Abstract—This paper proposes a practical synchronization waveform that is resilient to frequency error for machine-type communications (MTC) with applications in massive Internet-of-Things (mIoT). Mathematical properties of the waveform are derived, which are keys to addressing the practical issues. In particular, it is shown that this type of waveform is asymptotically optimal in the presence of a frequency error, in the sense that its asymptotic performance is the same as the optimal matched-filter detector that is free of frequency error. This asymptotic property enables optimization of the waveform under the constraints imposed by an application. It is also shown that such optimized waveform comes in pairs, which facilitates the formation of a new waveform capable of frequency error estimation and timing refinement at the receiver. Detailed comparisons with the LTE narrowband IoT primary synchronization signal are provided.

Index Terms—Massive machine-type communications (mMTC), massive Internet-of-Things (mIoT), mMTC synchronization waveform, system acquisition, frequency offset/error estimation.

I. INTRODUCTION

Machine-type communications (MTC) is a type of wireless communications that support fully automatic data generation, exchange, processing, and actuation among intelligent machines, without or with low intervention of humans including utilities, sensing, health care, manufacturing, and transportation [1], [2]. Whereas massive MTC (mMTC) characterized by simultaneous support of a massive number of MTC devices is becoming the prominent communication paradigm for a wide range of emerging smart services with a typical application in the massive Internet of Things (mIoT) market where devices sending bits of information to other machines, servers, clouds, or humans account for a much larger proportion in wireless communication applications.

Although cellular networks such as GSM and LTE have long been used for MTC in various IoT applications, its capability to support mMTC is rather limited. Nevertheless, this is not surprising since cellular technologies were developed for “human-type” communications (HTC) in the first place. To provide a solution that are built on top of the traditional cellular network for mMTC, the Third Generation Partnership Project (3GPP) dedicated an immense effort during LTE Release 13 to develop a new radio access technology known as Narrow-Band Internet of Things (NB-IoT) [3] as part of the long-term evolution process towards a more versatile universal communication technology. As such, NB-IoT inherits most functionality from the legacy LTE system, such as the transmission frame structure and the data transmission waveform (i.e., OFDM). The most noticeable changes are probably the reduced minimum system bandwidth from 1.4 MHz to 180 kHz, mainly for exploiting the refarmed GSM spectrum that are channelized 200 kHz per carrier, and the redesigned synchronization waveform for better serving mIoT use cases that are commonly characterized by low-cost, extended coverage, and the unique short burst, long sleep transmission pattern.

Synchronization is the first and arguably the most challenging step of MTC in mIoT applications due to the largest time and frequency uncertainties present in transceivers. Because of the low-cost nature of an mIoT device, a local oscillator of the device may suffer from a large frequency error that creates an offset in carrier frequency between the incoming signal and the receiver. For instance, the initial frequency error of the local oscillator can be as large as 20 ppm for an mMTC device [4]. Moreover, the short-burst nature of an mMTC transmission makes the synchronization of each transmission a more significant factor in overall transmission efficiency compared to that of HTC. The prolonged sleep duration between transmissions (to save battery) also causes the local oscillator to drift further away from the default frequency. These unique characteristics of mMTC further burden the initial synchronization process. Yet, data transmissions can proceed only after time and frequency synchronization is established as required by data transmission waveforms. Since the purposes of the waveform used for synchronization and the ones for data transmission (i.e., the multiple access waveforms) are different, the design requirements for these two types of waveforms are very different as well. In general, interference between waveforms (directly related to the system capacity) is the key design parameter for multiple access, whereas it is the detectability (under large time and frequency uncertainties) for initial synchronization.

Compared to the multiple access waveforms [5]–[13], the synchronization waveform for mMTC so far has received much less attention in 5G technology development. Recently in [14], a general synchronization waveform resilient to frequency error is derived. It is shown that the effect of a frequency error on the well-known matched filter-based de-
The passband synchronization signal that arrives at the receive antenna is represented as
\[ x(t) \cdot e^{j2\pi f_c t}, \]
where \( x(t) \) is the baseband synchronization waveform, \( t \) denotes time, and \( f_c \) the carrier frequency. Assuming that there exists a frequency offset \( \Delta f \) between the carrier frequencies of the transmitter and the receiver due to, e.g., a frequency error of the local oscillator of the receiver, the received baseband signal can then be expressed as
\[ x(t) \cdot e^{j2\pi f_c t} \cdot e^{-j2\pi f \tau} = x(t) \cdot e^{-j2\pi \Delta f \tau}. \]
where \( f' = f_c + \Delta f \) is the receiver frequency. This frequency offset thus in effect introduces a linear phase ramping factor, \( e^{-j2\pi \Delta f \tau} \), on the received baseband signal \( x(t) \), henceforth referred to as the phase ramping effect.

A matched-filter based detector (also known as the cross-correlation based detector) performs the cross-correlation function between the synchronization signal \( x(t) \cdot e^{-j2\pi \Delta f t} \) and its local copy \( x(t) \) as
\[ \gamma(\tau, \Delta f) = \frac{1}{E} \int_{-T/2}^{T/2} x(t) e^{-j2\pi \Delta f t} \cdot x^*(t-\tau) dt, \]
where \( E = \int_{-T/2}^{T/2} |x(t)|^2 dt \), and \( \tau \) is the lag of the cross-correlation function.

In the absence of a frequency offset, i.e., \( \Delta f = 0 \), the maximum output of the correlator (or the correlation peak) occurs at \( \tau = 0 \),
\[ \gamma(\tau = 0, \Delta f = 0) = 1, \]
providing the optimal detection performance (in the sense of maximum likelihood) as asserted by the well-known matched-filter detection theory. While in the presence of a frequency offset, \( \Delta f \neq 0 \) (unknown to the receiver), the phase ramping component, \( e^{j2\pi \Delta f t} \), introduced by the frequency offset effectively creates a mismatch between the incoming synchronization signal and the local copy of the waveform, breaking the very premise of the optimality of a matched-filter detector, thereby inevitably resulting in a loss in detection energy, i.e.,
\[ \gamma(\tau = 0, \Delta f \neq 0) < 1, \]
and ergo a loss in detection performance. This phenomenon is well-documented in the literature [14]–[20], and becomes prominent in mIoT when the frequency offset is likely large—typical to an extent that the resulting mismatch totally fails a matched filter-based detector.

