Title
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***Abstract*—The use of wireless sensor networks for indoor localization application has emerged as a significant area of interest over the last decade, primarily motivated by its low cost and convenient deployment. The weighted centroid localization algorithm is a suitable positioning technique in a wireless sensor network due to its easy implementation. However, the performance of this method is easily affected by outliers and interference in the measurement of radio signal strength. In order to overcome this limitation, a more robust ARMA filter using generalized t-distribution noise model based on influence function approach is proposed. A hardware prototype was implemented to demonstrate that the ARMA filter could improve system performance, especially when dealing with the case of measurement outliers.**

I. INTRODUCTION

The use of wireless sensor networks (WSNs) for indoor localization application has emerged as a significant area of interest over the last decade, primarily motivated by its low cost and convenient deployment. A survey of indoor positioning technologies can be found in [1]. A standard positioning technique is centroid determination and the most widely used algorithm for fusion of the positions is the Kalman Filter [1].

By formal definition, the centroid of any n-dimensional object is the average position of all the points along each coordinate direction. This definition transplanted to the application of indoor positioning involves different beacons with known positions as reference nodes and simply locating a target at the centroid of these nodes. The centroid localization (CL) was first proposed by Bulusu in [2]. As an alternative, a weighted centroid method [3] can be used to improve the accuracy of the system, where the weights are functions of ranges, signal strength information or uncertainty of each beacon [1]. Actually, the centroid method is highly suitable in WSNs because of its easy implementation without requiring too much computing resources. However, due to the multipath effect and the shadow fading, which are always present in signal propagation in an indoor environment, the performance of centroid method is unsatisfactory [4].

The AutoRegressive-Moving-Average with eXogenous inputs model (ARMAX) with Gaussian noise is commonly used to model a dynamic system. However, the Gaussian noise assumption is an approximation to reality. The occurrence of outliers, transient data in steady-state measurements, instrument failure, human error, model nonlinearity, etc. can all induce non-Gaussian data [5]. Indeed, whenever the central limit theorem is invoked, the central limit theorem being a limit theorem can at most suggest approximate normality for real data [6]. However, even high-quality model data may not fit the Gaussian distribution and the presence of a single outlier can spoil the statistical analysis completely for the case of the Kalman filter [7].

The generalized t-distribution (GT) was employed in the data reconciliation problem to model random noise [5], [8], [9]. GT distribution was also used in econometrics [10], [11], [12], [13] to model random noise in the parameter estimation problem. By being a superset encompassing Gaussian, uniform, t and double exponential distributions, GT distribution has the flexibility to characterize noise with Gaussian or non-Gaussian statistical properties. For instance, in our case of using the weighted centroid localization algorithm to track positions of a target, the results are usually spoiled by outliers due to non-line-of-sight (NLoS) conditions, high attenuation and signal scattering or fast temporal changes caused by opening doors. In a 1D framework, over 4600 data samples of position coordinates computed by the weighted centroid method are shown in Fig.1. Maximum likelihood criterion is used to fit the distribution of these data. It can be clearly seen in Fig.1 that the GT (t3 distribution) curve in red dashed line fit the histogram better than Gaussian curve in green solid line.

The problem of estimation with GT noise can be solved numerically using the Newton Raphson or the Expectation Maximization algorithm [5], [8], [9], [10], [11], [12], [13]. Unlike a recursive algorithm such as the recursive least-squares estimator, such methods are not suitable for real-time applications.

In this paper, influence function (IF), an analysis tool in robust statistics [14], [6], is used to formulate a recursive algorithm that gives an approximate solution, making it suitable for real-time and on-line implementation. Specifically, the problem is formulated as the filtering of the ARMA process with GT

