11-1-2005

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Comments:
UTEP-CS-05-28.
Published in *Reliable Computing*, 2006, Vol. 12, No. 4, pp. 273-280.

Recommended Citation

Dantsin, Evgeny; Kreinovich, Vladik; Wolper, Alexander; and Xiang, Gang, "Population Variance under Interval Uncertainty: A New Algorithm" (2005). *Departmental Technical Reports (CS)*. Paper 260.
http://digitalcommons.utep.edu/cs_techrep/260

Population Variance under Interval Uncertainty: A New Algorithm

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Abstract

In statistical analysis of measurement results, it is often beneficial to compute the range $\mathbf{V}$ of the population variance $V = \frac{1}{n} \cdot \sum_{i=1}^{n} (x_i - E)^2$ (where $E = \frac{1}{n} \sum_{i=1}^{n} x_i$) when we only know the intervals

$$[\widetilde{x}_i - \Delta_i, \widetilde{x}_i + \Delta_i]$$

of possible values of the x_i. In general, this problem is NP-hard; a polynomial-time algorithm is known for the case when the measurements are sufficiently accurate, i.e., when $|\widetilde{x}_i - \widetilde{x}_j| \geq \frac{\Delta_i}{n} + \frac{\Delta_j}{n}$ for all $i \neq j$. In this paper, we show that we can efficiently compute $\mathbf{V}$ under a weaker (and more general) condition $|\widetilde{x}_i - \widetilde{x}_j| \geq \frac{|\Delta_i - \Delta_j|}{n}$.

Formulation of the problem. Once we have n measurement results $x_1, \ldots, x_n$, the traditional statistical analysis starts with computing the standard statistics such as population mean $E = \frac{1}{n} \cdot \sum_{i=1}^{n} x_i$ and population variance $V = M - E^2$, where $M \stackrel{\text{def}}{=} \frac{1}{n} \cdot \sum_{i=1}^{n} x_i^2$; see, e.g., [7].

In many real-life situations, due to measurement uncertainty, instead of the actual values x_i of the measured quantity, we only have intervals $\mathbf{x}_i = [\underline{x}_i, \overline{x}_i]$ of possible values of x_i [5, 7]. Usually, the interval $\mathbf{x}_i$ has the form $[\widetilde{x}_i - \Delta_i, \widetilde{x}_i + \Delta_i]$, where $\widetilde{x}_i$ is the measurement result, and Δ_i is the known upper bound on the absolute value of the measurement error $\Delta x_i \stackrel{\text{def}}{=} \widetilde{x}_i - x_i$.

Different values $x_i \in \mathbf{x}_i$ lead, in general, to different values of E and V. It is therefore desirable to compute the ranges $\mathbf{E} = [\underline{E}, \overline{E}]$ and $\mathbf{V} = [\underline{V}, \overline{V}]$ of possible values of E and V when $x_i \in \mathbf{x}_i$.

Since the population mean E is a monotonic function of its n variables $x_1, \ldots, x_n$, its range can be easily computed as $\mathbf{E} = \left[\frac{1}{n} \cdot \sum\limits_{i=1}^n \underline{x}_i, \frac{1}{n} \cdot \sum\limits_{i=1}^n \overline{x}_i\right]$. For the variance V, there exist polynomial-time algorithms for computing the lower bound $\underline{V}$, but computing the exact upper bound $\overline{V}$ is, in general, an NP-hard problem; see, e.g., [2, 3].

There exist polynomial-time algorithms for computing $\overline{V}$ in many practically reasonable situations; see, e.g., [2, 3, 4, 6, 8]. One such known case is when measurements are sufficiently accurate, e.g., when the "narrowed intervals"

$$\left[\widetilde{x}_i - \frac{\Delta_i}{n}, \widetilde{x}_i + \frac{\Delta_i}{n}\right] \tag{1}$$

do not intersect. In other words, we know how to efficiently compute $\overline{V}$ when for every $i \neq j$, we have

$$|\widetilde{x}_i - \widetilde{x}_j| \geq \frac{\Delta_i}{n} + \frac{\Delta_j}{n}. \tag{2}$$

The known algorithm requires $O(n \cdot \log(n))$ computational steps.

In this paper, we propose a new algorithm that computes $\overline{V}$ in $O(n \cdot \log(n))$ time under the weaker (hence more general) condition

$$|\widetilde{x}_i - \widetilde{x}_j| \geq \frac{|\Delta_i - \Delta_j|}{n}. \tag{3}$$

This condition is indeed much weaker: e.g., for the case when all measurements are equally accurate, i.e., $\Delta_i = \Delta$ for all i, the previously known condition (2) is only valid for $\Delta \leq (n/2) \cdot \min\limits_{i \neq j} |\widetilde{x}_i - \widetilde{x}_j|$, while the new condition (3) holds for every Δ. Thus, we can have larger measurement uncertainty Δ than before and still be able to compute the exact bound $\overline{V}$ in polynomial time.