A variant of the matched-filter or cross-correlation based detector can also be found in practice [14], [16]. The effect of waveform distortion from frequency offset on the matched-filter detection performance is mitigated by using a joint time and frequency detection structure which can be viewed as a bank of matched-filters to a set of waveforms pre-distorted with a set of frequency offsets (hypotheses) spread over the whole frequency uncertainty range (determined by local oscillator accuracy), and applied over the entire time uncertainty duration (signal transmission period). The matched-filter with the largest output energy, i.e., the winning hypothesis, is used as the frequency estimate, and the time location where the largest output occurs is the timing estimate. This joint time and frequency detector effectively extends its overall frequency error tolerance, however at a cost of complexity growing linearly with the number of the hypothesized frequency offsets. Since the frequency offset is continuous in nature, the higher the required detection performance is, the greater the number of hypotheses is needed. This method is thus more popular in HTC where complexity is less of an issue and the oscillator is more accurate, whereas in mMTC, a compromise on performance must be made in order to keep the complexity and cost manageable.

In NB-IoT, this issue is dealt with by repeating a baseline waveform multiple times consecutively in time, and a differential correlator between repeated signals (also known as an auto-correlator) is employed at the receiver to suppress the phase ramping effect. Specifically, the waveform is repeated 11 times to form a synchronization signal with a total length of ~780µs. Although very effective (in removing the signal distortion due to phase ramping), this type of auto-correlation-based detector is not optimal\(^1\), causing at least 3 dB degradation at its best (as SNR → +∞) with respect to

\(^1\)The autocorrelation-based detector is not optimal under the context that the waveform of the input signal is known, which is not exploited by this type of detectors.
the optimal matched-filter detector (without frequency offset). The degradation quickly increases as SNR deteriorates, e.g., close to 5 dB degradation at an SNR of −5 dB, and ~10 dB at −10 dB. This behavior, known as the “noise amplification” phenomenon, could be problematic in a low SNR scenario which is not uncommon in mIoT deployments. Again, we see a compromise made on detection performance for lower complexity.

In search for a solution such that the optimality of a matched filter detector can be maximally retained under frequency offset, in [14], the cross-correlation based detection is re-examined using the Cauchy-Schwartz inequality, which indicates that

\[
\left| \gamma (\tau, \Delta f) \right| \leq \frac{1}{E} \sqrt{\int_{-T/2}^{T/2} |x(t)|^2 dt} \cdot \sqrt{\int_{-T/2}^{T/2} |x^*(t-\tau)|^2 dt}.
\]

That is,

\[
|\gamma(\tau, \Delta f)| \leq 1, \ \forall \Delta f \text{ and } \forall x(t),
\]

with equality if and only if

\[
x(t) e^{j2\pi \Delta f t} = C \cdot x(t-\tau),
\]

where \( C \in \mathbb{C} \) is a non-zero constant, and \( \mathbb{C} \) denotes the set of complex numbers.

The significance of this result is obvious in that it claims the mathematical existence of such a waveform that attains the optimality of a matched filter even in the presence of a frequency offset between the received signal and the local waveform, as long as condition (8) is met.

It can be shown that the waveform that satisfies condition (8) is of the following general form

\[
\tilde{x}(t) = e^{j\pi (\alpha t^2 + \beta t)}, \quad \alpha, \beta \in \mathbb{R}, \tag{9}
\]

where \( \mathbb{R} \) denotes the set of real numbers. The matched filter output energy based on this type of waveform transforms the frequency error of the detector, \( \Delta f \), into a time deviation from the original position by an amount of

\[
\tau^1 = -\alpha^{-1} \Delta f. \tag{10}
\]

This linear relationship between the frequency offset and time deviation shows the capability of converting a frequency offset into a time offset for this type of waveforms defined in (9). The graph on the left of Fig. 1 clearly shows this property which is exploited in this paper for the design of a practical synchronization waveform.

However, it is worth noting that some of the well-known sequences, e.g., the Zadoff-Chu (ZC) sequences in general do not possess this property even though they bear a strong resemblance to (9),

\[
s_n = e^{-j\frac{\pi n^2 u}{N}} = e^{-j\frac{\pi}{N^2} (n^2+u)}, \quad n = -\frac{N-1}{2}, \cdots, -1, 0, 1, \cdots, \frac{N-1}{2},
\]

where \( u \in \{1, 2, \cdots, N-1\} \), a positive integer, is the root index of the ZC sequence, and \( N \), a prime integer, is the period of the ZC sequence [3].

Indeed, it can be shown from the analysis in [14] that a lower bound of the bandwidth for the waveform in (9) is \( |\alpha| T \).

Consequently, in order to obtain (11) from (9), \( \tilde{x}(t) \) must first be sampled at a rate of

\[
T_s^{-1} > |\alpha| T, \tag{12}
\]
according to the Nyquist theorem, producing \( N \Delta T = \left\lfloor T/T_s \right\rfloor \) samples,
\[
x_n = \hat{x}(nT_s) = e^{j\pi(\alpha(nT_s)^2 + \beta(nT_s))},
\]
where \( T_s \) is the sample interval.

In order for (13) to become the ZC sequence in (11), it requires that
\[
\alpha = -\frac{u}{NT_s},
\]
and
\[
\beta = -\frac{u}{NT_s}.
\]

Condition (14) means that
\[
T_s^{-1} = -\frac{NT_s}{u} \alpha = -\frac{1}{u} \alpha T \leq |\alpha| T,
\]
which conflicts with (12), noting that the root index of a ZC (one-to-one) function of the frequency offset.

As shown by the graph on the right side of Fig. 1, although
\[
\text{PROP 1: The ZC sequences do not belong to the class of waveforms defined in (9).}
\]

As shown by the graph on the right side of Fig. 1, although the peak location (lag) of the cross-correlation of the ZC sequence varies with the frequency offset, it is not an injective (one-to-one) function of the frequency offset.

III. Prototype Waveform and Optimality

In the previous section, we have briefly reviewed the derivation of a class of waveforms in [14], which shows the mathematical existence of such type of waveform that has the capability of converting a frequency offset between the transmitted signal and the detector into a time offset in a simple linear fashion. However, the practicality regarding how to take advantage of this property of this type of waveform to build a practical synchronization waveform remains to be answered since to be a practical synchronization waveform, it must allow us to select waveform parameters to satisfy the application requirements; and more importantly, enable the estimation of the frequency and time offset/error at the receiver, which is, after all, one of the essential functions of a synchronization signal, nevertheless unavailable in [14]. In this section, we first form a prototype waveform, and show its asymptotic optimality. We then utilize this property for optimizing the waveform subject to practical constraints. The analytical results from this section pave the way to Section IV.