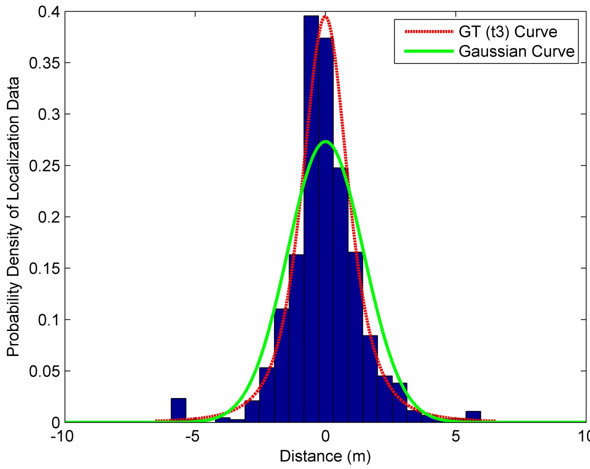

Fig. 1. The weighted centroid data distribution.

noise[15]. Other well-known approaches [16], [17], [18] for handling non-Gaussian noise include the approach of particle filters which is based on point mass or particle representation of probability densities. The IF was also used in [19] to analyze parameter estimation with GT noise. Our algorithm consists of first using the weighted centroid localization method to give rough position results and then using the proposed ARMA filter to refine the results.

The rest of this paper is organized as follows: Section II gives background knowledge on a log-distance path loss model, which maps the received signal strength to the distance, and the weighted centroid localization algorithm. Next Section III introduces the ARMA process for indoor tracking application. Then Section IV describes our proposed ARMA filter with GT noise model. After that Section V establishes the test-bed for experiments and provides the results. Finally, Section VI concludes the whole paper.

II. Background Knowledge

A. The Path Loss Model

In order to adopt distance as weights for the weighted centroid localization algorithm, we need a mapping scheme from radio signal strength indicators (RSSIs) to distance. In this case, a log-distance path loss model (PLM) is commonly used [20]. It provides a relation between the total path loss, PL (dBm) and distance, D (m) as:

$$PL = 20\log(f) + Nlog(D) + Lf(n) - 28dB \quad (1)$$

where f is the radio frequency in MHz; N is the distance power decay index; Lf(n) is an empirical floor loss penetration factor; and n is the number of floors between transmitter and receiver. In our case, f is 2.4 GHz and since transmitters and receivers are placed in the same floor, therefore, n is equal to 1.

Equation (1) is usually simplified as:

$$PL_d = PL_0 + 10\alpha\log(D) \quad (2)$$

where PL_0 is the reference pass loss coefficient by combining the terms $20log(f)$, $Lf(n)$ and $-28dB$ in Equation (1), and α is the pass loss exponent. α is typically determined empirically, ranging from 2 to 4 depending on different indoor environments.

B. The Weighted Centroid Localization Algorithm

We can obtain the distance between a moving transmitter and a reference node with known position using Equation (2). Let x, y be the xy-coordinate of the moving transmitter, and $(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)$ be the positions of n receivers. $D_i, i = 1, 2, \ldots, n$ denote the distance between the transmitter and receiver i. Thus, the location estimation formula for x and y are given as the following:

$$x = \frac{\frac{1}{D_1^g}x_1 + \frac{1}{D_2^g}x_2 + \frac{1}{D_3^g}x_3 + \cdots + \frac{1}{D_n^g}x_n}{\frac{1}{D_1^g} + \frac{1}{D_2^g} + \frac{1}{D_3^g} + \cdots + \frac{1}{D_n^g}} \quad (3)$$

$$y = \frac{\frac{1}{D_1^g}y_1 + \frac{1}{D_2^g}y_2 + \frac{1}{D_3^g}y_3 + \cdots + \frac{1}{D_n^g}y_n}{\frac{1}{D_1^g} + \frac{1}{D_2^g} + \frac{1}{D_3^g} + \cdots + \frac{1}{D_n^g}} \quad (4)$$

Exponent $g > 0$ determines the weight of the contribution of each reference node. The larger value of g makes the range of "attraction field" of reference nodes wrt. the mobile target smaller, making the relative weights of the nearest reference nodes dominate. In our case, the value of g is set to 1.8, typically based on empirical results [21].

III. The ARMA Process

Consider the single-output double integrator ARMA model with $deg(C) = deg(A) = 2$:

$$A(q^{-1})y(k) = C(q^{-1})\varepsilon(k) \quad (5)$$

where

$$A(q^{-1}) = (1 - q^{-1})^2$$
$$C(q^{-1}) = 1 + c_1q^{-1} + c_2q^{-2}$$

$k = 1, \ldots, N$ is the sampling instance and q^{-1} is the backward shift operator, i.e., $q^{-1}y(k) = y(k-1)$.

