**GRADUATION THESIS**

**Tên đề tài:** Định vị trong hệ thống 5G MIMO Millimeter wave bằng phương pháp Distributed Compressive Sensing (S-OMP)

**THESIS TITLE:** Position Estimation Through MillimeterWave MIMO in 5G Systems using Distributed Compressive Sensing (S-OMP)

**ABSTRACT**

Nowadays, large antenna arrays and millimeter wave signals are thought to be key technology for upcoming 5G networks. Their potential benefits for precise positioning are largely unexplored, despite their well-known benefits for attaining high-data rate communications. In this thesis, a 5G channel using millimeter-wave (mmWave) and massive Multiple-Input Multiple-Output (mMIMO) technologies is simulated, considering the following localization parameters: Time of Arrival (TOA), Angle of Departure (AoD), and Angle of Arrival (AoA). To achieve these precise estimations, I employ an approach built upon the Distributed Compressed Sensing—Subspace Orthogonal Matching Pursuit (DCS-SOMP) algorithm. In the presence of scatterers, we estimate the Cramér-Rao bound (CRB) on location and rotation angle estimation uncertainty from millimeter wave signals from a single transmitter. Additionally, we describe a ***novel*** two-stage algorithm for position and rotation angle estimation that attains the CRB for average to high signal-to-noise ratio. For coarse estimation, the approach is based on the multiple measurement vectors matching pursuit, followed by a refinement stage based on the space alternating generalized expectation maximization (SAGE) algorithm. Finally, we estimate accurate position and rotation angle, which is possible using signals from a single transmitter, in line-of-sight, non-line-of-sight, or obstructed-line-of-sight scenarios.

***Keywords: :*** *5G; Distributed* *compressed sensing; DCS-SOMP; parameter estimation; position estimation; mmWave; mMIMO*

**TÓM TẮT**

***Từ khóa:*** *5G; Distributed* *compressed sensing; DCS-SOMP; parameter estimation; position estimation; mmWave; mMIMO*

**AUTHORSHIP**

*“I hereby declare that the work contained in this thesis is of my own and has not been previously submitted for a degree or diploma at this or any other higher education institution. To the best of my knowledge and belief, the thesis contains no materials previously published or written by another person except where due reference or acknowledgement is made.”*

Signature:………………………………………………

**SUPERVISOR’S APPROVAL**

*“I hereby approve that the thesis in its current form is ready for committee examination as a requirement for the Bachelor of Electronics and Telecommunication degree at the University of Engineering and Technology.”*

Signature:………………………………………………

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I would like to also thank … (should be your colleagues, friends who have helped you along)

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**ABBREVIATIONS**

**CHAPTER 1: INTRODUCTION**

*(Tính cần thiết của đề tài, ý nghĩa khoa học và thực tiễn, đối tượng và phương pháp nghiên cứu, nội dung nghiên cứu)*

**1.1. Motivation**

In today's technological age, the application of 5G networks is growing in popularity, and having the ability to accurately estimate the location and angle of rotation of devices in 5G networks will play an important role in many areas such as intelligent transportation, object tracking and positioning, and personal communications

Mm-wave and massive multiple-input-multiple-output (MIMO) will likely be adopted in fifth generation (5G) communication networks, thanks to a number of favorable properties. Particularly, due to exploiting the carrier frequencies beyond 30 GHz and large available bandwidth, mm-wave can provide high data rate. This can be obtained through dense spatial multiplexing with large antennas. A sparse signal recovery problem exploiting the sparse nature of mm-wave channels is formulated for channel estimation based on the parametric channel model with quantized angles of departures/arrivals (AoDs/AoAs), called the angle grids. The problem is solved by the orthogonal matching pursuit (OMP) algorithm employing a redundant dictionary consisting of array response vectors with finely quantized angle grids. However, OMP (Orthogonal matching pursuit) is only used for single subcarriers, to estimate accurate position and rotation angle, S-OMP Algorithm for multiple subcarriers (Simultaneous orthogonal matching pursuit) is used. Due to the linear antenna array, the method applies to a 2D environment. Additionally, the DCS-SOMP method provides only a coarse parameter estimate, demanding further fine-tuning using the SAGE method.