Algorithm. Let us first describe the algorithm itself; in the next section, we provide the justification for this algorithm.

- First, we sort of the values $\widetilde{x}_i$ into an increasing sequence. Without losing generality, we can assume that $\widetilde{x}_1 \leq \widetilde{x}_2 \leq \ldots \leq \widetilde{x}_n$.
- Then, for every k from 0 to n, we compute the value $V^{(k)} = M^{(k)} - E^{(k)}$ of the population variance V for the vector $x^{(k)} = (\underline{x}_1, \ldots, \underline{x}_k, \overline{x}_{k+1}, \ldots, \overline{x}_n)$.
- Finally, we compute $\overline{V}$ as the largest of $n+1$ values $V^{(0)}, \ldots, V^{(n)}$.

To compute the values $V^{(k)}$, first, we explicitly compute $M^{(0)}$, $E^{(0)}$, and $V^{(0)} = M^{(0)} - (E^{(0)})^2$. Once we know the values $M^{(k)}$ and $E^{(k)}$, we can compute $M^{(k+1)} = M^{(k)} + \frac{1}{n} \cdot (\underline{x}_{k+1})^2 - \frac{1}{n} \cdot (\overline{x}_{k+1})^2$ and $E^{(k+1)} = E^{(k)} + \frac{1}{n} \cdot \underline{x}_{k+1} - \frac{1}{n} \cdot \overline{x}_{k+1}$.

Number of computation steps. Sorting requires $O(n \cdot \log(n))$ steps; see, e.g., [1]. Computing the initial values $M^{(0)}$, $E^{(0)}$, and $V^{(0)}$ requires linear time $O(n)$. For each k from 0 to $n-1$, we need a constant number of steps to compute the next values $M^{(k+1)}$, $E^{(k+1)}$, and $V^{(k+1)}$. Finally, finding the largest of $n+1$ values $V^{(k)}$ also requires $O(n)$ steps. Thus, overall, we need

$$O(n \cdot \log(n)) + O(n) + O(n) + O(n) = O(n \cdot \log(n))$$

steps.

It is worth mentioning that if the measurement results $\widetilde{x}_i$ are already sorted, then we only need linear time to compute $\overline{V}$.

Justification of the algorithm. With respect to each variable x_i, the population variance is a quadratic function which is non-negative for all x_i. It is well known that a maximum of such a function on each interval $[\underline{x}_i, \overline{x}_i]$ is attained at one of the endpoints of this interval. Thus, the maximum $\overline{V}$ of the population variance is attained at a vector $x = (x_1, \ldots, x_n)$ in which each value x_i is equal either to $\underline{x}_i$ or to $\overline{x}_i$.

We will first justify our algorithm for the case when $|\widetilde{x}_i - \widetilde{x}_j| > \frac{|\Delta_i - \Delta_j|}{n}$ for all $i \neq j$.

To justify our algorithm, we need to prove that this maximum is attained at one of the vectors $x^{(k)}$ in which all the lower bounds $\underline{x}_i$ precede all the upper bounds $\overline{x}_i$. We will prove this by reduction to a contradiction. Indeed, let us assume that the maximum is attained at a vector x in which one of the lower bounds follows one of the upper bounds. In each such vector, let i be the largest upper bound index preceded by the lower bound; then, in the optimal vector x, we have $x_i = \overline{x}_i$ and $x_{i+1} = \underline{x}_{i+1}$.

Since the maximum is attained for $x_i = \overline{x}_i$, replacing it with $\underline{x}_i = \overline{x}_i - 2 \cdot \Delta_i$ will either decrease the value of the variance or keep it unchanged. Let us describe how variance changes under this replacement. In the sum for M, we replace $(\overline{x}_i)^2$ with

$$(\underline{x}_i)^2 = (\overline{x}_i - 2 \cdot \Delta_i)^2 = (\overline{x}_i)^2 - 4 \cdot \Delta_i \cdot \overline{x}_i + 4 \cdot \Delta_i^2.$$

Thus, the value M changes into $M + \Delta M_i$, where

$$\Delta M_i = -\frac{4}{n} \cdot \Delta_i \cdot \overline{x}_i + \frac{4}{n} \cdot \Delta_i^2.$$