A. Waveform Constraints

In the mathematical treatment of Section II, it is implicitly assumed that \( \hat{x}(t) \) extends beyond the correlation interval, \([-T/2, T/2]\). In practice, a synchronization waveform is time-bounded within length \( T \), i.e.,
\[
\hat{x}_{\alpha, \beta}(t) \triangleq \begin{cases} \hat{x}(t), & -T/2 \leq t \leq T/2 \\ 0, & \text{otherwise} \end{cases}
\]
This practical form of \( \hat{x}(t) \) defined in (9) is the prototype for the following analysis, and serves as the building block for creating the ultimate synchronization waveform in Section IV.

As such, when a frequency error causes a shift of the correlation peak from \( \tau = 0 \) to \( \tau^\dagger \), it creates a time offset or misalignment, \( \tau^\dagger \), between the received waveform and the local one, causing that only partial signal energy can be detected, which consequently results in a loss in detection peak energy. Therefore, the effect of this time misalignment on the detection energy (and ergo the detection performance) needs to be taken into account in practical designs.

It is apparent that the misalignment, \( \tau^\dagger \), between the incoming signal and the local waveform must be less than the waveform length, \( T \), in order for the correlator to output nonzero detection energy, i.e.,
\[
|\tau^\dagger| < T.
\]

It is not difficult to find that the loss in detection energy due to a time offset \( \tau^\dagger \) is
\[
\ell(\tau^\dagger) = \left(1 - |\tau^\dagger|/T \right)^2.
\]

From (20) it is clear that
\[
0 < \ell(\tau^\dagger) < 1
\]
in linear, or
\[
\ell(\tau^\dagger) < 0
\]
in dB, for \( \tau^\dagger \neq 0 \) (i.e., \( \Delta f \neq 0 \)).

Hence, the practical form of the mathematical waveform \( \hat{x}(t) \), i.e., the prototype \( \hat{x}_{\alpha, \beta}(t) \) given in (17), no longer attains the maximum detection energy of an actual matched filter. In fact, it is \( -\ell(\tau^\dagger) \) dB away from the optimal. The selection of the waveform parameters, i.e., \( \alpha \) and \( \beta \), therefore needs to minimize this deficit, or maximize \( \ell(\tau^\dagger) \), i.e.,
\[
\left\{\alpha, \beta\right\} = \arg \max_{\alpha, \beta \in \mathbb{R}} \ell(\tau^\dagger).
\]

From (10) this deficit is found to be a sole function of parameter \( \alpha \) (not a function of \( \beta \)). Substituting (10) into (19) follows that
\[
\ell(\alpha) = \left(1 - T^{-1} |\Delta f|/|\alpha| \right)^2
= \left(1 - \mu/|\alpha| \right)^2,
\]
where
\[
\mu \triangleq T^{-1} \cdot |\Delta f| > 0.
\]
Clearly, \( \ell(\alpha) = 1 \) (or 0 dB), i.e., no loss with respect to the optimal, when \( \mu = 0 \) or \( \Delta f = 0 \).

Equation (22) then becomes
\[
\dot{\alpha} = \arg \max_{\alpha \in \mathbb{R}} \ell(\alpha),
\]
which is equivalent to
\[
\dot{\alpha} = \arg \max_{\alpha \in \mathbb{R}} |\alpha|.
\]
From (10), (18) and (24), it is clear that
\[
|\alpha| > \mu.
\]
that, for nonzero $\mu$, i.e., $\Delta f \neq 0$, 
$$\ell (\alpha) \rightarrow 1^{-} \text{ or } 0^{-} \text{ dB},$$
(28)
as $|\alpha| \rightarrow +\infty$. We thus have the following proposition:

Proposition 2: Waveform $\hat{x} (t)$ defined in (17) asymptotically attains the optimality of a matched-filter detector, in the presence of a frequency error. The rate of convergence is determined by $\mu$ defined in (24), which is irrelevant of SNR.

This asymptotic behavior of $\hat{x}_{\alpha,\beta} (t)$ is graphically shown in Fig. 2, where the dotted line is the asymptote, i.e., $\ell (\alpha) = 0$ (dB) for $\mu = 0$ (i.e., $\Delta f = 0$), as promised by an actual matched-filter detector that has the full knowledge of the input signal frequency, i.e., zero frequency error, and the cases with $\mu \neq 0$ ($\Delta f \neq 0$): $\mu = 0.0256$ and $0.0512$ (kHz/μs), corresponding to $T = 780\mu$s and $T/2 = 390\mu$s, respectively, given $|\Delta f| = 1$ GHz × 20 ppm = 20 kHz. Here we have borrowed the NB-IoT parameters, the primary synchronization signal length ($T = 780\mu$s), and maximum frequency error ($|\Delta f| = 20$ ppm), as example.

It is now evident that the design of the prototype waveform $\hat{x}_{\alpha,\beta} (t)$ optimized for a particular application becomes maximization of the magnitude of the waveform parameter $\alpha$, subject to the specific constraint imposed by the application.

B. Frequency Error constraint

From (10) and (18), it is clear that
$$|\alpha^{-1}| \Delta f | < T.$$
(29)
This implies that for a maximum supported frequency error requirement, $|\Delta f_{\text{max}}|$, the selection of $\alpha$ must satisfy
$$S_1: \quad |\alpha| > |\Delta f_{\text{max}}| / T.$$
(30)
That is to say, for a given waveform length, the larger the maximum frequency error that a practical system is designed to tolerate, the greater the magnitude of $\alpha$ is required.

For NB-IoT, the maximum supported frequency error is $|\Delta f_{\text{max}}| = 20$ ppm, corresponding to $\sim 20$ kHz at 1 GHz carrier frequency. Hence the solution to (30) is
$$S_1: \quad \langle \alpha_1, \beta_1 \rangle \in O_1^1 \quad \text{ (31)}$$
where
$$O_1^1 \triangleq \{ \langle \alpha, \beta \rangle | |\alpha| > 0.0256 \} \quad \text{(32)}$$
with $T = 780\mu$s.

For the same frequency error tolerance but a shorter waveform length, e.g., $T/2 = 390\mu$s, the corresponding solution is
$$O_1^2 \triangleq \{ \langle \alpha, \beta \rangle | |\alpha| > 0.0512 \} \quad \text{(33)}$$

C. Spectral Constraints

Both (26) and (30) demand a large $|\alpha|$. Nevertheless, in practice, the selection of $\alpha$ cannot be arbitrarily large and is often limited by the application-specific constraints. A typical example of such constraints is the spectral requirements, e.g., the maximum occupied bandwidth restriction, and the adjacent channel leakage ratio (ACLR) requirement [21], [22]. The occupied bandwidth is the width of a frequency band such that, below the lower and above the upper frequency limits, the powers emitted are each equal to a specified percentage $\sigma/2$ (e.g., $\sigma = 1\%$) of the total transmitted power, while ACLR is the ratio of the power centred on the assigned channel frequency to that centred on an adjacent channel frequency.