**1.2. Related work**

Channel estimation in mobile communication systems is very necessary. Channel estimation aims to reduce the variance of the function transmission of the transmit channel compared to the receive channel due to many reasons transmission process. Channel estimation can be performed in different ways: with or without the support of parametric modeling, using correlation Observe the frequency or time of the radio channel, based on the blind or pilot (training), adaptive or non-adaptive. Among them, channel estimation using compressed sensing is one of the most popular methods. In [1] presents the method to estimate accurate position and rotation angle estimation is possible using signals from a single transmitter, in either line-of-sight, non-line-of-sight, or obstructed-line-of-sight conditions. Knowledge about Distributed Compressive Sensing and Joint Sparsity Modles is discussed in two studies [2] and [7]. In [4], author model a 5G downlink channel using millimeter-wave (mmWave) and massive Multiple-Input Multiple-Output (mMIMO) technologies, considering the following localization parameters: Time of Arrival (TOA), Two-Dimensional Angle of Departure (2D-AoD), and Two-Dimensional Angle of Arrival (2D-AoA), both encompassing azimuth and elevation. In [5], the classic method to solve problem optimizing L1 norm (direct L1) is alternating minimization (AM) via proximal gradient descent. A joint heuristic beam selection and user position and orientation tracking approach is proposed in [6].

The OMP algorithm and variations of the OMP algorithm using for channel estimation are also studied in the articles below. In paper [8] demonstrates theoretically and empirically that a greedy algorithm called Orthogonal Matching Pursuit (OMP). Paper [11] seeks to bridge the two major algorithmic approaches to sparse signal recovery from an incomplete set of linear measurements – L1-minimization methods and iterative methods (Matching Pursuits) and a simple regularized version of Orthogonal Matching Pursuit (ROMP). Stagewise Orthogonal Matching Pursuit algorithm is proposed in [12]. Channel estimation provides information of the AOA/AOD and thus of the relative location of the transmitter and receiver. In [9], author propose an efficient open-loop channel estimator for a millimeter-wave (mm-wave) hybrid multiple-input multiple-output (MIMO) system consisting of radio-frequency (RF) beamformers with large antenna arrays followed by a baseband MIMO processor. Article [10] reconsider the role of NLOS components for position and orientation estimation in 5G millimeter wave MIMO systems and is based on the concept of Fisher information

**1.3. Contributions and thesis overview**

The contributions of this thesis are described as follows:

- This thesis presents a method for estimating position and angle of rotation accurately through mm-wave signals from a single transmitter, even in conditions of obstructions. - This method achieves the Cramér-Rao limit (CRB) for the estimation of position and angle of rotation under the signal-from-one-way-mains-correct condition from a single transmitter.

- The method proposed in the thesis uses advanced signal processing and measurement techniques such as compressed sensing and expectation maximization algorithms to achieve accurate position and angle estimation. This method is different and advanced from traditional methods. This opens up the potential of mm-wave signals and large MIMO antennas in locating and orienting devices in 5G networks.

- This thesis proposes a method for determining position and direction using mm-wave signals from a single emitter, including in conditions of obstacles.

- The results of the study show that it is possible to determine the correct position and direction using magnetic signals from a single emitter, regardless of whether or not a direct line of sight, an indirect line of sight, or an obscured line of sight.

**1.4. Thesis layout**

The remainder of this article is organized as follows:

In Chapter 2, a literature review about basic theories of 5G system including system model, basic theory of compressed sensing and methods for 5G mm-wave channel estimation is presented.

Chapter 3 presented the details of positioning problem through millimeter wave MIMO in a 5G systemincluding overview about channel estimation, OMP Algorithm, S-OMP Algorithm and positioning methods using channel information (channel estimation).

In Chapter 4, simulation results are presented and discussed.

