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Minimal parameterization of fundamental matrices 3 using motion and camera properties 4 **Diane Lingrand** 5 INRIA-Projet RobotVis, 2004 route des Lucioles, BP 93, 06902 Sophia Antipolis Cedex, France 6 7 Abstract 8 This paper addresses the optimal recovery of the displacement and projection parameters from uncalibrated monocular 9 video sequences. We study the particular cases of camera and objects displacements and camera projection in order to extract 10 an optimized parameterization of the problem of parameters recovery for each cases. 11 This work follows previous studies on particular cases of displacement, scene geometry and camera analysis and focuses

This work follows previous studies on particular cases of displacement, scene geometry and camera analysis and focuses on the particular forms of fundamental matrices. This paper introduces the idea of using not all particular cases as individual cases but grouping these cases into a tractable number of sets, using properties on fundamental matrices.

Some experiments were performed in order to demonstrate that if several models are correct, the model with the least parameters gives the best estimate, corresponding to the true case. © 2002 Published by Elsevier Science B.V.

17 Keywords: Fundamental matrix; Particular displacement; Parameters estimation

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19 1. Introduction

This paper deals with video sequences taken by an uncalibrated camera in an unknown environment. Our interest is to estimate as many parameters as possible on the camera and objects motion and the camera projection using a strategy of hypothesis testing. Many efforts have been made in the Computer Vi-

sion community for determining motion and camera
parameters from video sequences. Relations between
2D views exist [7] as the fundamental matrix F, but,

in the general case, we cannot extract all the unknown
parameters from this F matrix. It is however possible

31 in some particular situations.

This work follows previous work on particular cases of displacement, scene geometry and camera analysis [10,11,18]. It focuses on the particular forms of fun-

35 damental matrices.

1

Several authors have already been interested in particular cases of projection [2,5,9,13,14,16] or displacement [3,4,8,17]. Some of them consider several cases and compare each result, in order to automatically determine which case was performed.

We call by general case the situation where we do not know anything about motion or camera projection. 42 A particular case is when we know (or make the hypothesis) that a parameter is null, constant or known, 44 or related to other parameters. A particular case has fewer parameters and/or simpler equations than the general one. 47

The motivations for these studies are threefold:

 to eliminate singularities of general equations by considering each case that may conduct to singularity,
 50

48

• to estimate the parameters with more robustness using a simplified model (an adapted model gives more accuracy than the general one as shown in [18]), 55

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to retrieve parameters that cannot be retrieved in
the general case because we eliminate some unknowns that are meaningless in the particular case
studied.

It is already known that the large number of par-60 ticular cases prevent examining all the cases linearly. 61 62 In this paper, we introduce a new way to deal with this amount of cases in three steps. (1) We eliminate, 63 with some simple rules, some redundant cases and 64 some physically impossible cases. (2) We divide the 65 set of cases into two sets, each corresponding to homo-66 graphic or fundamental relations. (3) We divide again 67 the fundamental cases into sets corresponding to par-68 ticular forms. We will provide details for each of these 69

70 steps in the following sections.

71 2. Stereo framework

In this section, we present the stereo framework andthe notations we will use in this paper.

74 2.1. Rigid displacements

We consider a rigid or piecewise rigid scene. A 3D-point $\mathbf{M} = [X Y Z 1]^{\mathrm{T}}$ is moving onto $\mathbf{M}' = [X' Y' Z' 1]^{\mathrm{T}}$ by a rotation \mathbf{R} followed by a translation $\mathbf{t} = [t_0 t_1 t_2]^{\mathrm{T}}$:

79 $\mathbf{M}' = \mathbf{R}\mathbf{M} + \mathbf{t}.$

A rotation matrix **R** depends only on three parameters $\mathbf{r} = [r_0 r_1 r_2]^{\mathrm{T}}$ related to the rotation angle θ and axis \mathbf{u} by

83 $\mathbf{r} = 2 \tan\left(\frac{1}{2}\theta\right) \mathbf{u} \Leftrightarrow \theta = 2 \arctan\left(\frac{1}{2}\|\mathbf{r}\|\right).$

A rigid displacement is then parameterized by six parameters.

We note by $\tilde{\mathbf{r}}$ the antisymmetric matrix representing the cross product $\mathbf{r} \wedge \cdot$:

88
$$\tilde{\mathbf{r}}\mathbf{x} = \mathbf{r} \wedge \mathbf{x} \quad \forall \mathbf{x}$$

The rotation matrix $\mathbf{R} = e^{\mathbf{r} \wedge \cdot} = e^{\tilde{\mathbf{r}}}$ can be developed as a rational Rodrigues formula [15]

P1
$$\mathbf{R} = \mathbf{I} + \left[\frac{\tilde{\mathbf{r}} + (1/2)\tilde{\mathbf{r}}^2}{1 + \mathbf{r}^{\mathrm{T}} \cdot \mathbf{r}/4}\right]$$

2.2. Camera projection

~

The most commonly camera model states that a 93 3D-point $\mathbf{M} = [X Y Z 1]^{\mathrm{T}}$ is projected with a perspective projection onto an image plane on a 2D-point 95 $\mathbf{m} = [uv1]^{\mathrm{T}}$. In the reference frame attached to the 96 camera, the projection equation is 97

$$Z\mathbf{m} = \underbrace{\begin{pmatrix} \alpha_u & \gamma & u_0 & 0\\ 0 & \alpha_v & v_0 & 0\\ 0 & 0 & 1 & 0 \end{pmatrix}}_{\mathbf{A}} \mathbf{M}, \qquad (1)$$

where α_u and α_v represent the horizontal and vertical lengths, u_0 and v_0 correspond to the image of the optical center and γ is the skew factor. Those parameters are the intrinsic parameters and are collected in the projection matrix **A**.

Let
$$I_1$$
 and I_2 denote two images. In the general 105
case, there exists a fundamental relation [7] between 106
points \mathbf{m}_2 in I_2 and points \mathbf{m}_1 in I_1 : 107

$$\mathbf{m}_2^{\mathrm{T}}\mathbf{F}\mathbf{m}_1 = \mathbf{0},$$
 108

where **F** is called the fundamental matrix and is related 109 to the intrinsic and extrinsic parameters by 110

$$\mathbf{F} = (\mathbf{A}_2 t) \mathbf{A}_2 \mathbf{R} \mathbf{A}_1^{-1},$$
 111

where A_1 and A_2 are the projection matrix for the first 112 and second frames, respectively, see (1). 113

This kind of relationship vanishes if the displacement is a pure rotation or if the scene is planar. The relation between points is homographic: 116

$$\mathbf{m}_2 = \mathbf{H}\mathbf{m}_1, \tag{117}$$

where **H** is called the homographic matrix. Another 118 study on homographic matrices can be found in [11]. 119