The population mean E changes into $E+\Delta E_i$, where $\Delta E_i=-\dfrac{2\cdot\Delta_i}{n}$. Thus, the value E^2 changes into $(E+\Delta E_i)^2=E^2+\Delta(E^2)_i$, where

$$\Delta(E^2)_i=2\cdot E\cdot\Delta E_i+\Delta E_i^2=-\frac{4}{n}\cdot E\cdot\Delta_i+\frac{4}{n^2}\cdot\Delta_i^2.$$

So, the variance V changes into $V+\Delta V_i$, where

$$\Delta V_i=\Delta M_i-\Delta(E^2)_i=-\frac{4}{n}\cdot\Delta_i\cdot\overline{x}_i+\frac{4}{n}\cdot\Delta_i^2+\frac{4}{n}\cdot E\cdot\Delta_i-\frac{4}{n^2}\cdot\Delta_i^2=$$

$$\frac{4}{n}\cdot\Delta_i\cdot\left(-\overline{x}_i+\Delta_i+E-\frac{\Delta_i}{n}\right).$$

By definition, $\overline{x}_i=\widetilde{x}_i+\Delta_i$, hence $-\overline{x}_i+\Delta_i=-\widetilde{x}_i$. Thus, we conclude that

$$\Delta V_i=\frac{4}{n}\cdot\Delta_i\cdot\left(-\widetilde{x}_i+E-\frac{\Delta_i}{n}\right).$$

Since V attains maximum at x, we have $\Delta V_i\le 0$, hence

$$E\le\widetilde{x}_i+\frac{\Delta_i}{n}. \tag{4}$$

Similarly, since the maximum is attained for $x_{i+1}=\underline{x}_i$, replacing it with $\overline{x}_{i+1}=\underline{x}_{i+1}+2\cdot\Delta_{i+1}$ will either decrease the value of the variance or keep it unchanged. Let us describe how variance changes under this replacement. In the sum for M, we replace $(\underline{x}_{i+1})^2$ with

$$(\overline{x}_{i+1})^2=(\underline{x}_{i+1}+2\cdot\Delta_{i+1})^2=(\underline{x}_{i+1})^2+4\cdot\Delta_{i+1}\cdot\underline{x}_{i+1}+4\cdot\Delta_{i+1}^2.$$

Thus, the value M changes into $M+\Delta M_{i+1}$, where

$$\Delta M_{i+1}=\frac{4}{n}\cdot\Delta_{i+1}\cdot\underline{x}_{i+1}+\frac{4}{n}\cdot\Delta_{i+1}^2.$$

The population mean E changes into $E+\Delta E_{i+1}$, where $\Delta E_{i+1}=\dfrac{2\cdot\Delta_{i+1}}{n}$. Thus, the value E^2 changes into $(E+\Delta E_{i+1})^2=E^2+\Delta(E^2)_{i+1}$, where

$$\Delta(E^2)_{i+1}=2\cdot E\cdot\Delta E_{i+1}+\Delta E_{i+1}^2=\frac{4}{n}\cdot E\cdot\Delta_{i+1}+\frac{4}{n^2}\cdot\Delta_{i+1}^2.$$

So, the variance V changes into $V+\Delta V_{i+1}$, where

$$\Delta V_{i+1}=\Delta M_{i+1}-\Delta(E^2)_{i+1}=$$

$$\frac{4}{n}\cdot\Delta_{i+1}\cdot\underline{x}_{i+1}+\frac{4}{n}\cdot\Delta_{i+1}^2-\frac{4}{n}\cdot E\cdot\Delta_{i+1}-\frac{4}{n^2}\cdot\Delta_{i+1}^2=$$

$$\frac{4}{n}\cdot\Delta_{i+1}\cdot\left(\underline{x}_{i+1}+\Delta_{i+1}-E-\frac{\Delta_{i+1}}{n}\right).$$

By definition, $\underline{x}_{i+1}=\widetilde{x}_{i+1}-\Delta_{i+1}$, hence $\underline{x}_{i+1}+\Delta_{i+1}=\widetilde{x}_{i+1}$. Thus, we conclude that

$$\Delta V_{i+1}=\frac{4}{n}\cdot\Delta_{i+1}\cdot\left(\widetilde{x}_{i+1}-E-\frac{\Delta_{i+1}}{n}\right).$$