**CHAPTER 2: BASIC THEORIES OF 5G SYSTEM**

**2.1. System Model**

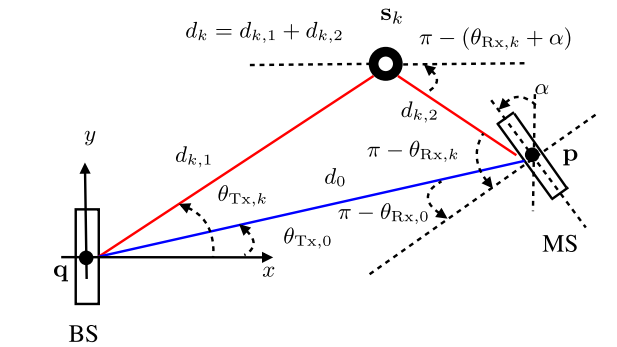
A MIMO system with a BS equipped with antennas and a MS equipped by antennas operating at a carrier frequency (corresponding to wavelength ) and bandwidth B. Locations of the BS and MS are denoted by and with the α ∈ [0, 2π) denoting the rotation angle of the MS’s antenna array. While *p* and *α* are unknown, the value of *q* is assumed to be known.

*2.1.1. Transmitter Model*

The transmission of orthogonal frequency division multiplexing (OFDM) signals, where a BS with hybrid analog/digital precoder communicates with a single MS. At the BS, *G* signals are transmitted sequentially, where the *g*-th transmission comprises simultaneously transmitted symbols for each subcarrier . The symbols are first precoded and then transformed to the time-domain using Npoint inverse fast Fourier transform (IFFT). A cyclic prefix (CP) of length is added before applying the radio-frequency (RF) precoding where D is the length of CP in symbols. Here, denotes the sampling period and is assumed to exceed the delay spread of the channel. The transmitted signal over subcarrier n at time g can be expressed as . The beamforming matrix is defined as where is implemented using the analog phase shifters with the entries of the form , where are given phases, and is the digital beamformer, and overall they satisfy a total power constraint .

Considering the sparsity of the mm-wave channels one usually needs much less beams than antenna elements , i.e., . Also, the presence of in the proposed model leads to the extension of system model to multi-user mm-wave downlink systems with a limited feedback channel from MSs to the BS. A general expressions that permit the study of the impact on performance and optimization of different choices of beamformers and signals , although this is out of the scope of the paper. My approach is also compatible with beam reference signal (initial access) procedures, and it could be complemented with a Bayesian recursive tracker with user-specific precoding.

*2.1.2. Channel Model*



*Figure 1*: Two dimensional illustration of the LOS (blue link) and NLOS (red link) based positioning problem. The BS location ***q*** and BS orientation are known, but arbitrary. The location of the MS ***p***, scatterer , rotation angle ***α,*** *AOAs(, AODs(),* the channel between BS and MS, and scatterers and the distance between the antenna centers are unknown

Fig. 1 shows the position-related parameters of the channel. These parameters include , and , , denoting the AOA, AOD, and the path length (with time-of-arrival (TOA) and the speed of light ) of the k-th path (k = 0 for the LOS path and k > 0 the NLOS paths). For each NLOS path, there is a scatterer with unknown location , for which we define and

The channel model is introduced, under a frequency-dependent array response, suitable for wideband communication (with fractional bandwidth up to 50%). Assuming K +1 paths and a channel that remains constant during the transmission of G symbols, the channel matrix associated with subcarrier n is expressed as

for response vectors

,

,

and

for path loss and complex channel gain , respectively, of the *k-th* path. For later use, and

The structure of the frequency-dependent antenna steering and response vectors and depends on the specific array structure. For the case of a uniform linear array (ULA), which will be the example studied in this thesis, (the response vector is obtained similarly)

where is the signal wavelength at the *n*-th subcarrier and d denotes the distance between the antenna elements (we will use ). When , , and reverts to the standard narrow-band model.

*2.1.3. Received Signal Model*

The received signal for subcarrier n and transmission , after CP removal and fast Fourier transform (FFT), can be expressed as

where is a Gaussian noise vector with zero mean and variance per real dimension.

Now, the goal is estimating the position **p** and orientation α of the MS from .