3. Deriving all particular cases 120

In order to study all particular cases of cameras, 121 object displacements and camera projection, we will 122 examine each particular value, considering each parameter at a time. A particular model is obtained by combining several particular values. 125

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3.1. Particular cases of intrinsic parameters 126

127 Authors generally make several hypotheses regarding intrinsic parameters. For example, the most gen-128 eral auto-calibration hypothesis states that the intrinsic 129 parameters are constant. They can be known or un-130 known. However, usually, some parameters are con-131 stant while others are not. 132

- 133 • The principal point of coordinates (u_0, v_0) can be fixed and/or known in some cases (e.g. in the image 134 center), thus changing the reference frame, regard-135 ing the principal point position. 136
- The ν parameter is usually assumed to be null or. 137 at least, considered to be a constant value. 138

• Enciso [6] has experimentally proven that for a large 139 number of cameras α_u / α_v can be considered to be 140 constant even if other intrinsic parameters change. 141

We express this as $f = \alpha_u = \alpha_v$. 142

Table 1 summarizes, for each intrinsic parameter, 143 the particular cases of interest (constant values are in-144 dexed by zero). Subsequently, we will refer to each 145 case by the label given in the first column. For exam-146 ple, g1 means that the γ parameter is null.

147

3.2. Particular cases of displacement 148

3.2.1. Discrete motion-continuous motion 149

In an image sequence, if the displacement between 150 two frames is small, we can approximate the rotation 151 equations by their first order:

 $\mathbf{R} = e^{\tilde{\mathbf{r}}} = \mathbf{I} + \tilde{\mathbf{r}} + o(\tilde{\mathbf{r}})$ 153

152

Table 1 Table of particular cases of intrinsic parameters for two frames

gl	$\gamma = 0$	γ constant and null
g2	$\gamma = \gamma_0$	γ constant
g3	$\gamma = \gamma(\tau)$	γ free
sl	$\alpha_u = \alpha_v(\tau)$	α_u/α_v constant and known
s2	$\alpha_u = \alpha_u(\tau)$	α_u free
f1	$\alpha_v = 1$	α_v constant and known
f2	$\alpha_v = f_0$	α_v constant
£3	$\alpha_v = \alpha_v(\tau)$	α_v free
cl	$u_0 = v_0 = 0$	u_0 and v_0 constant and known
c2	$u_0 = u_{0_0}$ and	u_0 and v_0 constant
	$v_0 = v_{0_0}$	
с3	$u_0 = u_0(\tau)$ and	u_0 and v_0 free
	$v_0 = v_0(\tau)$	

which occurs frequently in images sequences except 154 with high speed objects. 155

If the motion is larger, we can also consider the 156 second order expansion 157

$$\mathbf{R} = \mathbf{I} + \tilde{\mathbf{r}} + \frac{1}{2}\tilde{\mathbf{r}}^2 + \mathbf{o}(\tilde{\mathbf{r}}^2).$$
 158

3.2.2. About extrinsic parameters

The rotation parameters are related to the rotation 160 axis and the rotation angle by $\mathbf{r} = 2 \tan (\theta/2) \mathbf{u}$, where 161 **u** is a unitary vector giving the direction of the rotation 162 axis. 163

Some components of **u** can be known or null. Some 164 value of θ may yield singularities; $\theta = \pi/4$ and the 165 rotation axis is parallel to the translation vector for a 166 screw displacement. 167

Some robotic systems give precise values of the 168 robot displacements (angle, axis, translation). Some 169 values may be known (we denote by $_{-}\theta_{0}$ a constant and 170 known value of a parameter θ). Other informations 171 regarding parallelism or orthogonality to a known di-172 rection or to an other vector may also be available: 173

• the rotation axis is orthogonal to the translation 174 plane (e.g. planar motion): 175

 $\mathbf{r} \perp \mathbf{t} \Leftrightarrow \mathbf{r} \cdot \mathbf{t} = 0$, 176

• screw displacement: 177

$$\mathbf{r} \| \mathbf{t} \Leftrightarrow \exists \kappa / \mathbf{r} = \kappa \mathbf{t}.$$
 178

3.2.3. All constraints on motion 179

All these constraints, also called "atomic particu-180 lar cases", have simple expressions that can be easily 181 combined. In this purpose, we use the fact that **u** is 182 a unitary vector and that, for monocular systems, the 183 norm of translation cannot be recovered. To parame-184 terize these vectors with only two parameters, we di-185 vide each component by a non-zero component. Then, 186 the dot product and scalar product induce linear rela-187 tions. For example, $t_2 = 1$ and $\mathbf{t} \perp \mathbf{r}$ are equivalent 188 to $t_0u_0 + t_1u_1 + u_2 = 0 \Rightarrow u_2 = -t_0u_0 - t_1u_1$. All 189 cases are collected in Table 2. 190

3.2.4. Generating all cases 191

All particular cases, each called a "molecular case", 192 are generated by combining the atomic cases and solv-193

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Table	2				
Table	of	particular	cases	of	displacements

ul	$u_0 = u_2 = 0, u_1 = 1$	Rotation axis y-axis	R1	$\mathbf{R} = \mathbf{I}$	Null rotation
u2	$u_0 = 0, u_1 = 1$	Rotation axis $\perp x$ -axis	R2	$\mathbf{R} = \mathbf{I} + \tilde{\mathbf{r}}$	First order
u3	$u_2 = 0, u_1 = 1$	Rotation axis $\perp z$ -axis	R3	$\mathbf{R} = \mathbf{I} + \tilde{\mathbf{r}} + \frac{1}{2}\tilde{\mathbf{r}}^2$	Second order
u4	$u_1 = 1$	General case	R4	$\mathbf{R} = \mathbf{I} + (\tilde{\mathbf{r}} + 1/2\tilde{\mathbf{r}}^2) / (1 + \mathbf{r}^{\mathrm{T}}\mathbf{r}/4)$	General case
u5	$u_0 = u_2 = 0, u_1 = -1$	Rotation axis y-axis			
uб	$u_0 = 0, u_1 = -1$	Rotation axis $\perp x$ -axis	al	$\theta = \pi/2$	Quarter turn
u7 u8	$u_2 = 0, u_1 = -1$ $u_1 = -1$	Rotation axis $\perp z$ -axis General case	a2	heta	Free angle
u9	$u_0 = u_1 = 0, u_2 = 1$	Rotation axis z-axis	t1	$t_1 = t_2 = 0, t_0 = 1$	Translation $ x$ -axis
u10	$u_0 = 0, u_2 = 1$	Rotation axis $\perp x$ -axis	t2	$t_1 = 0, t_0 = 1$	Translation \perp y-axis
u11	$u_1 = 0, u_2 = 1$	Rotation axis \perp y-axis	t3	$t_2 = 0, t_0 = 1$	Translation $\perp z$ -axis
u12	$u_2 = 1$	General case	t4	$t_0 = 1$	General translation
u13	$u_0 = u_1 = 0, u_2 = -1$	Rotation axis z-axis	t5	$t_0 = t_2 = 0, t_1 = 1$	Translation y-axis
u14	$u_0 = 0, u_2 = -1$	Rotation axis $\perp x$ -axis	tб	$t_0 = 0, t_1 = 1$	Translation $\perp x$ -axis
u15	$u_1 = 0, u_2 = -1$	Rotation axis \perp y-axis	t7	$t_2 = 0, t_1 = 1$	Translation $\perp z$ -axis
u16	$u_2 = -1$	General case	t8	$t_1 = 1$	General translation
u17	$u_1 = u_2 = 0, \ u_0 = 1$	Rotation axis x-axis	t9	$t_0 = t_1 = 0, t_2 = 1$	Translation $\parallel z$ -axis
u18	$u_1 = 0, u_0 = 1$	Rotation axis \perp y-axis	t10	$t_0 = 0, t_2 = 1$	Translation $\perp x$ -axis
u19	$u_2 = 0, u_0 = 1$	Rotation axis $\perp z$ -axis	t11	$t_1 = 0, t_2 = 1$	Translation \perp <i>y</i> -axis
u20	$u_0 = 1$	General case	t12	$t_2 = 1$	General translation
u21	$u_1 = u_2 = 0, \ u_0 = -1$	Rotation axis x-axis			
u22	$u_1 = 0, u_0 = -1$	Rotation axis \perp y-axis	Z1	$\mathbf{t} \cdot \mathbf{u} = 0$	Translation \perp rotation axis
u23	$u_2 = 0, u_0 = -1$	Rotation axis $\perp z$ -axis	Z2	$\mathbf{t} \wedge \mathbf{u} = 0$	Screw displacement
u24	$u_0 = -1$	General case	Z3		No relation

