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Interior-Point Methods Applied to Linear and Semi Definite Programming.

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To my bride, my beloved, and my best friends

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ABSTRACT

Most interior-point methods (IPMs) use a modified Newton method to determine the search direction at each iteration. The system of equations corresponding to the modified Newton system can often be reduced to the so-called "normal equation" a system of equations whose matrix is positive definite, yet often ill-conditioned. Using an appropriately preconditioned iterative linear solver, the so-called "the maximum weight basis (MWB) preconditioner" of **J. W. O'Neal** into infeasible, long-step, primal-dual, path-following algorithms for linear programming (LP), we show that the number of iterative solver ("inner") iterations of the algorithms can be uniformly bounded by n (length of the decision vector) and the condition number of constrains matrix A, while the algorithmic ("outer") iterations of the IPMs can be polynomially bounded by n and the logarithm of the desired accuracy. We extend our study to semi definite programming in which, basing on the "Adaptive Preconditioned Steepest Descent" (APSD) algorithm of **J. W. O'Neal**, we proposed new algorithm, called "Adaptive Preconditioned Conjugate Gradient"(APCG). Numerical tests are conducted to compare our algorithm with **J.W. O'Neal** APSD algorithm basing on execution time.

مستخلص البحث

معظم طرق النقطة الداخلية تستخدم طريقة نيوتن المعدلة لتحديد متوجه بحث عند أي تكرار. منظومة المعادلات الخطية لمنظومة نيوتن المعدلة يمكن اختزالها عادةً لما يسمى "بالمعادلة الطبيعية" وهي منظومة معادلات مصفوفتها موجبة تحديداً وعادةً معمولة الشرط. باستخدام طرق خطية تكرارية في J. W. O'Neal مناسبة مشروطة مسبقاً ما يسمى بـ "أساس الوزن الأعظم المشروط مسبقاً" لخوارزميات النقاط الخارجية منطقة الحل خطوة - طوبية بدائي - ثانوي مسار - متبع للبرمجة الخطية أثبتنا أن عدد تكرارات الطريقة التكرارية (الداخلية) للخوارزميات يمكن أن يكون محدوداً بانتظام ب بينما الخوارزمية التكرارات (الخارجية) لطرق A طول متوجه القرار) وبعد الشرط لمصفوفة القيود ولو غاريتم الدقة المطلوبة. مددنا دراستنا إلى n النقطة الداخلية يمكن أن تكون محدودة بكثيرة الحدود في البرمجة شبه المحددة التي فيها اعتمدنا على خوارزمية "انحدار اشد شرطي مسبق مكيف" لـ J. W. O'Neal خوارزمية جديدة تسمى "انحدار مرافق شرطي مسبق مكيف". أجريت عددياً اختبارات اعتماداً على زمن التنفيذ. لمقارنة خوارزميتنا مع خوارزمية

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