**2.2. Basic theory of compressed sensing**

Compressed sensing is an emerging field based on the revelation that a small collection of linear projections of a sparse signal contains enough information for reconstruction. A new framework for single-signal sensing and compression has developed recently under the rubric of Compressed Sensing (CS) [2, 3]. CS builds on the surprising revelation that a signal having a sparse representation in one basis can be recovered from a small number of projections onto a second basis that is incoherent with the first. (Roughly speaking, incoherence means that no element of one basis has a sparse representation in terms of the other basis). In fact, for an N-sample signal that is K-sparse (By K-sparse, we mean that the signal can be written as a sum of K basis functions.), roughly *cK* projections of the signal onto the incoherent basis are required to reconstruct the signal with high probability (typically c ≈ 3). This has promising implications for applications involving sparse signal acquisition. Instead of sampling a K-sparse signal N times, only *cK* incoherent measurements suffice, where K can be orders of magnitude less than N. Moreover, the *cK* measurements need not be manipulated in any way before being transmitted, except possibly for some quantization. Interestingly, independent and identically distributed Gaussian or Rademacher (random ±1) vectors provide a useful universal measurement basis that is incoherent with any given basis with high probability.

Suppose that *x* is a signal, and let be a basis or *dictionary* of vectors. When we say that *x* is sparse, we mean that *x* is well approximated by a linear combination of a small set of vectors from . That is, where ; we say that *x* is *K-sparse* in *Ψ* and call *Ψ* the sparse basis. The CS theory states that it is possible to construct an M × N *measurement* matrix Φ, where , yet the measurements *y =* Φ*x* preserve the essential information about *x*. For example, let Φ be a *cK × N* random matrix with independently and identically distributed. Gaussian entries, where *c = c(N, K)* is an *oversampling factor*. Using such a matrix it is possible, with high probability, to recover any signal that is *K*-sparse in the basis Ψ from its image under Φ. For signals that are not *K*-sparse but *compressible*, meaning that their coefficient magnitudes decay exponentially, there are tractable algorithms that achieve not more than a multiple of the error of the best *K*-term approximation of the signal.

Several algorithms have been proposed for recovering *x* from the measurements *y*, each requiring a slightly different constant *c*. The canonical approach uses linear programming to solve the minimization problem.

subject to Φ*Ψθ* = *y*.

This problem requires but has somewhat high computational complexity. Additional methods have been proposed involving greedy pursuit methods. Examples include Matching Pursuit (MP) and Orthogonal Matching Pursuit (OMP), which tend to require fewer computations but at the expense of slightly more measurements [5].

**2.3. Methods for 5G mm-wave channel estimation**

*2.3.1. Channel estimation using sparse CS methods*

2.3.1.1. L1 norm minimization (L1 trực tiếp)

2.3.1.2. Tối thiểu tổng các giá trị suy biến (L1 gián tiếp)

- FISTA

- L1-LS

*2.3.2. Sparse Bayesian Inference*

**Tổng kết chương II**

**CHAPTER 3: POSITIONING PROBLEM THROUGH MILLIMETER WAVE MIMO IN 5G SYSTEM**

**3.1. Overview about channel estimation**

**3.2. Distributed Compressive Sensing – Joint Sparsity Modles (JSM)**

*3.2.1. Theory for DCS*

In this thesis, theory and algorithms for *distributed compressed sensing* (DCS) that exploit both intra- and inter-signal correlation structures is presented. In a typical DCS scenario, a number of sensors measure signals (of any dimension) that are each individually sparse in some basis and also correlated from sensor to sensor. Each sensor *independently* encodes its signal by projecting it onto another, incoherent basis (such as a random one) and then transmits just a few of the resulting coefficients to a collection point. Under the right conditions, a decoder at the collection point can jointly reconstruct all of the signals precisely.

The DCS theory rests on a concept that we term the *joint sparsity* of a signal ensemble. The first model for jointly sparse signals and proposed corresponding joint reconstruction algorithms is introduced. Derived results on the required measurement rates for signals that have sparse representations under each of the models: while the sensors operate entirely *without collaboration*, dramatic savings relative to the number measurements required for separate CS decoding.