Therefore, the optimization of the waveform in (26) can be reformulated as
$$\hat{\alpha} = \arg \max_{S_1 \cap S_2 \cap S_3} |\alpha|,$$
(34)
where $S_1$ is the constraint from the supported maximum frequency error requirement given in (30), $S_2$ is the occupied bandwidth requirement, and $S_3$ the ACLR requirement.

In detail, $S_2$ requires that a specified percent of the waveform energy be confined within a given bandwidth $W \in \mathbb{R}^+$, i.e.,
$$S_2: \quad \frac{1}{T} \int_{-W/2}^{W/2} \hat{x}_{\alpha,\beta} (f) df \geq 1 - \sigma,$$
(35)
where
$$\hat{x}_{\alpha,\beta} (f) \triangleq \int_{-T/2}^{T/2} \hat{x}_{\alpha,\beta} (t) e^{-j2\pi ft} dt, \quad \forall f \in \mathbb{R},$$
(36)
is the power spectrum of waveform $\hat{x} (t)$, and noting that $E = \int_{-T/2}^{T/2} |\hat{x}_{\alpha,\beta} (t)|^2 dt = T$.

Using NB-IoT as example, $W = 200$ kHz, $\sigma = 1\%$, and $T = 780\mu$s [23].

To see the implication of $S_2$ on the waveform parameters $\alpha$ and $\beta$, let us first look at (35) with equality, from which the occupied bandwidth, $W$, of waveform $\hat{x}_{\alpha,\beta} (t)$ can be plotted as a function of $\alpha$ and $\beta$, which produces a surface as illustrated in Fig. 3(a). Every point on this surface is a pair of $\alpha$ and $\beta$ values, $\langle \alpha, \beta \rangle$, associated with a $W \in \mathbb{R}^+$ that corresponds to a particular bandwidth, within which $1 - \sigma = 99\%$ of the energy of $\hat{x}_{\alpha,\beta} (t)$ is confined. This surface,
Among these $\alpha, \beta$ pairs on $W_\sigma$, we are particularly interested in the ones that correspond to a given $W, W^\dagger$, i.e.,

$$C^\dagger = \left\{ (\alpha, \beta) \mid W_\sigma (\alpha, \beta) = W^\dagger \right\},$$  

which forms a closed symmetric contour $C^\dagger$ on the $\alpha, \beta$ plane as illustrated in Fig. 3(b) where $W^\dagger = 200$ kHz (or 53 dBHz) and $\sigma = 99\%$, which can be viewed as the intersection between the occupied bandwidth surface $W_\sigma (\alpha, \beta)$ and the $W^\dagger = 200$ kHz plane [see Fig. 3(a)].

In fact, it can be further shown that any $\alpha, \beta$ pair that falls within the area enclosed by $C^\dagger$ satisfies (35). If we denote this enclosure (including $C^\dagger$) as $O^\dagger_2$, we can conclude that $S_2$ in (35) is satisfied by $\forall (\alpha, \beta) \in O^\dagger_2$. Consequently, $\hat{X}_{\alpha, \beta} (f)$ with parameters $\alpha$ and $\beta$ selected from any point in $O^\dagger_2$ meets the maximum occupied bandwidth requirement, $S_2$.

The occupied bandwidth requirement in (35) thus implies

$$S_2 : \left\langle \alpha_2, \beta_2 \right\rangle \in O^\dagger_2,$$  

as graphically shown in Fig. 3(b).

$S_3$, the ACLR restriction requires that

$$S_3 : \hat{X}_{\alpha, \beta} (f) \leq M(f), \quad \forall f \in \mathbb{R},$$  

where $M(f)$ is the spectral mask.

The ACLR from NB-IoT indicates that for adjacent channel with 300 kHz offset is $-40$ dBc and with 500 kHz is $-50$ dBc, which can be represented as

$$M(f) = \begin{cases} 
40 \text{ dBc} & |f| \leq 300 \text{ kHz} \\
-50 \text{ dBc} & |f| \geq 500 \text{ kHz} 
\end{cases}$$  

as shown in Fig. 4, where $f$ is the frequency offset with respect to the carrier frequency. It is not surprising to see the much relaxed ACLR requirement since the adjacent channel interference from NB-IoT is suppressed by the 1/12 frequency reuse plan for GSM, recalling that NB-IoT mainly targets the refarmed GSM bands. Nevertheless, the solution to (40) can be found to be

$$S_3 : \left\langle \alpha_3, \beta_3 \right\rangle \in O^\dagger_3,$$  

which is graphically shown in Fig. 5.
Now we are ready to find the solution to (34) by combining (31), (39), and (42),

$$\langle \hat{\alpha}, \hat{\beta} \rangle = \arg\max_{\alpha, \beta} |\alpha| \quad \text{subject to} \quad S_1 \cap S_2 \cap S_3$$

for $T = 780 \mu s$.

The solution in (43) gives the optimal parameters in the sense that the synchronization waveform, $\hat{x}_{\alpha, \beta}(t)$, parameterized by $\langle \hat{\alpha}, \hat{\beta} \rangle$ has the least performance loss (with respect to the optimal matched-filter) among all the waveforms in $\{\hat{x}_{\alpha, \beta}(t) | \alpha, \beta \in \mathbb{R}\}$, constrained by the maximum frequency error tolerance, maximum occupied bandwidth, and ACLR spectrum mask. Waveform $\hat{x}_{\alpha, \beta}(t)$ is hence referred to as the optimal waveform in the same sense. The power spectrum $X_{\hat{x}_{\alpha, \beta}}(f)$ of the optimal waveform $\hat{x}_{\alpha, \beta}(t)$ is plotted in Fig. 4 together with the ACLR mask $M(f)$.

From (19) or Fig. 2, the corresponding degradations of the optimal waveform parameterized by (43) at various magnitudes of frequency errors is plotted in Fig. 6. It is seen that the degradation is less than 1 dB at a maximum frequency error of 20 kHz, and dwindles to 0 dB as the frequency error becomes zero, which is significantly less than a differential error of 20 kHz, and dwindles to 0 dB as the frequency error.