Since V attains maximum at x, we have $\Delta V_{i+1}\le 0$, hence

$$E\ge\widetilde{x}_{i+1}-\frac{\Delta_{i+1}}{n}. \tag{5}$$

We can also change *both* x_i and x_{i+1} at the same time. In this case, the change ΔM in M is simply the sum of the changes coming from x_i and x_{i+1}: $\Delta M=\Delta M_i+\Delta M_{i+1}$, and the change ΔE in E is also the sum of the corresponding changes: $\Delta E=\Delta E_i+\Delta E_{i+1}$. So, for

$$\Delta V=\Delta M-\Delta(E^2)=\Delta M-2\cdot E\cdot\Delta E-\Delta E^2,$$

we get

$$\Delta V=\Delta M_i+\Delta M_{i+1}-$$
$$2\cdot E\cdot\Delta E_i-2\cdot E\cdot\Delta E_{i+1}-(\Delta E_i)^2-(\Delta E_{i+1})^2-2\cdot\Delta E_i\cdot\Delta E_{i+1}.$$

Hence,

$$\Delta V=(\Delta M_i-2\cdot E\cdot\Delta E_i-(\Delta E_i)^2)+(\Delta M_{i+1}-2\cdot E\cdot\Delta E_{i+1}-(\Delta E_{i+1})^2)$$
$$-2\cdot\Delta E_i\cdot\Delta E_{i+1},$$

i.e.,

$$\Delta V=\Delta V_i+\Delta V_{i+1}-2\cdot\Delta E_i\cdot\Delta E_{i+1}.$$

We already have the expressions for ΔV_i, ΔV_{i+1}, $\Delta E_i=-\dfrac{2\cdot\Delta_i}{n}$, and $\Delta E_{i+1}=\dfrac{2\cdot\Delta_{i+1}}{n}$, so we conclude that $\Delta V=\dfrac{4}{n}\cdot D(E)$, where

$$D(E)\overset{\text{def}}{=}\Delta_i\cdot\left(-\widetilde{x}_i+E-\frac{\Delta_i}{n}\right)+\Delta_{i+1}\cdot\left(\widetilde{x}_{i+1}-E-\frac{\Delta_{i+1}}{n}\right)+\frac{2}{n}\cdot\Delta_i\cdot\Delta_{i+1}. \tag{6}$$

Since the function V attains maximum at x, we have $\Delta V\le 0$, hence $D(E)\le 0$ (for the population mean E corresponding to the optimizing vector x).

The expression $D(E)$ is a linear function of E. From (4) and (5), we know that

$$\widetilde{x}_{i+1}-\frac{\Delta_{i+1}}{n}\le E\le\widetilde{x}_i+\frac{\Delta_i}{n}.$$

For $E = E^- \stackrel{\rm def}{=} \widetilde{x}_{i+1} - \dfrac{\Delta_{i+1}}{n}$, we have

$$D(E^-) = \Delta_i \cdot \left(-\widetilde{x}_i + \widetilde{x}_{i+1} - \frac{\Delta_{i+1}}{n} - \frac{\Delta_i}{n}\right) + \frac{2}{n} \cdot \Delta_i \cdot \Delta_{i+1} =$$

$$\Delta_i \cdot \left(-\widetilde{x}_i + \widetilde{x}_{i+1} + \frac{\Delta_{i+1}}{n} - \frac{\Delta_i}{n}\right).$$

We consider the case when $|\widetilde{x}_{i+1} - x_i| > \dfrac{|\Delta_i - \Delta_{i+1}|}{n}$. Since the values $\widetilde{x}_i$ are sorted in increasing order, we have $\widetilde{x}_{i+1} \ge \widetilde{x}_i$, hence

$$\widetilde{x}_{i+1} - \widetilde{x}_i = |\widetilde{x}_{i+1} - \widetilde{x}_i| > \frac{|\Delta_i - \Delta_{i+1}|}{n} \ge \frac{\Delta_i}{n} - \frac{\Delta_{i+1}}{n}.$$

So, we conclude that $D(E^-) > 0$.

For $E = E^+ \stackrel{\rm def}{=} \widetilde{x}_i + \dfrac{\Delta_i}{n}$, we have

$$D(E^+) = \Delta_{i+1} \cdot \left(\widetilde{x}_{i+1} - \widetilde{x}_i - \frac{\Delta_i}{n} - \frac{\Delta_{i+1}}{n}\right) + \frac{2}{n} \cdot \Delta_i \cdot \Delta_{i+1} =$$

$$\Delta_{i+1} \cdot \left(-\widetilde{x}_i + \widetilde{x}_{i+1} + \frac{\Delta_i}{n} - \frac{\Delta_{i+1}}{n}\right).$$

Here, from $|\widetilde{x}_{i+1} - x_i| > \dfrac{|\Delta_i - \Delta_{i+1}|}{n}$, we also conclude that $D(E^+) > 0$.