ing the constraints by a substitution.¹ A molecular
case is composed of one case in each family, a family
being named by a letter (g, s, f or c for projection
as seen in Table 1 and u, R, a, t or Z for motion as
seen in Table 2). Thus, a molecular case is identified
by the sequence:

201 g[1-3]f[1-3]s[1-3]c[1-3]R[1-4]a[1-2] 202 u[1-24]t[1-12]Z[1-3],

where g[1-3] means "one atomic case among g1, g2and g3".

205 3.2.5. How many cases do we have?

If we look at the expression of the particular above-mentioned cases, we obtain 6×10^6 particular cases. However, this is not the real number because of the incompatibility of some atomic cases and the redundancy of some constraints. Two different sets of

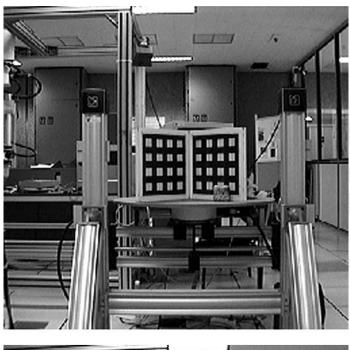
¹ This was done using Maple software for symbolic computations. atomic constraints can generate the same simplified 211 model. 212

It is easy to eliminate incompatible constraints. It 213 is not possible to deal with redundant constraints, because this requires to compare each set of combined 215 constraints with all others in order to determine the 216 similarity. The complexity of this process is $O(n^2)$. 217

Although we cannot remove redundant cases, we propose an adapted strategy to deal with the large number of cases. The idea of this paper is: (i) to eliminate some of the redundant cases by using some considerations on the atomic cases and (ii) to limit the number of cases by studying the particular forms of the matrices. 224

- 3.2.6. Reducing the number of cases225Some redundancy are obvious226
- In case (R1), one case of axis and angle is considered. 228
- In cases (R2) and (R3), we do not consider (a1) 229 when θ is equal to π/2.
- The case (a1) is only considered if $\mathbf{r} \| \mathbf{t}$, (Z2). 231

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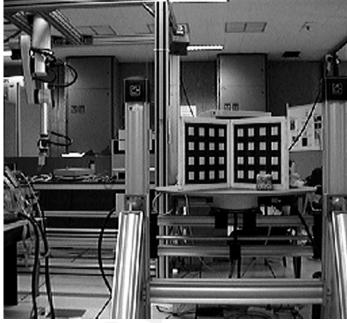


Fig. 1. Images for x-axis translation, small pan rotation and auto-focus.



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6

This reduces the amount of cases of fundamental relations to only 216756 cases.

234 4. Forms of fundamental matrices

We have significantly reduced the number of cases 235 but this is not small enough to be computation-236 ally tractable. We now split fundamental relations 237 238 in sets of matrices by forms. The matrix form is determined using simple rules in order to obtain a 239 very simple parameterization. We consider (3×3) 240 matrices having nine parameters (coefficients). If a 241 coefficient is equal to zero, then there is one less 242 parameter. If a coefficient has the same expression 243 or is opposite to another, there is one less param-244 eter again. These operations are very simple and 245 can be rapidly computed in each case. Furthermore, 246 we know that a fundamental matrix is defined up 247 to a scale factor, and that its determinant is fixed 248 to 0 (removing in most cases one parameter). This 249 process reduces the 216756 cases to only 188 sub-250 groups. 251

The table in Appendix A shows all the simplified forms obtained, and for each form, an example of case that has generated it. This table will be useful for people who want to implement the algorithm.

257 5. Experiments

We have recorded several video sequences for 258 which the camera displacement induces a funda-259 mental relation between image points \mathbf{m}_1 and \mathbf{m}_2 . 260 From each particular matrix form, we have estimated 261 the fundamental matrix parameters with the robust 262 least median square method in order to minimize 263 the distance between a 2D point \mathbf{m}_1 and its epipolar 264 line \mathbf{Fm}_2 . To deal with cases with different degrees 265 of freedom, we use an appropriate Akaike criterion 266 [1]. 267

For each recorded video sequence, we have verified that the model with the minimal residual error effectively corresponds to the displacement performed by the robotic system. We present one experiment in Fig. 1 for which the camera has performed a small pan rotation followed by a translation parallel to the x-axis. The auto-focus was also enabled. The case with274the minimal residual error corresponds to the funda-275mental matrix form number 59 in the table given in276Appendix A277

$$\mathbf{F} = \begin{pmatrix} 0 & 0 & 0 \\ x_0 & x_1 & x_2 \\ 0 & -x_2 & x_3 \end{pmatrix}.$$
 278

This particular form was obtained from cases where the rotation was approximated to its first and second order, the translation is parallel to the *x*-axis, the rotation axis is orthogonal to the optical axis and the intrinsic parameters are free.