It is noted that the optimal value of $\alpha$ is a function of the time duration $T$ of the waveform. For instance, following the same optimization procedure, the optimal $\alpha$ for $T/2 = 390 \mu s$ can be found to be

$$\hat{\alpha} = \arg\max_{\alpha} |\alpha| = \pm 0.481 \, \text{kHz/\mu s}.$$  

We summarize the above parametrization of the waveform as follows: 1) from the largest frequency error that the system is designed to tolerate, use (30) to obtain the first constraint, $S_1$; 2) from the maximum allowed occupied bandwidth, use (35) to form the second constraint, $S_2$; and 3) according to the required adjacent channel leakage ratio, use (40) to determine the third constraint, $S_3$. Finally, solve the following optimization problem:

$$\langle \hat{\alpha}, \hat{\beta} \rangle = \arg\max_{\alpha, \beta} |\alpha| \quad \text{subject to} \quad S_1, S_2, \text{and } S_3.$$  

**IV. Practical Waveform**

So far we have shown that the prototype waveform defined in (17) possesses certain useful mathematical properties that not only provide robust detection performance against frequency errors but also facilitate optimization to meet the application requirements. However, in addition to the primary role of detecting the presence and timing of a system, another essential function of a synchronization signal is to provide frequency synchronization. To this end, the frequency error $\Delta f$ needs to be obtained after signal $x_{\alpha, \beta}(t)$ is detected. From (10), $\Delta f$ is linearly related to $\tau^i$, the deviation of the detection peak from the actual timing position, however also unknown to the receiver. It is thus clear that, in its original form, the prototype waveform cannot be used as a practical synchronization signal.

To solve this dilemma, we need the following property, which is already seen from the solutions in (43), and is generally true.

**Proposition 3:** The optimal solutions to (34) come in symmetric pairs, i.e., if $\langle \hat{\alpha}, \hat{\beta} \rangle$ is the solution to (34), then $\langle -\hat{\alpha}, \hat{\beta} \rangle$ is also a solution.

This is because the constraint, $S_i$ ($i = 1, 2, 3$), is symmetric in terms of $\alpha$ and $\beta$. Consequently, $O^i_1$ is symmetric, i.e.,

1) symmetric about $\alpha = 0$, i.e.,

$$O^i_1(-\alpha, \beta) = O^i_1(\alpha, \beta);$$

2) symmetric about $\beta = 0$, i.e.,

$$O^i_1(\alpha, -\beta) = O^i_1(\alpha, \beta);$$

---

Fig. 6. Plot of the performance degradation (relative to the optimal matched-filter, 0 dB) of the optimal waveform $\hat{x}_{\alpha, 0}(t)$ against the frequency error $\Delta f$ ranging from $-20$ kHz to $+20$ kHz.
This symmetry property is straightforward for $i = 1$, while for $i = 2$, and $3$ it is a result from the fact that $\hat{X}_{\alpha, \beta}(f)$ is symmetric, i.e.,

$$\hat{X}_{-\alpha, \beta}(f) = \left| \int_{-T/2}^{T/2} \hat{X}_{\alpha, \beta}(t) e^{-j 2\pi f T} dt \right|^2$$

Substituting $-t$ with $\xi$ results in

$$\hat{X}_{-\alpha, \beta}(f) = \left( \int_{-T/2}^{T/2} e^{j 2\pi (\alpha^2 + \beta \xi)} e^{-j 2\pi f \xi} d\xi \right)$$

$$= \hat{X}_{\alpha, \beta}(f),$$

and (46) follows.

Similarly, it can be shown that

$$\hat{X}_{-\alpha, -\beta}(f) = \hat{X}_{\alpha, \beta}(-f),$$

which leads to (47) since

$$\frac{1}{T} \int_{-W^1/2}^{W^1/2} \hat{X}_{\alpha, \beta}(f) df = \frac{1}{T} \int_{-W^1/2}^{W^1/2} \hat{X}_{\alpha, \beta}(-\xi) d\xi$$

$$= \frac{1}{T} \int_{-W^1/2}^{W^1/2} \hat{X}_{-\alpha, -\beta}(f) df,$$

whereas (48) directly follows from (46) and (47).

Following Proposition 3, we conclude that the optimal waveforms come in pairs, meaning that if $\langle \alpha, \beta \rangle$ parameterizes an optimal waveform,

$$\hat{x}_{\alpha, \beta}(t) = \left\{ e^{j 2\pi (\beta t + \alpha t)}, \begin{array}{lr} -T/2 \leq t \leq T/2, \hfill \\ 0, \end{array} \right.$$  

then $\langle -\alpha, -\beta \rangle$ also yields an optimal waveform,

$$\hat{x}_{-\alpha, -\beta}(t) = \left\{ e^{j 2\pi (-\beta t + \alpha t)}, \begin{array}{lr} -T/2 \leq t \leq T/2, \hfill \\ 0, \end{array} \right.$$  

Together, (53) and (54) constitute the optimal waveform pair.

Following the same example from the previous section, waveforms

$$\hat{x}_{0,0}(t),$$

and

$$\hat{x}_{0,0}(t) = \hat{x}_{0,0}^*(t),$$

where $(\cdot)^*$ denotes conjugate operation, $\alpha = 0.251$ (kHz/µs) with $T = 780$µs or $\alpha = 0.481$ (kHz/µs) with $T/2 = 390$µs, form an optimal pair that are co-conjugate.

It is evident that the optimal waveform pair not only provide the same performance but also produce the same time deviation, only in opposite directions. That is to say, a frequency error $\Delta f$ causes the output of the matched filter to $\hat{x}_{-\alpha, -\beta}(t)$ to deviate from its original position by

$$-\tau^\dagger = \hat{x}_{\alpha, \beta}(t),$$

in response to an incoming signal $\hat{x}_{-\alpha, -\beta}(t)$, as opposed to

$$\tau^\dagger = -\hat{x}_{-\alpha, \beta}(t),$$

in response to $\hat{x}_{-\alpha, \beta}(t)$ from its corresponding matched filter [cf. (10)].

This property leads to a simple means to obtain the time deviation or timing error (and then the actual timing and the frequency error) by transmitting the paired optimal waveforms, $\hat{x}_{\alpha, 0}(t)$ and $\hat{x}_{-\alpha, 0}(t)$, alternatively in subsequent transmission opportunities, $P$ sec apart, i.e.,

$$\hat{x}(t) \Delta \left\{ \begin{array}{lr} \hat{x}_{\alpha, 0}(t), \hfill \\ \hat{x}_{-\alpha, 0}(t - P), \end{array} \right. \begin{array}{l} -T/2 \leq t < T/2, \\ -T/2 + P \leq t < T/2 + P \end{array}$$  

as depicted in Fig. 7(a).

