the moment of inertia about the yaw axis I_z , the moment of inertia about the wheel axis I_w and finally the lengths between axles and center of gravity l_f and l_r .

C. UKF-Estimator Model

A vehicle model was defined also in the estimator. Due to reasons of computation time for a future real-time application of the tire force estimator in a real vehicle and due to reasons of simplicity a bicycle model was implemented in the estimator. Therefore, only tire forces per axle and not per wheel were estimated. The bicycle model considers longitudinal (x), lateral (y) and yaw (ψ) motion neglecting roll while traveling on a smooth road. The wheels at the front and rear are lumped together, respectively. The assumption was that only the front wheel is steerable. Please note that grade resistance and aerodynamic drag were neglected. The complexity of this model is low.

Fig. 2 shows the configuration of the bicycle model with all relevant parameters and states. The dynamic equations are

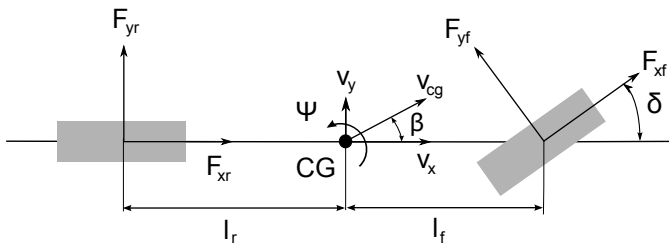


Fig. 2. Bicycle model with parameters and states

shown in state-space form:

$$\begin{bmatrix} \dot{v}_x \\ \dot{v}_y \\ \ddot{\psi} \\ \dot{w}_f \\ \dot{w}_r \\ \dot{F}_{xf} \\ \dot{F}_{xr} \\ \dot{F}_{yf} \\ \dot{F}_{yr} \end{bmatrix} = \begin{bmatrix} 0 & \dot{\psi} & 0 & 0 & \frac{1}{m_v} \cos(\delta) & \frac{1}{m_v} & -\frac{1}{m_v} \sin(\delta) & 0 \\ -\dot{\psi} & 0 & 0 & 0 & \frac{1}{m_v} \sin(\delta) & 0 & \frac{1}{m_v} \cos(\delta) & \frac{1}{m_v} \\ 0 & 0 & 0 & 0 & \frac{l_f}{I_z} \sin(\delta) & 0 & \frac{l_f}{I_z} \cos(\delta) & -\frac{l_r}{I_z} \\ 0 & 0 & 0 & 0 & -\frac{r}{I_w} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & -\frac{r}{I_w} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} v_x \\ v_y \\ \dot{\psi} \\ w_f \\ w_r \\ F_{xf} \\ F_{xr} \\ F_{yf} \\ F_{yr} \end{bmatrix} \quad (1)$$

$$+ \begin{bmatrix} 0 \\ 0 \\ 0 \\ \frac{1}{I_w} (T_{af} + T_{bf}) \\ \frac{1}{I_w} (T_{ar} + T_{br}) \\ w_{xf} \\ w_{xr} \\ w_{yf} \\ w_{yr} \end{bmatrix} ; \quad y = \begin{bmatrix} v_x \\ v_y \\ \dot{\psi} \\ w_f \\ w_r \end{bmatrix}$$

where w_{xf} , w_{xr} , w_{yf} , w_{yr} are Gaussian white noise terms which drive the tire force estimation process. T_{af} , T_{ar} , T_{bf} , T_{br} are accelerating and braking torques at the axles. y is the measurement vector and dt describes a constant time step.

The following gives an overview of the powertrain, braking and steering system models.

Powertrain

The dynamic equations for the bicycle model require the torques at the wheel. The engine torque is transmitted via the transmission to the front axle (front wheel drive). The following equation shows the simplified model:

$$T_{\text{axle,acc}} = T_{\text{eng}} i_{\text{gear}} i_{\text{diff}} \eta_{\text{diff}} \eta_{\text{gear}} \quad (3)$$

where $T_{\text{axle,acc}}$ is the accelerating torque at the front axle, T_{eng} is the engine torque, i_{gear} is the actual gear ratio, i_{diff} is a fixed ratio of the differential, η_{diff} is the efficiency of the differential and η_{gear} is the efficiency of the actual gear. The actual gear ratio is selected with the help of a sensor which gives the actual gear and a look-up table for the gear ratio.

Braking System

The model for the braking system is described as follows:

$$T_{\text{axle,br,f}} = p_{\text{br,f}} K_{\text{br,f}} \quad (4)$$

where $T_{\text{axle,br,f}}$ is the braking torque at the front axle, $p_{\text{br,f}}$ is the sum of the pressure values of the braking cylinders at the front wheels and $K_{\text{br,f}}$ is a braking constant for the

$$y = [v_x \quad a_x \quad a_y \quad \dot{\psi} \quad w_f \quad w_r]^T \quad (10)$$

$$R^n = \begin{bmatrix} 1e-3 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.0514 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.0514e-1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1.0890e-6 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.0070e-2 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.0070e-2 \end{bmatrix} \quad (11)$$

B. Results

In the following the reference values are shown in blue color whereas estimation values are shown in green.