6. Conclusion

284

In an earlier study on homographic matrices [11], 285 we have shown that it is possible to reduce the amount 286 of particular cases in order to make the case selection 287 computationally feasible. In this paper, we have shown 288 that a similar result can be obtained with fundamental 289 matrices using redundancies. We have experimentally 290 confirmed that our system is able to automatically se-291 lect the case corresponding to the performed displace-292 ment 293

The applications are twofold: (i) an incremental 294 reconstruction of the scene and (ii) the segmen-295 tation of objects moving with different displace-296 ments or with different geometric properties in video 297 sequences. 298

This work has also been extended to mo-299 tion estimation of human head inside MRI scanner, improving the registration of fMRI volumes 301 [12]. 302

Appendix A. Table of particular forms of303fundamental matrices304

We denote by \mathbf{n}^{0} the form number, by \mathbf{p} the 305 number of parameters (we have not taken into account the fact that the fundamental matrix is defined up to a scale factor and that det $\mathbf{F} = 0$ but 308 we do so in our implementation) and by \mathbf{n} the 309 number of molecular cases that have generated a 310 form. 311

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n ^o	p	Sim	plified	l forn	n of fun	dame	ntal n	natrix			For example generated by	n
1	1	[0	0	0	0	0	x_6	0	$-x_{6}$	0]	glflslcltlRlu24Z3a2	24
2	1	[0	0	<i>x</i> ₃	0	0	0	$-x_{3}$	0	0]	glf1s1c1t5R1u24Z3a2	4
3	1	[0	x_2	0	$-x_{2}$	0	0	0	0	0]	glflslclt9Rlu24Z3a2	-
4	2	[0	0	0	0	0	x_6	0	$-x_6$	x_9]	glflslc3tlRlu24Z3a2	12
5	2	[0	0	0	0	0	x_6	0	x_8	0]	glf3slcltlRlu24Z3a2	(
6	2	[0	0	0	0	0	x_6	<i>x</i> ₇	$-x_6$	0]	glflslcltlR2ul3Z2a2	1
7	2	[0	0	0	0	<i>x</i> ₅	x_6	0	$-x_6$	x_5]	glflslcltlR2u17Zla2	39
8	2	[0	0	0	x_4	0	x_6	0	$-x_6$	0]	glflslcltlR2ulZ2a2	1
9	2	[0	0	<i>x</i> ₃	0	0	0	$-x_{3}$	0	x_9]	glflslc3t5Rlu24Z3a2	
10	2	[0	0	<i>x</i> ₃	0	0	0	$-x_{3}$	x_8	0]	glflslclt5R2ul3Z2a2	:
11	2	[0	0	<i>x</i> ₃	0	0	0	<i>x</i> ₇	0	0]	glfls2clt5Rlu24Z3a2	4
12	2	[0	0	<i>x</i> ₃	0	0	x_6	$-x_{3}$	$-x_6$	0]	glflslclt3Rlu24Z3a2	1′
13	2	[0	x_2	0	$-x_{2}$	0	x_6	0	$-x_6$	0]	glflslcltllRlu24Z3a2	
14	2	[0	x_2	0	$-x_{2}$	0	x_6	0	0	0]	glflslclt9R2u1Z2a2	24
15	2	[0	x_2	0	$-x_{2}$	<i>x</i> ₅	0	0	0	0]	g2f3s1c1t9R1u24Z3a2	
16	2	[0	x_2	0	x_4	0	0	0	0	0]	glfls2clt9Rlu24Z3a2	
17	2	[0	x_2	<i>x</i> ₃	$-x_{2}$	0	0	$-x_{3}$	0	0]	glflslcltl0Rlu24Z3a2	
18	2	[0	x_2	<i>x</i> ₃	$-x_{2}$	0	0	0	0	0]	glflslclt9R2u17Z2a2	1
19	2	[0	x_2	<i>x</i> ₃	0	0	0	$-x_{3}$	0	0]	glflslclt5R2u17Z2a2	
20	2	[<i>x</i> ₁	0	<i>x</i> ₃	0	0	0	$-x_{3}$	0	x_1]	glflslclt5R2ulZla2	6
21	2	[<i>x</i> ₁	x_2	0	$-x_{2}$	x_1	0	0	0	0]	glflslclt10R2ul1Z1a2	19
22	3	[0	0	0	0	0	x_6	0	x_8	<i>x</i> 9]	glf3slc2t1R1u24Z3a2	1
23	3	[0	0	0	0	0	x_6	<i>x</i> ₇	$-x_6$	<i>x</i> 9]	glflslc2t1R2u13Z2a2	3
24	3	[0	0	0	0	0	x_6	<i>x</i> ₇	x_8	0]	glflslcltlR3ul3Z2a2	20
25	3	[0	0	0	0	<i>x</i> 5	x_6	0	$-x_6$	x_9]	glf2slcltlR2u17Z1a2	39
26	3	[0	0	0	0	<i>x</i> 5	x_6	<i>x</i> ₇	$-x_6$	x_5]	glflslcltlR2ullZ2a2	1
27	3	[0	0	0	x_4	0	x_6	0	x_8	0]	glflslcltlR3ulZ2a2	5
28	3	[0	0	0	x_4	0	x_6	<i>x</i> ₇	$-x_6$	0]	glflslcltlR2u10Z2a2	3
29	3	[0]	0	0	x_4	<i>x</i> 5	x_6	0	$-x_6$	0]	g2f1s1c1t1R2u1Z2a2	3
30	3	[0	0	0	x_4	x_5	x_6	0	$-x_6$	<i>x</i> ₅]	glflslcltlR2u19Z2a2	1
31	3	[0	0	x_3	0	0	0	$-x_{3}$	x_8	<i>x</i> 9]	glflslc2t5R2u13Z2a2	1
32	3	[0	0	x_3	0	0	0	<i>x</i> ₇	0	x9]	glfls2c2t5Rlu24Z3a2	
33	3	[0	0	x_3	0	0	0	x_7	<i>x</i> ₈	0]	glflslclt5R3ul3Z2a2	6
34	3	[0	0	x_3	0	0	x_6	$-x_{3}$	$-x_6$	x_9]	glflslc3t3Rlu24Z3a2	1
35	3	[0	0	x_3	0	0	x_6	$-x_3$	x_8	0]	g2f1s1c1t5R2u13Z2a2	2
36	3	[0	0	x_3	0	0	x_6	<i>x</i> ₇	$-x_6$	0]	glfls2clt3Rlu24Z3a2	
37	3	[0	x_2	0	$-x_{2}$	0	x_6	0	<i>x</i> ₈	0]	glf3slc1t11R1u24Z3a2	
38	3	[0	x_2	0	$-x_{2}^{-}$	<i>x</i> 5	<i>x</i> ₆	0	$-x_6$	0]	g3f1s1c1t11R1u24Z3a2	
39	3	[0	x_2	0	$-x_{2}^{-}$	x_5	<i>x</i> ₆	0	0	0]	g2f3s1c1t9R2u1Z2a2	1
40	3	[0	x_2	0	<i>x</i> ₄	0	<i>x</i> ₆	0	$-x_6$	0]	glfls2cltllRlu24Z3a2	
41	3	[0	x_2	0	x_4	0	<i>x</i> ₆	0	0	0]	glflslclt9R3ulZ2a2	6
42	3	[0	x_2	0	x_4	<i>x</i> 5	0	0	0	0]	g2f1s2c1t9R1u24Z3a2	
43	3	[0	x_2	<i>x</i> ₃	$-x_2$	0	0	x_7	0	0]	glf3slc1t10R1u24Z3a2	
44	3	[0	x_2	<i>x</i> ₃	$-x_{2}$	0	<i>x</i> ₆	$-x_{3}$	$-x_6$	0]	glflslcltl2Rlu24Z3a2	4
45	3	[0	x_2	x_3	$-x_{2}$	0	x_6	0	0	0]	glflslclt9R2u19Z2a2	6
46	3	[0	x_2	x_3	0	0	0	$-x_{3}$	x_8	0]	glflslclt5R2ul1Z2a2	1