Equation (5) is equivalent to the following constant velocity state-space model:

$$\begin{bmatrix} x_1(k+1) \\ x_2(k+1) \end{bmatrix} = \begin{bmatrix} 1 & T \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_1(k) \\ x_2(k) \end{bmatrix} + \begin{bmatrix} c_1 + 2 \\ \frac{c_1+c_2+1}{T} \end{bmatrix} \varepsilon(k) \quad (6)$$

$$y(k) = \begin{bmatrix} 1 & 0 \end{bmatrix} \begin{bmatrix} x_1(k) \\ x_2(k) \end{bmatrix} + \varepsilon(k) \quad (7)$$

where T is the sampling interval.

Let the noise $\varepsilon(k)$ be modeled by the zero-mean GT probability density function (PDF)

$$f(\varepsilon) = \frac{p}{2\sigma q^{1/p}\beta(1/p, q)\left(1 + \frac{|\varepsilon|^p}{q\sigma^p}\right)^{q+1/p}} \quad (8)$$

where σ is the scale parameter, p and q are the shape parameters. The beta function is given by $\beta(a, b) = \int_0^1 z^{a-1}(1-z)^{b-1}dz$. By different choices of p and q, GT distribution can represent a wide range of distributions as shown in Fig.2. The parameters of the PDFs in Fig.1 obtained via the maximum likelihood criterion are summarized in Table I.

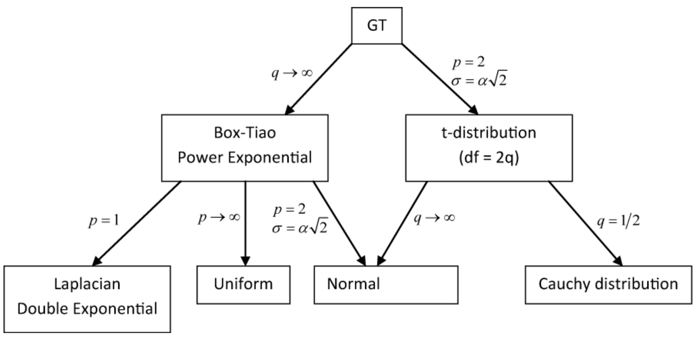

Fig. 2. Different choices of the GT distribution shape parameters p and q can give different well-known distributions.

TABLE I
PDF PARAMETERS OF DIFFERENT DISTRIBUTIONS VIA MAXIMUM LIKELIHOOD CRETERION

GT (t3) Distribution			Gaussian Distribution	
p	q	σ	μ	σ
2	1.5	1.3156	0	1.4601

IV. ARMA FILTER WITH GT NOISE MODEL

Substituting Equation (7) into (6) gives

$$\begin{aligned} x(k+1) &= \Phi x(k) + \Omega y(k) && (9) \\ y(k) &= Hx(k) + \varepsilon(k) && (10) \end{aligned}$$

where

$$\begin{aligned} \Phi &= \begin{bmatrix} -(c_1+1) & T \\ -\frac{c_1+c_2+1}{T} & 1 \end{bmatrix} \\ \Omega &= \begin{bmatrix} c_1+2 \\ \frac{c_1+c_2+1}{T} \end{bmatrix} \\ H &= \begin{bmatrix} 1 & 0 \end{bmatrix} \end{aligned}$$