For a given $\Delta f$, a paired correlator gives rise to two correlation peaks, one of which is located at $t^\dagger_1 = t_1 + \tau^\dagger_1$
Solving (61) for $\hat{\tau}$ in response to $\hat{x}_{\alpha,0}(t)$ at the output of the matched filter to $\hat{x}_{\alpha,0}(t)$, and the other at

$$t^\dagger_2 = t^\dagger_1 + P + 2\tau^\dagger,$$

in response to $\hat{x}_{-\alpha,0}(t)$ at the output of another matched filter to $\hat{x}_{-\alpha,0}(t)$. They are separated by a distance of

$$d \triangleq t^\dagger_2 - t^\dagger_1 = P + 2\cdot\tau^\dagger.$$  (61)

Solving (61) for $\tau^\dagger$ yields

$$\tau^\dagger = \frac{1}{2}(d - P),$$

and

$$\Delta f = -\frac{\hat{\alpha}}{2}(d - P)$$

immediately follows from (10).

Obviously, both $\tau^\dagger$ and $\Delta f$ are functions of a sole valuable $d$, which can be directly measured after detection.

Fig. 8 is the sample outputs of the matched-filter or cross-correlator pair,

$$\gamma_{\alpha}(t) = \left\| \int_{-T/2}^{T/2} \hat{x}(\tau) \hat{x}_{\alpha,0}^*(\tau - t) d\tau \right\|,$$  (64)

in response to the composite synchronization signal $\hat{x}(t)$ in (59), under frequency offsets of (a) $20$ kHz, (b) $-20$ kHz, and (c) $0$ kHz, where $\hat{\alpha} = \pm 0.251$ (kHz/µs).

Specifically, a maximum likelihood (ML) detector of the composite or paired waveform can be formulated as

$$\left( \hat{t}^\dagger_2, \hat{d} \right) = \arg\max_{\left|\hat{d} - P\right| < 2\hat{\alpha}^{-1}\Delta f_{\text{max}}} \Gamma_{\alpha}(t^\dagger_2, \hat{d}),$$  (65)
where the detection metric
\[ \Gamma_{\alpha}(\hat{t}_2^\dagger, d) = \gamma_{-\alpha}(\hat{t}_2^\dagger) + \gamma_{\alpha}(\hat{t}_2^\dagger - d), \]

as illustrated in Fig. 9, and \( \Xi \) is the search window (i.e., time uncertainty range) of width \( |\Xi| = P \). From the outcome of (65), estimates for both timing deviation and frequency offset, i.e., \( \hat{\tau}_1^\dagger \) and \( \hat{\Delta}f \), can be obtained from (62) and (63), respectively, with which the actual system timing is determined, i.e., \( \hat{t}_2^\dagger - \hat{\tau}_1^\dagger \), so is the system frequency, \( f'_c - \hat{\Delta}f \), referring back to (1).

It is also possible to construct a composite waveform composed of \( \hat{x}_{\alpha,0}(t) \) immediately followed by its counterpart \( \hat{x}_{-\alpha,0}(t) \), i.e.,
\[ \hat{x}(t) = \begin{cases} \hat{x}_{\alpha,0}(t), & -T/4 \leq t < T/4, \\ \hat{x}_{-\alpha,0}(t - T/2), & T/4 \leq t < 3T/4, \end{cases} \]

as depicted in Fig. 7(b), and the corresponding time deviation and frequency offset are
\[ \hat{\tau}_1^\dagger = \frac{1}{2} \left( d - \frac{T}{2} \right), \]
and
\[ \hat{\Delta}f = -\frac{\hat{\alpha}}{2} \left( d - \frac{T}{2} \right). \]

The composite waveform enables the estimation of a frequency error, and yet an efficient detection implementation by taking advantage of the fact that most of the computations can be shared between the paired correlators due to the conjugate nature. The overall complexity of such a detector is thus similar to the conventional matched-filter or cross-correlation based detectors.

\[ \text{CDF} \]

\[ \text{SNR} = 0 \text{ dB} \]
\[ \text{SNR} = 5 \text{ dB} \]
\[ \text{SNR} = -5 \text{ dB} \]

\[ \text{Frequency estimation error (Hz)} \]

\[ \text{Timing estimation error (µ s)} \]

\[ \text{CDF} \]

\[ \text{SNR} = 0 \text{ dB} \]
\[ \text{SNR} = 5 \text{ dB} \]
\[ \text{SNR} = -5 \text{ dB} \]

\[ \text{Frequency estimation error (Hz)} \]

\[ \text{Timing estimation error (µ s)} \]

\[ \text{CDF} \]

\[ \text{SNR} = 0 \text{ dB} \]
\[ \text{SNR} = 5 \text{ dB} \]
\[ \text{SNR} = -5 \text{ dB} \]

\[ \text{Frequency estimation error (Hz)} \]

\[ \text{Timing estimation error (µ s)} \]

\[ \text{CDF} \]
A frequency error $\Delta f$, uniformly distributed in the range from $-20$ kHz to $+20$ kHz, is introduced into the incoming signal. The detector employs a pair of matched filters to the two paired waveforms, and jointly detects the incoming paired signal according to (65) with $P = 10$ ms (i.e., the transmission period of the NB-IoT narrowband primary synchronization signal or NPSS for short) to obtain timing $t_2^{\dagger}$, along with $\hat{d}$.

With the knowledge of $\hat{d}$, both $\hat{\tau}^{\dagger}$ and $\Delta f$ are readily available from (62) and (63). However, to reduce the effect of time quantization error on the frequency error estimation, a simple parabolic interpolation is used to refine the detection peaks, and ergo, $\hat{d}$, which is then used to calculate the frequency offset via (63).

The evaluation is performed at SNR levels of $-5$ dB, as well as 0, and 5 dB for comparison. The cumulative distribution function (CDF) of the time and frequency estimation error is plotted in Fig. 11 and the synchronization procedure is outlined in Fig. 13(a). It is observed that the timing estimation error (i.e., $\tau^{\dagger}$ estimation error) falls well within $1 \mu s$, corresponding to a frequency estimation error (i.e., $\Delta f$ estimation error) of well below 200 Hz (150 Hz at 95 percentile and SNR $-5$ dB).

