Fundamentals of statistical signal processing estimation theory solution pdf

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Director, Division of Engineering Science, Will Cluett, BSc., PhD Room 2110, Bahen Centre 416-978-2903 engsci.chair@utoronto.ca Undergraduate Academic Advisors Stephen Johns, Academic Advisor, Years 1 & 2 Room 2110, Bahen Centre 416-946-7351 engsci12@utoronto.ca   Irma Berardi, Academic Advisor for International Students, Years 1 & 2 Room 2110, Bahen Centre 416-978-6162 engsci12.intl@utoronto.ca Brendan Heath, Academic Advisor, Years 3 & 4 Room 2110, Bahen Centre 416-946-7352 engsci34@utoronto.ca   Don Newton, Frontline Student Advisor Room 2110, Bahen Centre 416-978-2903 askengsci@utoronto.ca Engineering Science is an enriched program that provides excellent preparation for postgraduate studies in engineering and science as well as for other professional degree programs such as business, law and medicine. Program graduates are also well qualified to immediately embark on professional engineering-related careers. The Engineering Science program shares elements of the Faculty's engineering programs, but the program is distinct in many respects. Key differences include: The Engineering Science program is designed and delivered at a level that is more academically demanding. The Engineering Science program contains more mathematics, science and engineering science, with a greater focus on deriving results using a first-principles approach. The Engineering Science program has a distinct "2+2" curriculum structure, namely a two-year foundation curriculum followed by a two-year specialization curriculum in a diverse range of fields, many of which are unique to the Engineering Science program. The Engineering Science program requires that all students complete an independent research-based thesis project. Engineering Science students in years one, two, and three are required to maintain a full course load unless they obtain permission from their academic advisor to pursue part-time studies or less than a full course load. Students entering year four are expected to maintain a full course load, but students with medical or personal reasons or who have completed program requirements prior to year four may go part-time or less than a full course load in 4F and / or 4W. This is subject to the approval of the student's academic advisor. A reduced course load in 4F or 4W may impact award assessments. Please refer to the academic calendar under "Academic Regulations VII: Academic Standing" for Honours Standing criteria as related to course load and consult your academic advisor for more information. Transfers from first-year Engineering Science to one of the Faculty's Core 8 engineering programs are permitted early in the Fall Term (typically within the first two weeks of the Fall Term), the end of the Fall Term and the end of the Winter Term. Continuation into the Winter Term of year one requires a minimum average of 55% in the Fall Term; continuation into year two requires a minimum average of 65% in the Winter Term of year one. Students who do not meet these requirements are required to transfer into one of the Faculty's Core 8 programs, subject to the requirements and provisions outlined in the section on Academic Regulations in this Calendar.   Engineering Science Curriculum The first two years of the curriculum focus on the foundations of both engineering and science. The courses in the first two years of the program are common for all students and are only offered to students in the program. At the end of second year, each student selects one of the following majors (represents their major field of specialization) to pursue in their final two years: Aerospace Engineering Biomedical Systems Engineering Electrical & Computer Engineering Energy Systems Engineering Machine Intelligence Engineering Mathematics, Statistics & Finance Engineering Physics Robotics Engineering The curriculum for the first two years and the curricula for the eight majors are presented below. Degree Designation An Engineering Science student graduates with the degree "Bachelor of Applied Science in Engineering Science." On their official transcript, their chosen Major is indicated on their official transcript (e.g., Major in Aerospace Engineering). Degree Requirements To graduate, students must meet all of the degree requirements outlined in the section on Academic Regulations in this Calendar. In addition to these requirements, students must also complete their chosen Program of Study in Engineering Science as described on the following pages of this Calendar, as well as the curriculum requirements of the Canadian Engineering Accreditation Board (CEAB). To complete their chosen Program of Study, students are responsible for ensuring that they have taken all of the required courses and the correct number of technical electives for their Major. Students may request elective course substitutions, but any such substitutions must be approved in advance by the Division of