Combined Slip: Double Lane Change with Braking

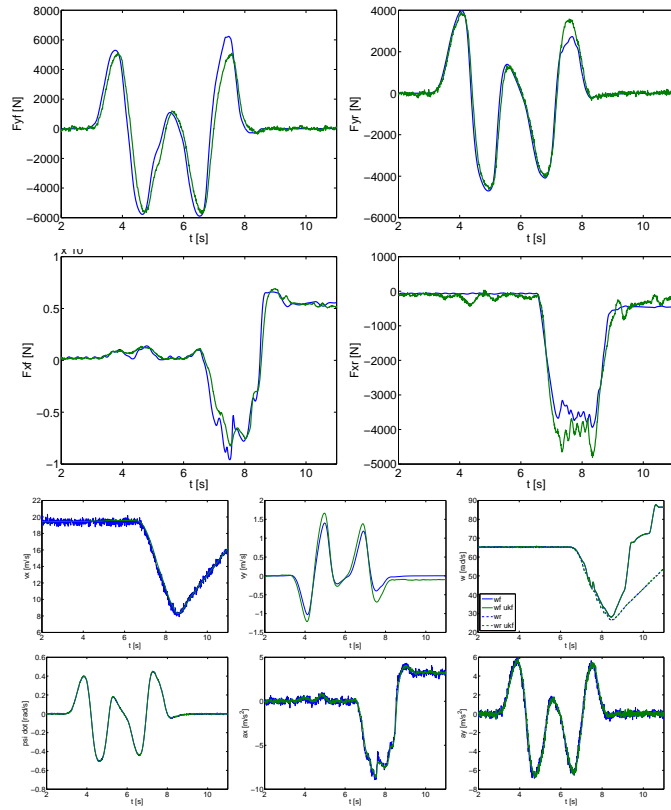


Fig. 3. Lateral tire forces F_{yf} , F_{yr} , longitudinal tire forces F_{xf} , F_{xr} and other states over time t

Fig. 3 shows that the longitudinal, lateral tire forces and other states are estimated with high accuracy. The lateral force at the front axle shows a small phase delay which the author could not avoid. At $t=6.5..8.5$ s a strong braking maneuver is applied during cornering. This leads to an estimation error in the lateral force. This error is not expected to be higher than shown in the plot because a strong combined slip condition was simulated. The longitudinal tire forces are estimated

with good accuracy although the braking force estimates at the rear axle are slightly too high. Please note that the ABS system is active in the reference model. The longitudinal tire force estimates show that the UKF-estimator can capture this effect at least qualitatively although no ABS model was implemented in the estimator.

Disturbance 1: Changes in Vehicle Mass

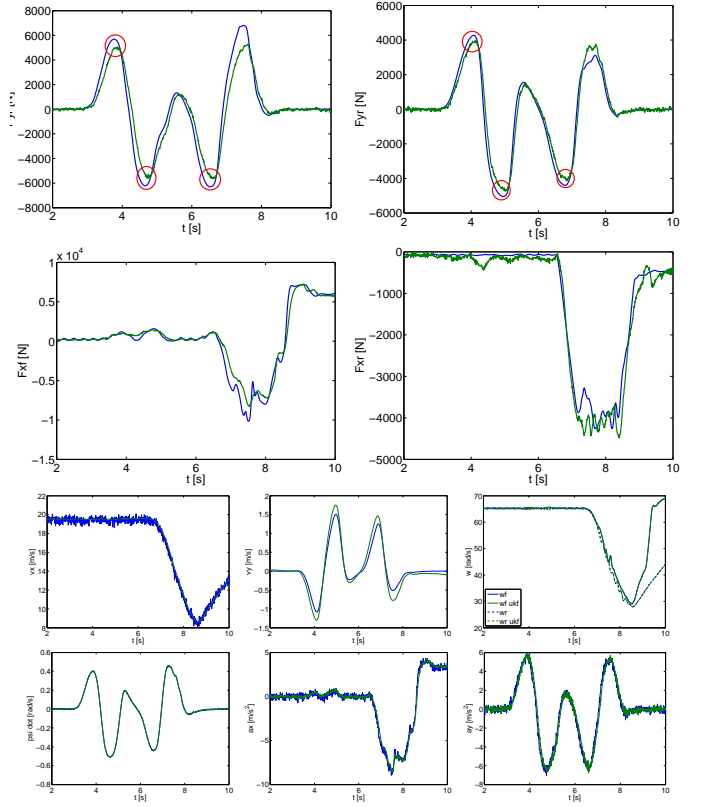


Fig. 4. Lateral tire forces F_{yf} , F_{yr} , longitudinal tire forces F_{xf} , F_{xr} and other states over time t for a change in vehicle mass

In the following the vehicle mass in the reference vehicle model will be increased from 1530kg to 1660kg. That is an increase of 8.5% in mass. Please note that the vehicle model mass in the estimator remains unchanged! Fig. 4 shows that the tracking performance of the UKF regarding tire forces during a double lane change with braking decreases. Especially for the lateral tire forces, the estimator tire force values are mostly below the reference values. This effect increases if the mass increase is even higher.