The accuracy can be further improved via a more advanced interpolation method if needed [24]. Nevertheless, it is worth noting that, like in most wireless communication systems, synchronization in legacy LTE as well as in NB-IoT is performed in an incremental rather than a “one-shot” fashion. In fact, synchronization for data communications is carried out in two stages. By design, PSS is used in the first stage mainly to deal with the largest time and frequency uncertainties to pull in the time and frequency error to a range (e.g., within the cyclic prefix (4.7$\mu s$) in time and a few 100s Hz in frequency) that enables efficient processing of the subsequent secondary synchronization signal (SSS). As the name implies, SSS carries cell-specific information capable of facilitating further time and frequency refinement such that the frequency error is within 0.1 ppm (100 Hz at 1 GHz), before data communication starts. Since the difference of SSS detection performance between 200 Hz and zero frequency offsets is a few tenths of a dB, the benefit is rather limited for further frequency accuracy improvement in the first synchronization stage. As a signal for the initial coarse synchronization, it is thus more efficient and effective for the paired waveform to leave the frequency refinement to the secondary synchronization stage.

While acceptable for data communications, the synchronization precision provided by these two stages may not be sufficient for certain applications, such as the time difference based positioning [24]. An additional synchronization stage employing a special positioning reference signal (PRS) is typically needed to further reduce the residual synchronization error from PSS/SSS.

Fig. 13(b) depicts a typical time and frequency synchronization procedure for NPSS. Auto-correlation is first used to suppress the effect of frequency error on NPSS signal detection performance. As seen in Fig. 10, NPSS detection performance is not sufficient to support the $-5$ dB coverage due to the use of sub-optimal autocorrelation. NPSS thus relies on combing the auto-correlations over multiple (typically

![Fig. 13. Synchronization procedures for: (a) the paired waveform; and (b) NB-IoT PSS (NPSS).](image)
transmissions to boost the autocorrelation SNR [25]. The detected timing error (with two combinations) is plotted in Fig. 12. Once detected, the resultant autocorrelation is further used for frequency estimation, which suffers from two well-known drawbacks, poor accuracy and ambiguity, inherent to the autocorrelation-based frequency estimation, also known as the classic Lank’s method [26]. The repetition interval of the NPSS signal causes the phase ramping to “wrap” under large frequency error. In the NPSS case, the repetition interval is one OFDM symbol, i.e., 1/14 ms. The frequency offset that can be estimated via autocorrelation without wrapping is between −7 and 7 kHz, whereas under the maximum frequency error of 20 kHz, i.e., \( \Delta f \in (-20, 20) \) (kHz), three frequency errors produce the same autocorrelation metric. This ambiguity can be represented as

\[
\Delta f_i = 14 \cdot i + \frac{\nu}{\text{integer}} + \frac{\nu}{\text{fraction}}, \quad i \in \{-1, 0, 1\},
\]

in kHz, where \( \nu \in (-7, 7) \), whose estimation error CDF is plotted in Fig. 12.

Once the “fractional frequency”, \( \nu \), is corrected from the received signal, three hypothesis tests via three cross-correlators that are individually matched to the three possible frequencies 14·i (kHz), where \( i = -1, 0, 1 \), are performed to determine the “integer frequency” that gives the greatest correlation energy. Despite the insufficient accuracy of the auto-correlation based timing and frequency estimation for subsequent narrowband SSS (NSSS) processing (see Fig. 12), both time and frequency uncertainties are reduced as a result. The cross-correlation based multiple frequency hypotheses tests (e.g., 100 Hz apart), similar to the joint time and frequency detection method, can then be employed without incurring excessive complexity to bring the timing accuracy to a few microseconds, and frequency accuracy to less than 100 Hz, sufficient for subsequent NSSS processing. It is apparent that the bottleneck of the NPSS scheme lies in the detection performance rather than synchronization. After all, synchronization can only be accomplished upon a successful detection of the synchronization signal.

VI. CONCLUSION

In this paper, we propose a practical design of the frequency-error-resilient synchronization waveform for massive MTC. We derive and exploit the key mathematical properties of the prototype waveform for waveform optimization, frequency error estimation, as well as timing refinement. The design is exemplified by a specific practical application, i.e., LTE NB-IoT. We show that the practical form of this waveform is asymptotically optimal, in the sense that its asymptotic detection energy in the presence of frequency error is the same as an optimal matched filter which has full knowledge of the input signal frequency (i.e., free of frequency error). Based on this property, the practical design problem boils down to maximization of the waveform parameter, i.e., \( \alpha \), under the constraints present in the application. We further show that the optimal parameter of this type of waveform comes in symmetric pairs, which facilitates the construction of a practical synchronization waveform consisting of paired optimal waveforms enabling frequency error estimation and time refinement at the receiver. As a final note, fading is always an issue for any narrowband signal due to lack of frequency diversity although a narrowband signal helps avoid “energy dilution” from multipath. The situation is even more prominent in mMTC as a result of lack of receive diversity since the device is typically equipped with one antenna. The same problem exists when the proposed waveform is applied to a narrowband system like NB-IoT. This issue in NB-IoT is mitigated via time diversity, i.e., the detection on multiple transmissions over an elongated detection time duration. For example, in NB-IoT, the detection period of NB-IoT PSS can be as long as 100 ms (11 PSS transmissions). Another potential improvement is to employ transmit diversity by spatially-encoding the synchronization signal, which is of interest for future study.

ACKNOWLEDGMENT

The authors are grateful for the excellent comments by the Editor and reviewers which greatly improved the presentation and the contents of this paper.