Engineering Science through the student's academic advisor. This also applies to any course listed as "Other Technical Elective." Students must also meet the Complementary Studies (CS) requirements of the program. This includes 2.0 credits, of which 1.0 credit must be in Humanities and Social Sciences (HSS). More information on CS and HSS electives may be found in the Curriculum & Programs section of this Calendar. Students may change the term in which they take Technical and CS/HSS Electives (for example, switch a CS/HSS elective in year three Fall with a Technical Elective in Year four Fall), as long as they meet the elective requirements for their Major. To satisfy CEAB requirements, students must accumulate during their program of study a minimum total number of accreditation units (AU) as well as a minimum number of AU in six categories: complementary studies, mathematics, natural science, engineering science, engineering design and combined engineering science and design. The Division of Engineering Science provides students with a planning tool called the AU Tracker to help students ensure that they satisfy these requirements. The AU Tracker, which lists all successfully completed courses as well as all of the courses they are enrolled in for the current academic year, confirms whether students are on track to meet or exceed the CEAB requirements. If a student is deficient in terms of the Program of Study or falls short in any of the CEAB categories, the student must adjust their course selection accordingly to graduate. Practical Experience Requirement Students are required to have completed a total of 600 hours of acceptable practical experience before graduation (normally during their summer vacation periods). Satisfactory completion of the Professional Experience Year (PEY) Co-op Program will also completely fulfil the Practical Experience Requirement (PER). Signal processing technique Compressed sensing (also known as compressive sensing, compressive sampling, or sparse sampling) is a signal processing technique for efficiently acquiring and reconstructing a signal, by finding solutions to underdetermined linear systems. This is based on the principle that, through optimization, the sparsity of a signal can be exploited to recover it from far fewer samples than required by the Nyquist–Shannon sampling theorem. There are two conditions under which recovery is possible.[1] The first one is sparsity, which requires the signal to be sparse in some domain. The second one is incoherence, which is applied through the isometric property, which is sufficient for sparse signals.[2][3] Overview A common goal of the engineering field of signal processing is to reconstruct a signal from a series of sampling measurements. In general, this task is impossible because there is no way to reconstruct a signal during the times that the signal is not measured. Nevertheless, with prior knowledge or assumptions about the signal, it turns out to be possible to perfectly reconstruct a signal from a series of measurements (acquiring this series of measurements is called sampling). Over time, engineers have improved their understanding of which assumptions are practical and how they can be generalized. An early breakthrough in signal processing was the Nyquist–Shannon sampling theorem. It states that if a real signal's highest frequency is less than half of the sampling rate, then the signal can be reconstructed perfectly by means of sinc interpolation. The main idea is that with prior knowledge about constraints on the signal's frequencies, fewer samples are needed to reconstruct the signal. Around 2004, Emmanuel Candès, Justin Romberg, Terence Tao, and David Donoho proved that given knowledge about a signal's sparsity, the signal may be reconstructed with even fewer samples than the sampling theorem requires.[4][5] This idea is the basis of compressed sensing. History Compressed sensing relies on L 1 {\displaystyle L^{1}} techniques, which several other scientific fields have used historically.[6] In statistics, the least squares method was complemented by the L 1 {\displaystyle L^{1}} -norm, which was introduced by Laplace. Following the introduction of linear programming and Dantzig's simplex algorithm, the L 1 {\displaystyle L^{1}} -norm was used in computational statistics. In statistical theory, the L 1 {\displaystyle L^{1}} -norm was used by George W. Brown and later writers on median-unbiased estimators. It was used by Peter J. Huber and others working on robust statistics. The L 1 {\displaystyle L^{1}} -norm was also used in signal processing, for example, in the 1970s, when seismologists constructed images of reflective layers within the earth based on data that did not seem to satisfy the Nyquist–Shannon criterion.[7] It was used in matching pursuit in 1993, the LASSO estimator by Robert Tibshirani in 1996[8] and basis pursuit in 1998.[9] There were theoretical results describing when these algorithms recovered sparse solutions, but the required type and number of measurements were sub-optimal and subsequently greatly improved by compressed sensing.