Iterating from the initial value $x(1)$, Equations (9) and (10) give

$$\begin{aligned} x(2) &= \Phi x(1) + \Omega y(1) \\ x(3) &= \Phi^2 x(1) + \Phi\Omega y(1) + \Omega y(2) \\ &\vdots \\ x(N) &= \Phi^{N-1} x(1) + \bar{x}(N) && (11) \\ y(N) &= H\Phi^{N-1} x(1) + H\bar{x}(N) + \varepsilon(N) && (12) \end{aligned}$$

where

$$\bar{x}(N) = \sum_{k=1}^{N-1} \Phi^{k-1}\Omega y(N-k) \quad (13)$$

TABLE II
ARMA FILTER (IN $\hat{x}(N|N)$) WITH EXPONENTIAL FORGETTING

$$\begin{aligned} \hat{x}(N|N) &= \hat{x}(N|N-1) + K_f(N)[z(N) + H\bar{x}(N) \\ &\quad -H\hat{x}(N|N-1)] && (16) \\ \hat{x}(N+1|N) &= \Phi\hat{x}(N|N) + \Omega y(N) && (17) \\ P(N+1|N) &= \frac{1}{\lambda}[\Phi P(N|N-1)\Phi^T \\ &\quad - \frac{\Phi P(N|N-1)H^T HP(N|N-1)\Phi^T}{\lambda + HP(N|N-1)H^T}] && (18) \\ \hat{y}(N|N) &= H\hat{x}(N|N) && (19) \end{aligned}$$

where $K_f(N) = \frac{P(N|N-1)H^T}{\lambda + HP(N|N-1)H^T}$

A. Maximum Likelihood Estimation

Given N measurements $y(k)$, $k = 1, \ldots N$, the initial condition, $x(1)$, can be estimated using Equation (12) in the minimization of the following maximum likelihood cost function

$$\begin{aligned} J &= -\sum_{k=1}^{N} \ln f(\varepsilon(k)) \\ &= -\sum_{k=1}^{N} \ln f\left(y(k) - H\Phi^{k-1}x(1) - H\bar{x}(k)\right) \end{aligned}$$

This can be done by differentiating wrt. $x(1)$ and then equating to zero giving

$$\frac{\partial J}{\partial x(1)} = \sum_{k=1}^{N} \psi_k(\varepsilon(k)) = 0 \quad (14)$$

where

$$\begin{aligned} \psi_k(\varepsilon(k)) &= -(pq+1)(H\Phi^{k-1})^T \frac{\varepsilon(k)|\varepsilon(k)|^{p-2}}{q\sigma^p + |\varepsilon(k)|^p} && (15) \\ \varepsilon(k) &= y(k) - H\Phi^{k-1}\hat{x}(1) - H\bar{x}(k) \end{aligned}$$

and $p > 1$. Equation (14) can be solved for $x(1)$ numerically using the Newton Raphson or the Expectation Maximization algorithm. Unlike a recursive algorithm such as the recursive least-squares estimator, Equation (14) is not suitable for real-time applications. For example, in real-time control, the information is used by the controller to calculate the control signal for the next sampling instance. The number of iterations required by Equation (14) to converge to a solution can be different for different samples and hence, there is no guarantee that the information is available before the next sampling instance.

The recursive ARMA filter algorithm for $N = 1, 2, 3 \ldots$ is summarized in Table II. The derivation is given in [15] and included in the Appendix for easy reference.

The covariance of $\hat{x}(1)$ and estimate $\hat{y}(N)$ at sample N are denoted by $P(1|N)$ and $\hat{y}(N|N)$ respectively. The forgetting factor is given by λ. For initialization, $P(1|0)$ can be set as an identity matrix multiplied by some large number.

V. EXPERIMENT

Fig.3 shows our test-bed which is a common corridor in a typical research building located in the University Town, National University of Singapore. In Fig.3, red spots represent receivers with known positions. To establish the WSN for experiments, Zigbee 2.4 GHz transmitter and receiver (TI CC2530) were used. A reader (TI CC2531) was connected to a local server. The working process of the communication system is given as follows: the transmitters first broadcast the packets with their unique ID signal every 0.5 seconds in the indoor environment; then the receivers pick up the the packets of each transmitter and send them to the CC2531 reader continuously through the WSN; after that, the reader transfers the data packets from all transmitters to the local server; finally, the local server decodes the packets and calculates the estimated location of each tracking transmitter.