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313 Appendix A (Continued)

47 48 49 50 51 52	3 3 3 3	[0 [0	<i>x</i> ₂	<i>x</i> ₃	0	_						
49 50 51	3 3	_			0	0	0	<i>x</i> ₇	0	0]	glflslclt5R3u17Z2a2	64
50 51	3	r	x_2	<i>x</i> ₃	x_4	0	0	0	0	0]	glflslclt9R3u17Z2a2	60
51	-	$[x_1$	0	<i>x</i> ₃	0	0	0	$-x_{3}$	0	<i>x</i> 9]	glf2slclt5R2u1Zla2	66
	0	$[x_1$	0	<i>x</i> ₃	0	0	0	$-x_{3}$	x_8	x_1]	glflslclt5R2u10Z2a2	8
52	3	$[x_1$	x_2	0	$-x_{2}$	x_1	x_6	0	0	0]	glflslclt9R2u10Z2a2	24
	3	$[x_1$	x_2	<i>x</i> ₃	$-x_{2}$	x_1	0	0	0	0]	glflslclt9R2ullZ2a2	24
53	3	$[x_1$	x_2	<i>x</i> ₃	0	0	0	$-x_{3}$	0	x_1]	glflslclt5R2u19Z2a2	8
54	4	[0	0	0	0	0	x_6	<i>x</i> ₇	x_8	<i>x</i> 9]	glflslc2t1R3u13Z2a2	400
55	4	[0	0	0	0	<i>x</i> ₅	x_6	0	x_8	<i>x</i> 9]	glflslc2t1R2u17Z1a2	2772
56	4	[0	0	0	0	<i>x</i> ₅	x_6	<i>x</i> ₇	$-x_6$	<i>x</i> 9]	glf2slcltlR2ullZ2a2	16
57	4	[0	0	0	0	<i>x</i> ₅	x_6	<i>x</i> ₇	x_8	x_5]	g2f1s1c1t1R2u11Z2a2	32
58	4	[0	0	0	x_4	0	x_6	<i>x</i> ₇	x_8	0]	glf3slcltlR2u10Z2a2	16
59	4	[0	0	0	x_4	x_5	x_6	0	$-x_6$	<i>x</i> 9]	glf2slcltlR2u19Z2a2	80
60	4	[0	0	0	x_4	<i>x</i> ₅	x_6	0	x_8	0]	g2f1s1c1t1R3u1Z2a2	112
61	4	[0	0	0	x_4	<i>x</i> ₅	x_6	<i>x</i> ₇	$-x_6$	x_5]	glflslcltlR2ul2Z2a2	24
62	4	[0	0	<i>x</i> ₃	0	0	0	<i>x</i> ₇	x_8	<i>x</i> 9]	glflslc2t5R3u13Z2a2	128
63	4	[0	0	<i>x</i> ₃	0	0	x_6	$-x_{3}$	x_8	<i>x</i> 9]	g2f1s1c2t5R2u13Z2a2	44
64	4	[0	0	<i>x</i> ₃	0	0	x_6	<i>x</i> ₇	$-x_6$	<i>x</i> 9]	glfls2c2t3Rlu24Z3a2	8
65	4	[0	0	<i>x</i> ₃	0	0	x_6	<i>x</i> ₇	x_8	0]	glflslclt3R2ul3Z2a2	588
66	4	[0	x_2	0	$-x_{2}$	<i>x</i> 5	x_6	0	x_8	0]	g2f3s1c1t11R1u24Z3a2	4
67	4	[0	x_2	0	x_4	0	x_6	0	x_8	0]	glflslcltllR2ulZ2a2	146
68	4	[0	x_2	0	x_4	x_5	x_6	0	$-x_6$	0]	g2f1s2c1t11R1u24Z3a2	8
69	4	[0	x_2	0	x_4	<i>x</i> 5	x_6	0	0	0]	g2f1s1c1t9R3u1Z2a2	120
70	4	[0	x_2	x_3	$-x_{2}$	0	x_6	$-x_{3}$	$-x_6$	x_9]	glf3slc2t9Rlu24Z3a2	9
71	4	[0]	x_2	x_3	$-x_{2}^{-}$	x_5	x_6	0	$-x_6$	$x_5]$	glflslcltllR2u17Z2a2	8
72	4	[0]	x_2	x_3	$-x_{2}^{-}$	<i>x</i> ₅	x_6	0	0	0]	g2f3s1c1t9R2u17Z2a2	36
73	4	[0	x_2	x_3	0	0	0	x_7	x_8	0]	glfls2clt5R2ullZ2a2	32
74	4	[0	x_2	x_3	0	x_5	<i>x</i> ₆	$-x_{3}$	$-x_6$	0]	g2f1s1c1t5R2u17Z2a2	12
75	4	[0	x_2	x_3	0	x_5	x_6	$-x_3$	$-x_6$	x_5]	glflslclt3R2u17Z2a2	8
76	4	[0	x_2	x_3	x_4	0	0	<i>x</i> ₇	0	0]	glflslclt10R2u17Z2a2	150
77	4	[0]	x_2	x_3	x_4	0	x_6	0	0	0]	qlfls2clt9R2u19Z2a2	24
78	4	$[x_1]$	0	x_3	0	0	0	$-x_3$	<i>x</i> ₈	x_9]	glf2slclt5R2u10Z2a2	8
79	4	$[x_1]$	0	x_3	0	0	0	<i>x</i> ₇	0	<i>x</i> 9]	glflslc2t5R2u1Z1a2	1056
80	4	$[x_1]$	0	x_3	x_4	0	x_6	$-x_3$	$-x_6$	x_1]	glflslclt3R2u1Z2a2	8
81	4	$[x_1]$	x_2	0	$-x_2$	x_1	x_6	<i>x</i> ₇	$-x_6$	0]	glflslcltllR2ul3Z2a2	16
82	4	$[x_1]$	x_2	0	x_4	<i>x</i> 5	0	0	0	0]	glfls2clt10R2ul1Zla2	990
83	4	$[x_1]$	x_2	<i>x</i> ₃	$-x_{2}$	0	<i>x</i> ₆	$-x_3$	0	x_1]	glflslclt10R2u1Z2a2	8
84	4	$[x_1]$	$\tilde{x_2}$	x_3	$-x_{2}^{2}$	x_1	0	$-x_{3}^{3}$	x_8	0]	glflslclt10R2u13Z2a2	16
85	4	$[x_1]$	x_2	x_3	$-x_{2}^{2}$	x_1	x_6	0	0	0]	glflslclt9R2u12Z2a2	36
86	4	$[x_1]$	x_2	x_3	0	0	0	$-x_3$	0	x_9]	glf2slclt5R2u19Z2a2	8
87	4	$[x_1]$	x_2	x_3	0	0	0	$-x_3$	<i>x</i> ₈	x_{1}]	glflslclt5R2u12Z2a2	12
88	5	[0]	0	0	0	<i>x</i> 5	x_6	x ₇	x_8	x_9]	qlflslc2tlR2ullZ2a2	368
89	5	[0	ů 0	0	x_4	0	x_6	x_7	x_8	x_9]	glflslc2tlR2u10Z2a2	240
90	5	[0	0	0	x_4	<i>x</i> ₅	x_6	0	х ₈	x_9]	glf3slcltlR2u19Z2a2	48