[citation needed] At first glance, compressed sensing might seem to violate the sampling theorem, because compressed sensing depends on the sparsity of the signal in question and not its highest frequency. This is a misconception, because the sampling theorem guarantees perfect reconstruction given sufficient, not necessary, conditions. A sampling method fundamentally different from classical fixed-rate sampling cannot "violate" the sampling theorem. Sparse signals with high frequency components can be highly under-sampled using compressed sensing compared to classical fixed-rate sampling.[10] Method Underdetermined linear system An underdetermined system of linear equations has more unknowns than equations and generally has an infinite number of solutions. The figure below shows such an equation system y = D x {\displaystyle \mathbf {y} =D\mathbf {x} } where we want to find a solution for x {\displaystyle \mathbf {x} } . In order to choose a solution to such a system, one must impose extra constraints or conditions (such as smoothness) as appropriate. In compressed sensing, one adds the constraint of sparsity, allowing only solutions which have a small number of nonzero coefficients. Not all underdetermined systems of linear equations have a sparse solution. However, if there is a unique sparse solution to the underdetermined system, then the compressed sensing framework allows the recovery of that solution. Solution / reconstruction method Example of the retrieval of an unknown signal (gray line) from few measurements (black dots) using the knowledge that the signal is sparse in the Hermite polynomials basis (purple dots show the retrieved coefficients). Compressed sensing takes advantage of the redundancy in many interesting signals—they are not pure noise. In particular, many signals are sparse, that is, they contain many coefficients close to or equal to zero, when represented in some domain.[11] This is the same insight used in many forms of lossy compression. Compressed sensing typically starts with taking a weighted linear combination of samples also called compressive measurements in a basis different from the basis in which the signal is known to be sparse. The results found by Emmanuel Candès, Justin Romberg, Terence Tao, and David Donoho showed that the number of these compressive measurements can be small and still contain nearly all the useful information. Therefore, the task of converting the image back into the intended domain involves solving an underdetermined matrix equation since the number of compressive measurements taken is smaller than the number of pixels in the full image. However, adding the constraint that the initial signal is sparse enables one to solve this underdetermined system of linear equations. The least-squares solution to such problems is to minimize the L 2 {\displaystyle L^{2}} norm—that is, minimize the amount of energy in the system. This is usually simple mathematically (involving only a matrix multiplication by the pseudo-inverse of the basis sampled in). However, this leads to poor results for many practical applications, for which the unknown coefficients have nonzero energy. To enforce the sparsity constraint when solving for the underdetermined system of linear equations, one can minimize the number of nonzero components of the solution. The function counting the number of non-zero components of a vector was called the L 0 {\displaystyle L^{0}} "norm" by David Donoho.[note 1] Candès et al. proved that for many problems it is probable that the L 1 {\displaystyle L^{1}} norm is equivalent to the L 0 {\displaystyle L^{0}} norm, in a technical sense: This equivalence result allows one to solve the L 1 {\displaystyle L^{1}} problem, which is easier than the L 0 {\displaystyle L^{0}} problem. Finding the candidate with the smallest L 1 {\displaystyle L^{1}} norm can be expressed relatively easily as a linear program, for which efficient solution methods already exist.[13] When measurements may contain a finite amount of noise, basis pursuit denoising is preferred over linear programming, since it preserves sparsity in the face of noise and can be solved faster than an exact linear program. Total variation-based CS reconstruction See also: Total variation denoising Motivation and applications Role of TV regularization Total variation can be seen as a non-negative real-valued functional defined on the space of real-valued functions (for the case of functions of one variable) or on the space of integrable functions (for the case of functions of several variables). For signals, especially, total variation refers to the integral of the absolute gradient of the signal. In signal and image reconstruction, it is applied as total variation regularization where the underlying principle is that signals with excessive details have high total variation and that removing these details, while retaining important information such as edges, would reduce the