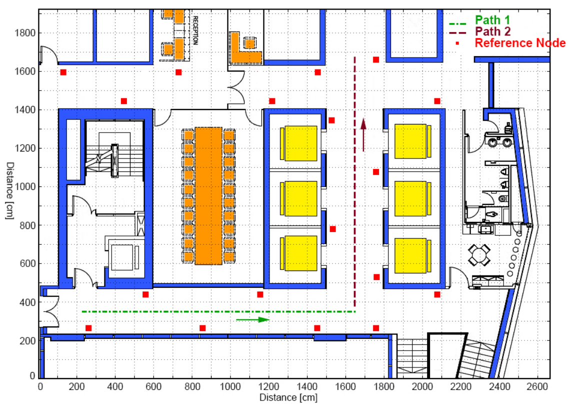

Fig. 3. The layout of the test-bed.

A. Calibration

Seven different positions in the test-bed were chosen to collect data. The main purpose of this experiment was to calibrate each receiver (estimating parameters PL_0 and α in the log-distance path loss model). A best-fit method [22] was adopted for the use of calibration. An example of calibration result for a particular receiver is shown in Fig.4. As can be seen from Fig.4, the depth of the color represents the distribution of the collected data and most of the data points were clustered near the fitted PLM curve.

B. Tracking of A Moving Transmitter

In most indoor environments, furniture are arranged such that there are only a small number of paths for people to walk on. Hence, most indoor tracking problems can be reduced to a one-dimension problem. In order to evaluate our proposed ARMA filter, the Kalman filter was used as a comparison. From Fig.3 we can see that the test path consists of two parts, Path 1 and Path 2. The arrows show the moving direction. With the forgetting factor $\lambda = 0.5$, the experimental results of these two paths are shown in Fig.5 and Fig.6, respectively.

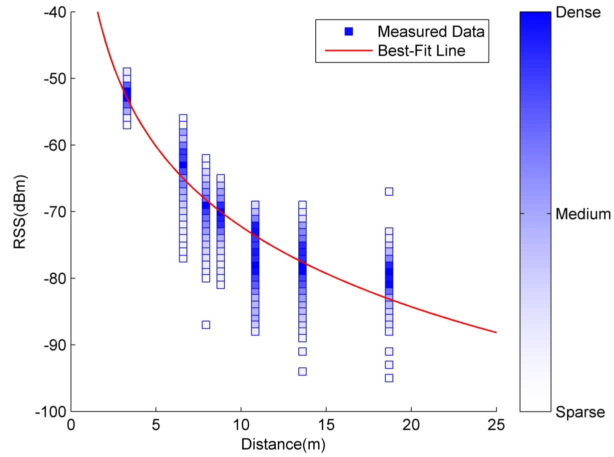

Fig. 4. An example of calibration result for a receiver.

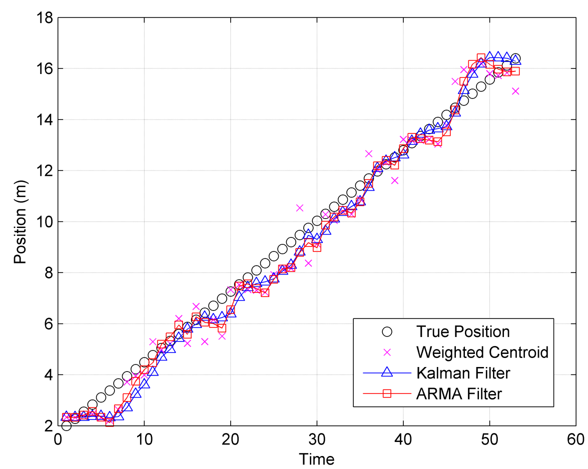

Fig. 5. Tracking results of Path 1.

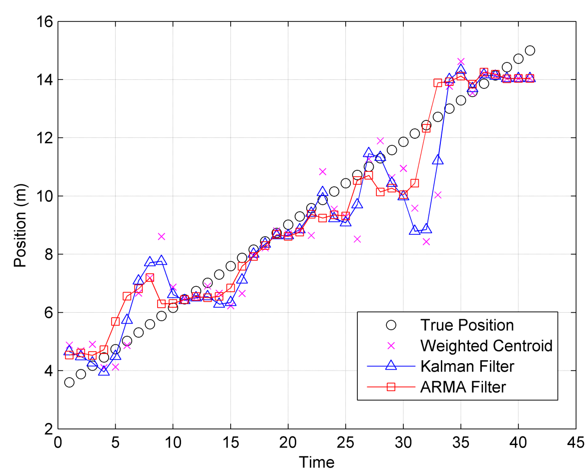

Fig. 6. Tracking results of Path 2.