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n ^o	р	Sim	plified	form	of fun	dament	al ma	trix			For example generated by	n
91	5	[0	0	0	<i>x</i> ₄	<i>x</i> 5	<i>x</i> ₆	<i>x</i> ₇	$-x_{6}$	<i>x</i> 9]	glf2slcltlR2u12Z2a2	24
92	5	[0	0	0	x_4	<i>x</i> ₅	x_6	<i>x</i> ₇	<i>x</i> ₈	$-x_{5}]$	glfls1clt1R3u10Z2a2	32
93	5	[0	0	0	x_4	x_5	x_6	x_7	x_8	0]	g2f1s1c1t1R2u10Z2a2	90
94	5	[0	0	0	x_4	<i>x</i> ₅	x_6	<i>x</i> ₇	x_8	x_5]	glflslcltlR3ullZ2a2	64
95	5	[0	0	x_3	0	0	x_6	<i>x</i> ₇	x_8	x_9]	glflslc2t3R2ul3Z2a2	1170
96	5	[0	x_2	0	x_4	x_5	x_6	0	x_8	0]	g2f1s1c1t11R2u1Z2a2	292
97	5	[0	x_2	<i>x</i> ₃	$-x_{2}$	0	x_6	$-x_{3}$	x_8	x_9]	glfls1c2t9R2u1Z2a2	2
98	5	[0	x_2	<i>x</i> ₃	$-x_{2}$	0	x_6	<i>x</i> ₇	$-x_6$	x_9]	glfls1c2t9R2u17Z2a2	1
99	5	[0	x_2	<i>x</i> ₃	$-x_{2}$	0	x_6	<i>x</i> ₇	x_8	0]	glf3s1c1t12R1u24Z3a2	
100	5	[0	x_2	<i>x</i> ₃	$-x_{2}$	x_5	x_6	$-x_{3}$	x_8	0]	g3f1s1c1t10R1u24Z3a2	1
101	5	[0	x_2	x_3	$-x_{2}$	<i>x</i> 5	x_6	0	$-x_{6}$	x_9]	glf2s1c1t11R2u17Z2a2	1
102	5	[0	x_2	x_3	$-x_{2}$	<i>x</i> 5	x_6	0	x_8	x_5]	g2f1s1c1t11R2u17Z2a2	12
103	5	[0	x_2	x_3	0	0	0	<i>x</i> ₇	x_8	x_9]	glfls1c2t5R2u11Z2a2	240
104	5	[0	x_2	x_3	0	<i>x</i> 5	x_6	$-x_{3}$	$-x_6$	<i>x</i> 9]	glf2slclt3R2u17Z2a2	32
105	5	[0	x_2	x_3	0	x_5	x_6	$-x_{3}$	x_8	0]	g2f1s1c1t5R2u11Z2a2	30
106	5	[0	x_2	x_3	0	<i>x</i> 5	x_6	<i>x</i> ₇	$-x_{6}$	x_5]	glflslclt3R3ul7Z2a2	40
107	5	[0	x_2	x_3	x_4	0	x_6	<i>x</i> ₇	$-x_{6}$	0]	glfls2cltl2Rlu24Z3a2	
108	5	[0	x_2	x_3	x_4	x_5	x_6	0	$-x_6$	<i>x</i> ₅]	glflslcltllR3ul7Z2a2	4
109	5	[0	x_2	x_3	x_4	<i>x</i> ₅	x_6	0	0	0]	g2f1s1c1t9R3u17Z2a2	16
110	5	$[x_1]$	0	x_3	0	0	0	<i>x</i> ₇	x_8	<i>x</i> 9]	glfls1c2t5R2u10Z2a2	12
111	5	$[x_1]$	0	x_3	x_4	0	x_6	$-x_3$	$-x_6$	x9]	glf2s1c1t3R2u1Z2a2	:
112	5	$[x_1]$	0	x_3	x_4	0	x_6	$-x_{3}^{2}$	<i>x</i> ₈	x_1	glfls1clt3R3ulZ2a2	1
113	5	$[x_1]$	x_2	0	$-x_{2}$	x_1	x_6	<i>x</i> ₇	x_8	0]	glflslcltllR3ul3Z2a2	50
114	5	$\begin{bmatrix} x_1 \end{bmatrix}$	x_2	0	x_4	x_5	x_6	0 [′]	0	0]	glfls2clt9R2ul0Z2a2	120
115	5	$\begin{bmatrix} x_1 \end{bmatrix}$	x_2	x_3	$-x_{2}$	0	x_6	$-x_{3}$	0	x9]	glf2s1c1t10R2u1Z2a2	1
116	5	$\begin{bmatrix} x_1 \end{bmatrix}$	x_2	x_3	$-x_2$	x_1	0	<i>x</i> ₇	x_8	0]	glflslcltl0R3ul3Z2a2	5
117	5	$[x_1]$	x_2	<i>x</i> ₃	0 -	0	0	$-x_{3}$	x_8	x9]	glf2slclt5R2ul2Z2a2	1
118	5	$[x_1]$	x_2	<i>x</i> ₃	0	0	0	<i>x</i> ₇	0	x9]	glfls2clt5R2u19Z2a2	3
119	5	$[x_1]$	x_2	<i>x</i> ₃	0	0	0	x_7	<i>x</i> ₈	$-x_{1}$]	glflslclt5R3ullZ2a2	1
120	5	$[x_1]$	x_2	x_3	0	0	0	<i>x</i> ₇	<i>x</i> ₈	x_1]	glflslclt5R3u10Z2a2	3
121	5	$[x_1]$	x_2	<i>x</i> ₃	x_2	<i>x</i> 5	x_6	$-x_3$	$-x_{6}$	x_1]	g2f1s1c1t5R2u1Z1a2	7
122	5	$[x_1]$	x_2	x_3	x_4	$-x_1$	x_6	0	0	0]	glflslclt9R3u19Z2a2	4
123	5	$[x_1]$	x_2	<i>x</i> ₃	x_4	0	x_6	$-x_3$	0	x_1]	glflslcltl0R3ulZ2a2	1
124	5	$\begin{bmatrix} x_1 \end{bmatrix}$	x_2	<i>x</i> ₃	x_4	x_1	x_6	0	0	0]	glflslclt9R3u10Z2a2	9
125	5	$[x_1]$	x_2	x_3	x_4	<i>x</i> ₅	0	0	0	0]	glfls2clt9R2ullZ2a2	2
126	6	[0]	0	0	x_4	<i>x</i> 5	<i>x</i> ₆	<i>x</i> ₇	x_8	x_9]	glflslcltlR3ul2Z2a2	516
127	6	[0	x_2	<i>x</i> ₃	$-x_2$	0	x_6	x_7	<i>x</i> ₈	x9]	glflslc2t9R2u19Z2a2	19
128	6	[0	x_2	<i>x</i> ₃	$-x_{2}$	<i>x</i> ₅	x_6	$-x_{3}$	x_8	x_9]	g2f3s1c2t11R1u24Z3a2	3
129	6	[0	x_2	<i>x</i> ₃	$-x_{2}$	x5	x_6	0	<i>x</i> ₈	x9]	glf3slc1t11R2u17Z2a2	4
130	6	[0	x_2	x_3	$-x_{2}$	x5	x_6	x ₇	<i>x</i> ₈	0]	g2f3s1c1t10R1u24Z3a2	1
131	6	[0	x_2	x_3	0^{λ_2}	x_5	x_6	$-x_3$	л8 X8	x_9]	q3f1s1c1t3R2u17Z2a2	1
131	6	[0]	$\frac{x_2}{x_2}$	л3 X3	0	x_5	x_6	x_7	$-x_{6}$	x_9	glf2slclt3R3ul7Z2a2	4
132	6	[0]	$\frac{x_2}{x_2}$	л3 Х3	0						g2f1s1c1t5R3u17Z2a2	19
133 134	6	[0 [0	$\frac{x_2}{x_2}$	x_3 x_3	0	x_5 x_5	$\frac{x_6}{x_6}$	x_7 x_7	$\frac{x_8}{x_8}$	x_5]	glflslclt3R2ullZ2a2	19