REFERENCES

[1] E. Dutkiewicz, X. Costa-Perez, I. Z. Kovacs, and M. Mueck, “Massive machine-type communications,” IEEE Network, vol. 31, no. 6, pp. 6–7, 2017.
[2] M. Wang, W. Yang, J. Zou, B. Ren, M. Hua, J. Zhang, and X. You, “Cellular machine-type commun ications: physical challenges and solutions,” IEEE Wireless Communications, vol. 23, no. 2, pp. 126–135, 2016.
[3] 3rd Generation Partnership Project Technical Specification Group Radio Access Network Evolved Universal Terrestrial Radio Access (E-UTRA) Physical channels and modulation (Release 13), TS 36.211 ver. 13.2.0, June 2016.
[4] Y-P. E. Wang, X. Lin, A. Adhikary, A. Grovlen, Y. Sui, Y. Blankenship, J. Bergman, and H. S. Razaghi, “A primer on 3gpp narrowband internet of things,” IEEE Communications Magazine, vol. 55, no. 3, pp. 117–123, 2017.
[5] B. M. Popovic, “Optimum sets of interference-free sequences with zero autocorrelation zones,” IEEE Transactions on Information Theory, 2017.
[6] G. Berardelli, K. I. Pedersen, T. B. Sorensen, and P. Mogensen, “Generalized dft-spread-ofdm as 5g waveform,” IEEE Communications Magazine, vol. 54, no. 11, pp. 99–105, 2016.
[7] X. Zhang, L. Chen, J. Qiu, and J. Abdoli, “On the waveform for 5g,” IEEE Communications Magazine, vol. 54, no. 11, pp. 74–80, 2016.
[8] A. A. Zaidi, R. Baldemair, H. Tullberg, H. Björkgrén, L. Sundstrom, J. Medbo, C. Kilinc, and I. Da Silva, “Waveform and numerology to support 5g services and requirements,” IEEE Communications Magazine, vol. 54, no. 11, pp. 90–98, 2016.
[9] J. Yli-Kaakinen, T. Levanen, S. Valkonen, K. Pajukoski, J. Pirskanen, M. Renfors, and M. Valkama, “Efficient fast-convolution-based waveform processing for 5g physical layer,” IEEE Journal on Selected Areas in Communications, vol. 35, no. 6, pp. 1309–1326, 2017.
[10] P. Guan, D. Wu, T. Tian, J. Zhou, X. Zhang, L. Gu, A. Benjebbour, M. Iwabuchi, and Y. Kishiyama, “5g field trials: Ofdm-based waveforms,” IEEE Journal on Selected Areas in Communications, vol. 35, no. 6, pp. 1234–1243, 2017.
[11] Y. Liu, X. Chen, B. Ai, Z. Zhong, D. Miao, Z. Zhao, J. Sun, Y. Teng, and H. Guan, “Waveform design for 5g networks: Analysis and comparison,” IEEE Access, vol. 5, pp. 19282–19292, 2017.
[12] B. Farhang-Boroujeny and H. Moradi, “Ofdm inspired waveforms for 5g,” IEEE Communications Surveys & Tutorials, vol. 18, no. 4, pp. 2474–2492, 2016.
[13] J. M. Haminreh and H. Arslan, “Secure orthogonal transform multiplexing (otdm) waveform for 5g and beyond,” IEEE Communications Letters, vol. 21, no. 5, pp. 1191–1194, 2017.
[14] J. Zhang, M. Wang, M. Hua, W. Yang, and X. You, “Robust synchronization waveform design for massive IOT,” IEEE Transactions on Wireless Communications, vol. 16, no. 11, pp. 7551–7559, 2017.

[15] H. Kroll, M. Korb, B. Weber, S. Willi, and Q. Huang, “Maximum-likelihood detection for energy-efficient timing acquisition in nbiot,” in Wireless Communications and Networking Conference Workshops (WCNCW), 2017 IEEE. IEEE, 2017, pp. 1–5.

[16] S. Lippuner, B. Weber, M. Salomon, M. Korb, and Q. Huang, “Ec-gsm-iot network synchronization with support for large frequency offsets,” in Wireless Communications and Networking Conference (WCNC), 2018 IEEE. IEEE, 2018, pp. 1–6.

[17] M. Hua, M. M. Wang, K. W. Yang, X. You, F. Shu, J. Wang, W. Sheng, and Q. Chen, “Analysis of the frequency offset effect on random access signals,” IEEE Trans. Communications, vol. 61, no. 11, pp. 4728–4740, 2013.

[18] M. Hua, M. Wang, K. W. Yang, and K. J. Zou, “Analysis of the frequency offset effect on zadoff–chu sequence timing performance,” IEEE Transactions on Communications, vol. 62, no. 11, pp. 4024–4039, 2014.

[19] H. Puska and H. Saarnisaari, “Matched filter time and frequency synchronization method for ofdm systems using pn-sequence preambles,” in Personal, Indoor and Mobile Radio Communications, 2007. PIMRC 2007. IEEE 18th International Symposium on. IEEE, 2007, pp. 1–5.

[20] F. Tufvesson, O. Editors, and M. Faulkner, “Time and frequency synchronization for ofdm using pn-sequence preambles,” in Vehicular Technology Conference, 1999. VTC 1999-Fall. IEEE VTS 50th, vol. 4. IEEE, 1999, pp. 2203–2207.

[21] ITU-R recommendation SM.328, “Spectra and bandwidth of emissions.”

[22] ITU-R recommendation SM.329, “Unwanted emissions in the spurious domain.”

[23] Third Generation Partnership Program (3GPP): Evolved Universal Terrestrial Radio Access Base Station (BS) radio transmission and reception, Tech. Specification 36.104 V 14.0.0, Jun. 2016.

[24] S. Hu, A. Berg, X. Li, and F. Rusek, “Improving the performance of otdoa based positioning in nbiot systems,” arXiv preprint arXiv:1704.05539, 2017.

[25] A. Ali and W. Hamouda, “On the cell search and initial synchronization for nbiot lte systems,” IEEE Communications Letters, vol. 21, no. 8, pp. 1843–1846, 2017.

[26] T. Brown and M. M. Wang, “An iterative algorithm for single-frequency estimation,” IEEE Transactions on Signal Processing, vol. 50, no. 11, pp. 2671–2682, 2002.

Jingjing Zhang is working towards her Ph.D. degree at Nanjing University of Science and Technology, Nanjing, China. She is with the Wireless Networking and Mobile Communications Group, School of Electronic and Optical Engineering. Her current research interests are in the areas of wireless communications and signal processing.

Michael Mao Wang received the master’s degree in biomedical engineering and the Ph.D. degree in electrical engineering and computer science from the University of Kentucky, Lexington, KY, USA. He was a Distinguished Member of Technical Staff with Motorola Advanced Radio Technology Group, Arlington Heights, IL, USA, from 1995 to 2003, and joined Qualcomm Research, San Diego, CA, USA, in 2003. He became a Professor with the School of Information Science and Technology and the National Mobile Communications Research Laboratory at Southeast University, Nanjing, China, in 2015. He is also an Adjunct Professor with the School of Electronic and Optical Engineering, Nanjing University of Science and Technology. He holds more than 90 U.S. patents and has over 30 IEEE journal publications. His research interests include communication theory and wireless networking.

Tingting Xia is working towards her Ph.D. degree at Nanjing University of Science and Technology, Nanjing, China. She is with the Wireless Networking and Mobile Communications Group, School of Electronic and Optical Engineering. Her current research interests are in the areas of wireless communications and signal processing.