TABLE III
LOCALIZATION ACCURACY SUMMARY

Algorithm	Ave. Error (m)	Max. Error (m)
Weighted Centroid	0.8726	5.0297
Karlman Filter	0.6497	3.5582
ARMA Filter	0.4773	1.9419

In Fig.5, both the ARMA filter and the Kalman filter give similar performance because the centroid results are close to the true positions along Path 1. This is due to the fact that there is not much noise in the environment. However, along Path 2 there are six lifts with metal doors. These exacerbated the effect of multi-paths and resulted in outliers as shown in Fig.6. In this case, the ARMA filter showed a better result than the Kalman filter in reducing the effect of outliers.

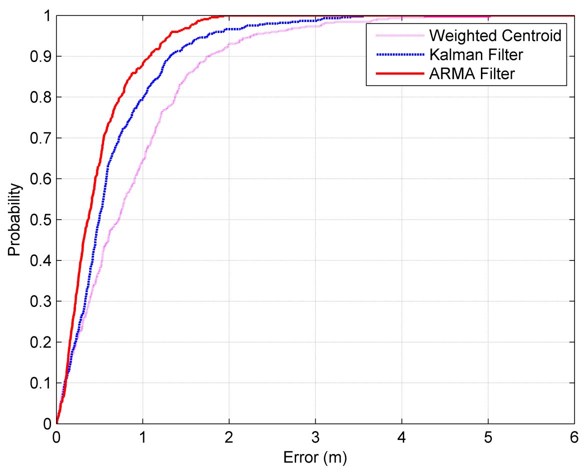

Fig. 7. CDF of error by using the three methods.

After a tester's walking along both the paths several times and collecting 447 data samples, the cumulative distribution function (CDF) of error is shown in Fig.7. The ARMA filter is able to localize positions within 1m error 87% of the time while the Kalman filter and the weighted centroid give the same performance 80% and 64% of the time, respectively. The maximum error of the ARMA filter is much less than the Kalman filter and the weighted centroid as shown in Table III. This is consistent with the observation that the ARMA filter is less sensitive to outliers. From Table III, it is notable that the ARMA filter improved the system performance for average error by 45.30% ($= \frac{0.8726-0.4773}{0.8726} \times 100\%$) over the weighted centroid algorithm and by 26.54% ($= \frac{0.6497-0.4773}{0.6497} \times 100\%$) over the Kalman filter. As for the maximum error, the ARMA filter improved the results by 61.39% ($= \frac{5.0297-1.9419}{5.0297} \times 100\%$) over the weighted centroid algorithm and by 45.42 % ($=\frac{3.5582-1.9419}{3.5582} \times 100\%$) over the Kalman filter. In summary, we can say that the ARMA filter is more robust to the effect of outliers and gives higher accuracy than the Kalman filter.

VI. CONCLUSION

In this paper, we proposed an ARMA filter using a GT distribution noise model based on IF approach. The novel ARMA filter was used to filter the weighted centroid results for indoor positioning and tracking. In order to evaluate our proposed algorithm, the Kalman filter was used as a comparison. Our experiment results showed that in a one-dimension framework, the ARMA filter is able to localize positions within 1m error 87% of the time while the Kalman filter and the weighted centroid give the same performance 80% and 64% of the time, respectively. Additionally, the ARMA filter was better at dealing with outliers.

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APPENDIX

The derivation of the ARMA Filter is given in [15] and included here for easy reference.

We introduce the influence function to approximate and solve Equation (15) recursively.