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n ^o	p	Sim	plified	form	n of fun	dame	ntal n	natrix			For example generated by	n
135	6	[0	x_2	<i>x</i> ₃	<i>x</i> ₄	0	<i>x</i> ₆	<i>x</i> ₇	<i>x</i> ₈	0]	g1f3s2c1t12R1u24Z3a2	3
136	6	[0	x_2	<i>x</i> ₃	x_4	<i>x</i> ₅	x_6	0	$-x_6$	<i>x</i> 9]	glf2s1c1t11R3u17Z2a2	40
137	6	[0	x_2	<i>x</i> ₃	x_4	<i>x</i> ₅	x_6	0	x_8	x_5]	glflslcltllR2u19Z2a2	32
138	6	[0	x_2	<i>x</i> ₃	x_4	<i>x</i> ₅	x_6	<i>x</i> ₇	$-x_{6}$	x_5]	glflslcltl2R2u17Z2a2	84
139	6	[<i>x</i> ₁	0	<i>x</i> ₃	x_4	0	x_6	$-x_{3}$	x_8	<i>x</i> 9]	glf2slclt3R3u1Z2a2	16
140	6	$[x_1$	0	<i>x</i> ₃	x_4	0	x_6	<i>x</i> ₇	$-x_6$	x_9]	glfls2clt3R2ulZ2a2	16
141	6	[<i>x</i> ₁	0	<i>x</i> ₃	x_4	0	x_6	<i>x</i> ₇	$-x_6$	<i>x</i> 9]	glf2s2clt6R2u5Z3a2	16
142	6	$[x_1$	x_2	0	x_4	x_1	x_6	<i>x</i> ₇	x_8	0]	glflslcltllR2ul0Z2a2	48
143	6	[<i>x</i> ₁	x_2	0	x_4	<i>x</i> ₅	x_6	<i>x</i> ₇	$-x_6$	0]	glfls2cltllR2ul3Z2a2	16
144	6	[<i>x</i> ₁	x_2	<i>x</i> ₃	$-x_{2}$	0	x_6	<i>x</i> ₇	0	<i>x</i> 9]	glf3slclt10R2u1Z2a2	8
145	6	[<i>x</i> ₁	x_2	<i>x</i> ₃	$-x_{2}$	x_1	x_6	<i>x</i> ₇	x_8	0]	glflslcltl2R2ul3Z2a2	126
146	6	[<i>x</i> ₁	x_2	<i>x</i> ₃	$-x_{2}$	<i>x</i> ₅	x_6	$-x_{3}$	x_6	x_9]	glflslc1t10R2u10Z1a2	144
147	6	[<i>x</i> ₁	x_2	<i>x</i> ₃	$-x_{2}$	x_5	x_6	<i>x</i> ₃	$-x_6$	<i>x</i> 9]	glflslcltllR2ullZla2	144
148	6	[<i>x</i> ₁	x_2	<i>x</i> ₃	0	0	0	<i>x</i> ₇	x_8	x_9]	glflslclt5R3ul2Z2a2	1536
149	6	[<i>x</i> ₁	x_2	x_3	x_2	<i>x</i> ₅	x_6	$-x_{3}$	$-x_6$	<i>x</i> 9]	glflslclt3R2u19Z1a2	358
150	6	[<i>x</i> ₁	x_2	x_3	x_2	<i>x</i> ₅	x_6	$-x_{3}$	x_8	x_1]	g2f1s1c1t5R2u10Z2a2	12
151	6	[<i>x</i> ₁	x_2	<i>x</i> ₃	x_4	0	x_6	$-x_{3}$	0	x_9]	glf2s1c1t10R3u1Z2a2	16
152	6	[<i>x</i> ₁	x_2	<i>x</i> ₃	x_4	0	x_6	$-x_{3}$	x_8	x_1]	glflslcltl2R2ulZ2a2	42
153	6	[<i>x</i> ₁	x_2	<i>x</i> ₃	x_4	0	x_6	<i>x</i> ₇	0	x_1]	glflslcltl0R2u19Z2a2	16
154	6	[<i>x</i> ₁	x_2	x_3	x_4	x_1	0	<i>x</i> ₇	x_8	0]	glflslcltl0R2ul1Z2a2	48
155	6	[<i>x</i> ₁	x_2	<i>x</i> ₃	x_4	<i>x</i> ₅	x_6	$-x_{3}$	$-x_6$	x_1]	g2f1s1c1t3R2u1Z2a2	24
156	6	[<i>x</i> ₁	x_2	x_3	x_4	<i>x</i> ₅	x_6	0	0	0]	glflslclt9R3u12Z2a2	1428
157	7	[0	x_2	x_3	$-x_{2}$	<i>x</i> ₅	x_6	<i>x</i> ₇	x_8	<i>x</i> 9]	glflslc2tllR2u17Z2a2	270
158	7	[0	x_2	x_3	0	<i>x</i> ₅	x_6	<i>x</i> ₇	x_8	<i>x</i> 9]	glflslc2t3R2u11Z2a2	2480
159	7	[0	x_2	x_3	x_4	0	x_6	<i>x</i> ₇	x_8	x_9]	glflslc2t10R2u17Z2a2	912
160	7	[0	x_2	x_3	x_4	<i>x</i> ₅	x_6	0	<i>x</i> ₈	<i>x</i> 9]	glf2s1c1t11R2u19Z2a2	536
161	7	[0	x_2	<i>x</i> ₃	x_4	<i>x</i> ₅	x_6	<i>x</i> ₇	$-x_6$	x_9]	glf2s1c1t12R2u17Z2a2	84
162	7	[0	x_2	<i>x</i> ₃	x_4	<i>x</i> ₅	x_6	<i>x</i> ₇	x_8	0]	g2f1s1c1t10R2u17Z2a2	318
163	7	[<i>x</i> ₁	0	<i>x</i> ₃	x_4	0	x_6	<i>x</i> ₇	x_8	<i>x</i> 9]	glflslc2t3R2u10Z2a2	640
164	7	[<i>x</i> ₁	x_2	0	x_4	<i>x</i> ₅	x_6	<i>x</i> ₇	x_8	0]	glfls2cltllR2ul0Z2a2	584
165	7	[<i>x</i> ₁	x_2	x_3	$-x_{2}$	0	x_6	<i>x</i> ₇	<i>x</i> ₈	<i>x</i> 9]	glflslc2t10R2u1Z2a2	48
166	7	[<i>x</i> ₁	x_2	x_3	$-x_{2}$	x_1	x_6	<i>x</i> ₇	<i>x</i> ₈	x_9]	glflslc2t10R2u11Z1a2	1104
167	7	[<i>x</i> ₁	x_2	x_3	$-x_{2}$	<i>x</i> ₅	x_6	$-x_{3}$	x_8	x_9]	glflslcltl0R2ul0Z2a2	32
168	7	[<i>x</i> ₁	x_2	<i>x</i> ₃	$-x_{2}$	<i>x</i> 5	x_6	<i>x</i> ₇	$-x_6$	x_9]	glflslcltllR2ullZ2a2	32
169	7	[<i>x</i> ₁	x_2	<i>x</i> ₃	x_2	<i>x</i> 5	x_6	$-x_{3}$	x_8	x_9]	g2f2s1c1t5R2u10Z2a2	12
170	7	$[x_1$	x_2	x_3	x_4	0	x_6	$-x_{3}$	<i>x</i> ₈	x_9]	glf2s1c1t12R2u1Z2a2	42
171	7	$[x_1$	x_2	x_3	x_4	0	<i>x</i> ₆	<i>x</i> ₇	0	x_9]	glfls2clt10R2u19Z2a2	168
172	7	$[x_1$	x_2	x_3	x_4	x_5	0	<i>x</i> ₇	x_8	0]	glfls2clt10R2ul1Z2a2	120
173	7	$[x_1$	x_2	<i>x</i> ₃	x_4	<i>x</i> 5	x_6	$-x_{3}$	$-x_6$	x_9]	glflslclt3R2u19Z2a2	104
174	7	$[x_1$	x_2	<i>x</i> ₃	x_4	<i>x</i> ₅	<i>x</i> ₆	$-x_{3}$	<i>x</i> ₈	0]	g2f1s1c1t10R2u13Z2a2	32
175	7	$[x_1]$	x_2	<i>x</i> ₃	<i>x</i> ₄	<i>x</i> 5	<i>x</i> ₆	$-x_{3}$	<i>x</i> ₈	x_1]	g2f1s1c1t10R2u1Z2a2	262
176	8	[0]	x_2	<i>x</i> ₃	x_4	<i>x</i> 5	<i>x</i> ₆	<i>x</i> ₇	x_8	<i>x</i> ₉]	glflslc2t11R2u19Z2a2	5220
177	8	$[x_1]$	x_2	x_3	$-x_{2}$	x_5	x_6	x_7	x_8	<i>x</i> ₉]	glflslc2t10R2u10Z1a2	1232
178	8	$[x_1]$	x_2^2	x_3	x_2^2	<i>x</i> ₅	x_6	x_7	x_8	<i>x</i> 9]	glflslc2t3R2u19Z1a2	1564