total variation of the signal and make the signal subject closer to the original signal in the problem. For the purpose of signal and image reconstruction, ℓ 1 {\displaystyle \ell _{1}} minimization models are used. Other approaches also include the least-squares as has been discussed before in this article. These methods are extremely slow and return a not-so-perfect reconstruction of the signal. The current CS Regularization models attempt to address this problem by incorporating sparsity priors of the original image, one of which is the total variation (TV). Conventional TV approaches are designed to give piece-wise constant solutions. Some of these include (as discussed ahead) – constrained ℓ 1 {\textstyle \ell _{1}} -minimization which uses an iterative scheme. This method, though fast, subsequently leads to over-smoothing of edges resulting in blurred image edges.[14] TV methods with iterative re-weighting have been implemented to reduce the influence of large gradient value magnitudes in the images. This has been used in computed tomography (CT) reconstruction as a method known as edge-preserving total variation. However, as gradient magnitudes are used for estimation of relative penalty weights between the data fidelity and regularization terms, this method is not robust to noise and artifacts and accurate enough for CS image/signal reconstruction and, therefore, fails to preserve smaller structures. Recent progress on this problem involves using an iteratively directional TV refinement for CS reconstruction.[15] This method would have 2 stages: the first stage would estimate and refine the initial orientation field – which is defined as a noisy point-wise initial estimate, through edge-detection, of the given image. In the second stage, the CS reconstruction model is presented by utilizing directional TV regularizer. More details about these TV-based approaches – iteratively reweighted l1 minimization, edge-preserving TV and iterative model using directional orientation field and TV- are provided below. Existing approaches Iteratively reweighted ℓ 1 {\displaystyle \ell _{1}} minimization Iteratively reweighted ℓ 1 {\textstyle \ell _{1}} minimization method for CS In the CS reconstruction models using constrained ℓ 1 {\displaystyle \ell _{1}} minimization,[16] larger coefficients are penalized heavily in the ℓ 1 {\displaystyle \ell _{1}} norm. It was proposed to have a weighted formulation of ℓ 1 {\displaystyle \ell _{1}} minimization designed to more democratically penalize nonzero coefficients. An iterative algorithm is used for constructing the appropriate weights.[17] Each iteration requires solving one ℓ 1 {\displaystyle \ell _{1}} minimization problem by finding the local minimum of a concave penalty function that more closely resembles the ℓ 0 {\displaystyle \ell _{0}} norm. An additional parameter, usually to avoid any sharp transitions in the penalty function curve, is introduced into the iterative equation to ensure stability and so that a zero estimate in one iteration does not necessarily lead to a zero estimate in the next iteration. The method essentially involves using the current solution for computing the weights to be used in the next iteration. Advantages and disadvantages Early iterations may find inaccurate sample estimates, however this method will down-sample these at a later stage to give more weight to the smaller non-zero signal estimates. One of the disadvantages is the need for defining a valid starting point as a global minimum might not be obtained every time due to the concavity of the function. Another disadvantage is that this method tends to uniformly penalize the image gradient irrespective of the underlying image structures. This causes over-smoothing of edges, especially those of low contrast regions, subsequently leading to loss of low contrast information. The advantages of this method include: reduction of the sampling rate for sparse signals; reconstruction of the image while being robust to the removal of noise and other artifacts; and use of very few iterations. This can also help in recovering images with sparse gradients. In the figure shown below, P1 refers to the first-step of the iterative reconstruction process, of the projection matrix P of the fan-beam geometry, which is constrained by the data fidelity term. This may contain noise and artifacts as no regularization is performed. The minimization of P1 is solved through the conjugate gradient least squares method. P2 refers to the second step of the iterative reconstruction process wherein it utilizes the edge-preserving total variation regularization term to remove noise and artifacts, and thus improve the quality of the reconstructed image/signal. The minimization of P2 is done through a simple gradient descent method. Convergence is determined by testing, after each iteration, for image positivity, by checking if f k − 1 = 0 {\displaystyle f^{k-1}=0} for the case when f k − 1 < 0 {\displaystyle f^{k-1}

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