Disturbance 2: Sudden Changes in Tire-Road Friction

Sudden changes in tire-road friction are introduced. The friction coefficient is initially 0.3, jumps to 0.5 at $t=5.5$ s and to 0.85 at $t=8$ s. Although the estimator has no knowledge of the tire-road friction available, Fig. 5 shows that the tire force estimates remain good. This shows how powerful the UKF-estimator is. Even in the presence of such disturbances in the form of extreme friction changes the estimation results remain

good. Also other state estimates remain good.

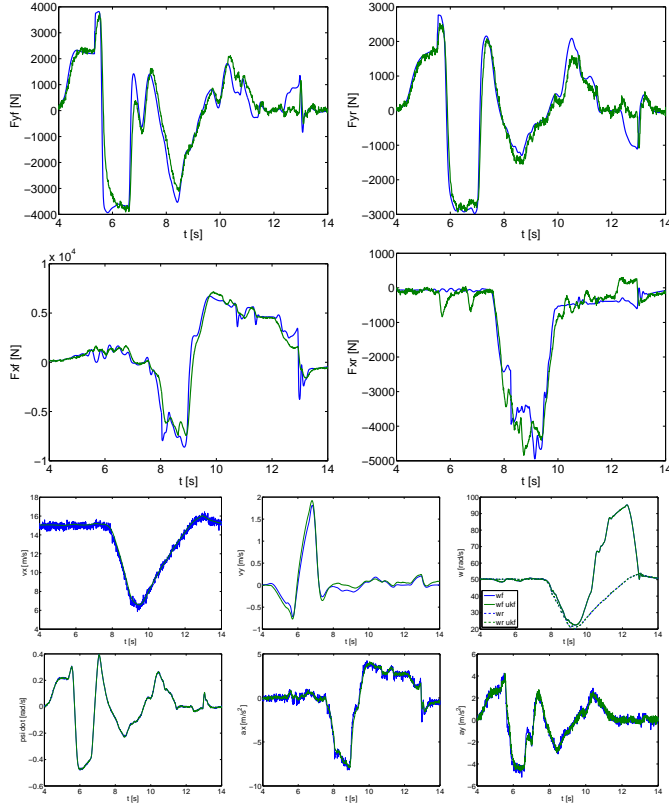


Fig. 5. Lateral tire forces F_{yf} , F_{yr} , longitudinal tire forces F_{xf} , F_{xr} and other states over time t for changes in tire-road friction

Quantitative Tire Force Estimation Error

The normalized error in % can be defined as follows according to [17, p. 6941]:

$$\epsilon_F = 100 \cdot \frac{|F_{ukf} - F_{ref}|}{\max(|F_{ref}|)} \quad (12)$$

where F_{ukf} is the force estimate and F_{ref} is the force reference value at each time instant. Table IV shows the quantitative error for the performed combined slip maneuvers for all three cases. The error expressed in mean and standard deviation keeps very small.

IV. CONCLUSION

The tire force estimation results with the UKF showed a good overall accuracy for a combined slip maneuver. The estimator is robust against changes in tire-road friction although no tire or road parameters are included in the estimator model. For some unknown parameter changes such as an unknown change in vehicle mass, the estimator leads to higher errors in tracking performance. Therefore, future works must consider possible changes of certain vehicle parameters. This can be achieved with a parameter estimation parallel to the state estimation process. Finally, the tire force estimator could be implemented in real time on a test vehicle due to the low computation times. Therefore, the MATLAB algorithm has to be converted into C-code.

TABLE IV
QUANTITATIVE TIRE FORCE ESTIMATION ERROR

	Case 1	Case 2	Case 3
$\max(F_{ref})$	$F_{xf}=8200$ N $F_{xr}=4600$ N $F_{yf}=5700$ N $F_{yr}=4700$ N	$F_{xf}=8200$ N $F_{xr}=4500$ N $F_{yf}=5600$ N $F_{yr}=4700$ N	$F_{xf}=7400$ N $F_{xr}=4800$ N $F_{yf}=3900$ N $F_{yr}=2900$ N
$\text{mean}(\epsilon_F)$	$F_{xf}=4.2\%$ $F_{xr}=4.9\%$ $F_{yf}=6.5\%$ $F_{yr}=3.8\%$	$F_{xf}=4.3\%$ $F_{xr}=3.2\%$ $F_{yf}=6.6\%$ $F_{yr}=4.5\%$	$F_{xf}=4.3\%$ $F_{xr}=3.8\%$ $F_{yf}=6.5\%$ $F_{yr}=5.8\%$
$\text{Std}(\epsilon_F)$	$F_{xf}=6.2\%$ $F_{xr}=5.8\%$ $F_{yf}=8.8\%$ $F_{yr}=5.0\%$	$F_{xf}=6.1\%$ $F_{xr}=4.1\%$ $F_{yf}=8.9\%$ $F_{yr}=5.3\%$	$F_{xf}=7.0\%$ $F_{xr}=5.0\%$ $F_{yf}=10.0\%$ $F_{yr}=7.9\%$

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