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319 Appendix A (*Continued*)

n ^o	р	Sim	plified	l form	n of fi	undame	ntal n	natrix			For example generated by	n
179	8	[<i>x</i> ₁	x_2	<i>x</i> ₃	<i>x</i> ₄	$-x_{1}$	<i>x</i> ₆	<i>x</i> ₇	<i>x</i> ₈	<i>x</i> 9]	glflslc2t9R3u19Z2a2	96
180	8	$[x_1$	x_2	x_3	x_4	0	x_6	x_7	x_8	x_9]	glflslc2t10R2u19Z2a2	1104
181	8	$[x_1$	x_2	x_3	x_4	x_1	x_6	x_7	x_8	x_9]	glflslc2t10R2ul1Z2a2	384
182	8	$[x_1]$	x_2	x_3	x_4	<i>x</i> ₅	x_6	$-x_3$	x_8	<i>x</i> 9]	g2f1s1c1t10R2u10Z1a2	774
183	8	$[x_1]$	x_2	x_3	x_4	x_5	x_6	<i>x</i> ₃	x_8	<i>x</i> ₉]	g2f1s1c1t11R2u11Z1a2	288
184	8	$[x_1$	x_2	x_3	x_4	x_5	x_6	x_7	$-x_6$	x_9]	glfls2cltllR2ullZla2	352
185	8	$[x_1]$	x_2	x_3	x_4	x_5	x_6	<i>x</i> ₇	x_6	x_9]	glfls2clt10R2u10Zla2	144
186	8	$[x_1]$	x_2	x_3	x_4	<i>x</i> ₅	x_6	<i>x</i> ₇	x_8	$-x_{1}$]	g2f1s1c1t5R3u11Z2a2	32
187	8	$[x_1]$	x_2	<i>x</i> ₃	x_4	<i>x</i> 5	x_6	<i>x</i> ₇	x_8	0]	glfls2cltl2R2ul3Z2a2	1078
188	8	$[x_1]$	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_1]	g2f1s1c1t10R2u19Z2a2	128

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