Since the linear function $D(E)$ is positive on both endpoints of the interval $[E^-, E^+]$, it must be positive for every value E from this interval, which contradicts to our conclusion that $D(E) \ge 0$ for the actual population mean value $E \in [E^-, E^+]$. This contradiction shows that the maximum of the population variance V is indeed attained at one of the values $x^{(k)}$, hence the algorithm is justified.

The general case when $|\widetilde{x}_i - \widetilde{x}_j| \ge \dfrac{|\Delta_i - \Delta_j|}{n}$ can be obtained as a limit of cases when we have strict inequality. Since the function V is continuous, the value $\overline{V}$ continuously depends on the input bounds, so by tending to a limit, we can conclude that our algorithm works in the general case as well.

The geometric meaning of the new condition. The condition $|\widetilde{x}_i - \widetilde{x}_j| \ge \dfrac{|\Delta_i - \Delta_j|}{n}$ means that if $\widetilde{x}_i \ge \widetilde{x}_j$, then we have

$$\widetilde{x}_i - \widetilde{x}_j \ge \frac{\Delta_i - \Delta_j}{n},$$

i.e.,

$$\widetilde{x}_i - \frac{\Delta_i}{n} \ge \widetilde{x}_j - \frac{\Delta_j}{n}$$

and also

$$\widetilde{x}_i - \widetilde{x}_j \geq \frac{\Delta_j - \Delta_i}{n},$$

i.e.,

$$\widetilde{x}_i + \frac{\Delta_i}{n} \geq \widetilde{x}_j + \frac{\Delta_j}{n}.$$

This means that no narrowed interval (1) is a proper subinterval of the interior of another narrowed subinterval.

Vice versa, if one of the narrowed intervals is a proper subinterval of another one, then the condition (3) is not satisfied. Thus, the condition (3) means that no *narrowed subintervals* are proper subintervals of each other.

It is worth mentioning that there is another polynomial-time algorithm for computing $\overline{V}$ [6] – an algorithm which computes $\overline{V}$ for the case when no *intervals* are proper subintervals of each other. That condition can be similarly described as $|\widetilde{x}_i - \widetilde{x}_j| \geq |\Delta_i - \Delta_j|$, hence that condition implies our condition (2). So, our algorithm generalizes that algorithm as well.

Acknowledgments. This work was supported in part by NASA under cooperative agreement NCC5-209, NSF grant EAR-0225670, NIH grant 3T34GM008048-20S1, and Army Research Lab grant DATM-05-02-C-0046. This work was mainly done during E. Dantsin's and A. Wolpert's visit to El Paso. The authors are thankful to Luc Longpré for valuable discussions.

References

[1] Th. H. Cormen, C. E. Leiserson, R. L. Rivest, and C. Stein, *Introduction to Algorithms*, MIT Press, Cambridge, MA, 2001.

[2] S. Ferson, L. Ginzburg, V. Kreinovich, L. Longpré, and M. Aviles, Computing Variance for Interval Data is NP-Hard, *ACM SIGACT News*, 2002, Vol. 33, No. 2, pp. 108–118.

[3] S. Ferson, L. Ginzburg, V. Kreinovich, L. Longpré, and M. Aviles, Exact Bounds on Finite Populations of Interval Data, *Reliable Computing*, 2005, Vol. 11, No. 3, pp. 207–233.

[4] L. Granvilliers, V. Kreinovich, and N. Müller, Novel Approaches to Numerical Software with Result Verification, In: R. Alt, A. Frommer, R. B. Kearfott, and W. Luther, editors, *Numerical Software with Result Verification*, Proceedings of the International Dagstuhl Seminar, Dagstuhl Castle, Germany, January 19–24, 2003, Springer Lectures Notes in Computer Science, 2004, Vol. 2991, pp. 274–305.

[5] L. Jaulin, M. Kieffer, O. Didrit, and E. Walter, *Applied interval analysis: with examples in parameter and state estimation, robust control and robotics*, Springer Verlag, London, 2001.

[6] V. Kreinovich, G. Xiang, S. A. Starks, L. Longpré, M. Ceberio, R. Araiza, J. Beck, R. Kandathi, A. Nayak, R. Torres, and J. Hajagos, "Towards combining probabilistic and interval uncertainty in engineering calculations: algorithms for computing statistics under interval uncertainty, and their computational complexity", *Reliable Computing* (to appear).

[7] S. Rabinovich, *Measurement Errors: Theory and Practice*, American Institute of Physics, New York, 1993.

[8] G. Xiang, "Fast algorithm for computing the upper endpoint of sample variance for interval data: case of sufficiently accurate measurements", *Reliable Computing* (to appear).