*3.2.2. Joint Sparsity Modles (JSM)*

In this section, we generalize the notion of a signal being sparse in some basis to the notion of an ensemble of signals being jointly sparse. Two different joint sparsity models (JSMs) that apply in different situations is considered. In these models, each signal is itself sparse, and so we could use the CS framework from above to encode and decode each one separately. However, there also exists a framework wherein a joint representation for the ensemble uses fewer total vectors. Thesis will use the following notation for signal ensembles and our measurement model. Denote the signals in the ensemble by , and assume that each signal . We use to denote sample *n* in signal *j*, and assume that there exists a known sparse basis Ψ for in which the can be sparsely represented. The coefficients of this sparse representation can take arbitrary real values (both positive and negative). Denote by the measurement matrix for signal *j*; is ×N and, in general, the entries of are different for each *j.* Thus, consists of < N incoherent measurements of . We will emphasize random with independently and identically distributed. Gaussian matrices in the following, but other schemes are possible, including random ±1 Bernoulli/Rademacher matrices, and so on.

3.2.2.1. JSM-1: Sparse common component + innovations

In this model, all signals share a *common* sapre component while each individual signal contains a sapre innovation component. That is,

with , and , . Thus, the signals is common to all the and has sparsity in basic . The signals are the unique portions of the and have sparsity in the same basis. A practical situation well-modeled by JSM-1 is a group of sensors measuring temperatures at a number of outdoor locations throughout the day. The temperature readings have both temporal (intra-signal) and spatial (inter-signal) correlations. Global factors, such as the sun and prevailing winds, could have an effect *z* that is both common to all sensors and structured enough to permit sparse representation. More local factors, such as shade, water, or animals, could contribute localized innovations that are also structured (and hence sparse). A similar scenario could be imagined for a network of sensors recording light intensities, air pressure, or other phenomena. All of these scenarios correspond to measuring properties of physical processes that change smoothly in time and in space and thus are highly correlated.

3.2.2.2. JSM-2: Common spare supports model

In this model all signals are constructed from the same sparse set of basis vectors, but with different coefficients:

where each is supported only on the same Ω ⊂ {1, 2,...,N} with |Ω| = K. Hence, all signals are K-sparse and are constructed from the same K elements of Ψ, but with arbitrarily different coefficients. A practical situation well-modeled by JSM-2 is where multiple sensors acquire the same signal but with phase shifts and attenuations caused by signal propagation. In many cases it is critical to recover each one of the sensed signals, such as in many acoustic localization and array processing algorithms. Another useful application for JSM-2 is MIMO communication [6].

*3.2.3. Reconstruction Algorithms*

The JSM-1 model is studied and proposed reconstruction algorithms in [4]. In this thesis we focus on the analysis of the JSM-2 model. Under the JSM-2 signal ensemble model, separate recovery via minimization would require *cK* measurements per signal. As we now demonstrate, the total number of measurements can be reduced substantially by employing specially tailored joint reconstruction algorithms that exploit the common structure among the signals, in particular the common coefficient support set Ω. The algorithms we propose are inspired by conventional greedy pursuit algorithms for CS (such as OMP ). In the single-signal case, OMP iteratively constructs the sparse support set Ω; decisions are based on inner products between the columns of ΦΨ and a residual. In the multi-signal case, more clues are available for determining the elements of Ω.

3.2.3.1. Recovery via One-Step Greedy Algorithm (OSGA)

3.2.3.2. Recovery via iterative greedy pursuit

*3.3. OMP Algorithm*

OMP (Orthogonal matching pursuit) - single subcarrier

*3.4. S-OMP Algorithm*

S-OMP (Simultaneous orthogonal matching pursuit) - multiple subcarrier

* AOA, AOD => Positioning
* Advantages of S-OMP compared to OMP

*3.5. Positioning methods using channel information (channel estimation)*

Tổng kết chương III

**CHAPTER 4: SIMULATION**

4.1. Simulation Setup

4.2. Simulation Results

4.3. Discussion

Tổng kết chương IV

**CONCLUSION**

Conclusions

Future Works

**APPENDIX**

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