Consider the function $x = f(h)$. The first-order Taylor series expansion

$$x = \left.\frac{dx}{dh}\right|_{h=0} h$$

makes use of the gradient $\left.\frac{dx}{dh}\right|_{h=0}$ to give the approximate value of x at h. Consider $\hat{x}(1)$, the asymptotic value of the estimate of $x(1)$. Let $\hat{x}(1)$ be associated with the PDF of $(1-h)f(\varepsilon)+h\delta(\varepsilon)$, where $\delta(\varepsilon(k))$ denotes the probability measure that puts mass 1 at the point $\varepsilon(k)$. Likewise the Taylor series expansion

$$\hat{x}(1) = \left.\frac{d\hat{x}(1)}{dh}\right|_{h=0} h \tag{20}$$

makes use of the gradient $\left.\frac{d\hat{x}(1)}{dh}\right|_{h=0}$, known as the influence function, $IF(\varepsilon(k))$ [6][14], to give the approximate value of $\hat{x}(1)$.

$$\begin{aligned} \hat{x}(1|N) &= \text{IF}(\varepsilon(k)) \\ &= \left(\sum_{k=1}^{N}(H\Phi^{k-1})^T H\Phi^{k-1}\right)^{-1}\left(\sum_{k=1}^{N}(H\Phi^{k-1})^T z(k)\right) \end{aligned} \tag{21}$$

TABLE IV
ARMA FILTER (IN $\hat{x}(1|N)$)

$$\begin{aligned} P(1|N) &= P(1|N-1) \\ &\quad - \frac{P(1|N-1)(H\Phi^{N-1})^T H\Phi^{N-1} P(1|N-1)}{1 + H\Phi^{N-1} P(1|N-1)(H\Phi^{N-1})^T} \end{aligned} \tag{24}$$

$$\begin{aligned} \hat{x}(1|N) &= \hat{x}(1|N-1) + P(1|N)(H\Phi^{N-1})^T \\ &\quad \times \left[z(N) - H\Phi^{N-1}\hat{x}(1|N-1) \right] \end{aligned} \tag{25}$$

$$\bar{x}(N+1) = \Phi\bar{x}(N) + \Omega y(N) \tag{26}$$

$$\hat{y}(N|N) = H\Phi^{N-1}\hat{x}(1|N) + H\bar{x}(N) \tag{27}$$

where

$$\begin{aligned} z(k) &= \left(\int_{-\infty}^{+\infty} \frac{[(p-1)q\sigma^p - |\varepsilon|^p]|\varepsilon|^{p-2}}{(q\sigma^2 + |\varepsilon|^p)^2} f(\varepsilon) d\varepsilon \right)^{-1} \\ &\quad \times \frac{\varepsilon(k)|\varepsilon(k)|^{p-2}}{q\sigma^p + |\varepsilon(k)|^p} | \end{aligned} \tag{22}$$

and $\hat{x}(1|N)$ denotes the estimate of $x(1)$ at sample N. Derivation of Equation (21) is given in [19]. When $h = 0$, the associated PDF of $\hat{x}(1)$ is $f(\varepsilon)$ and the usual assumption of zero initial condition for the ARMA transfer function is made i.e. $x(1) = 0$.

Notice that Equation (21) gives the well known least-squares estimates $\hat{x}(1|N)$ from the minimization of the least-squares loss function

$$V = \frac{1}{2} \sum_{k=1}^{N} \left(z(k) - H\Phi^{k-1}\hat{x}(1|N) \right)^2$$

and the recursive version in Equations (24) and (25) with the covariance matrix

$$P(1|N) = \left(\sum_{k=1}^{N} (H\Phi^{k-1})^T H\Phi^{k-1} \right)^{-1} \tag{23}$$

are given in many textbooks that discuss least-squares [23]. Equations (9) and (12) are then used to obtain $\bar{x}(N)$ and $\hat{y}(N|N)$ in Equations (26) and (27) respectively.

If we introduce a forgetting factor, λ, in the least-squares loss function

$$V = \frac{1}{2} \sum_{k=1}^{N} \lambda^{N-k} \left(z(k) - H\Phi^{k-1}\hat{x}(1|N) \right)^2$$

and estimate $\hat{x}(N|N)$ instead of $\hat{x}(1|N)$ then the derivation is complete and the recursive ARMA filter algorithm for $N = 1$, 2, 3 ... is given in Equations (16) to (19).

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