\$P Point-Cloud Gesture Recognizer Pseudocode

Radu-Daniel Vatavu University Stefan cel Mare of Suceava Suceava 720229, Romania vatavu@eed.usv.ro Lisa Anthony UMBC Information Systems 1000 Hilltop Circle Baltimore MD 21250 Ianthony@umbc.edu

In the following pseudocode, POINT is a structure that exposes x, y, and *strokeId* properties. *strokeId* is the stroke index a point belongs to (1, 2, ...) and is filled by counting pen down/up events. POINTS is a list of points and TEM-PLATES a list of POINTS with gesture class data.

Recognizer main function. Match *points* against a set of *templates* by employing the Nearest-Neighbor classification rule. Returns a normalized score in [0..1] with 1 denoting perfect match.

\$P-Recognizer (Points points, Templates templates)

1:	$n \leftarrow 32$ // number of points
2:	NORMALIZE($points, n$)
3:	$score \leftarrow \infty$
4:	for each template in templates do
5:	NORMALIZE $(template, n) //$ should be pre-processed
6:	$d \leftarrow \text{GREEDY-CLOUD-MATCH}(points, template, n)$
7:	if $score > d$ then
8:	$score \leftarrow d$
9:	$result \leftarrow template$
10:	$score \leftarrow Max((2.0 - score)/2.0, 0.0) // \text{ normalize score in } [01]$
11:	return $\langle result, score \rangle$

Cloud matching function. Match two clouds (*points* and *template*) by performing repeated alignments between their points (each new alignment starts with a different starting point index *i*). Parameter $\epsilon \in [0.1]$ controls the number of tested alignments $(n^{\epsilon} \in \{1, 2, ...n\})$. Returns the minimum alignment cost.

GREEDY-CLOUD-MATCH (POINTS points, POINTS template, int n)

1: $\epsilon \leftarrow .50$ 2: $step \leftarrow \lfloor n^{1-\epsilon} \rfloor$ 3: $min \leftarrow \infty$ 4: for i = 0 to n step step do 5: $d_1 \leftarrow \text{CLOUD-DISTANCE}(points, template, n, i)$ 6: $d_2 \leftarrow \text{CLOUD-DISTANCE}(template, points, n, i)$ 7: $min \leftarrow \text{MIN}(min, d_1, d_2)$ 8: return min

Distance between two clouds. Compute the minimum-cost alignment between points and tmpl starting with point start. Assign decreasing confidence $weights \in [0..1]$ to point matchings. CLOUD-DISTANCE (POINTS points, POINTS tmpl, int n, int start) 1: $matched \leftarrow new bool[n]$ 2: $sum \leftarrow 0$ 3: $i \leftarrow start // \text{ start matching with } points_i$ 4: **do** 5: $min \leftarrow \infty$ for each j such that not matched[j] do 6. $d \leftarrow \text{Euclidean-Distance}(points_i, tmpl_j)$ 7: 8: if d < min then 9: $min \leftarrow d$ $index \leftarrow j$ 10: 11: $matched[index] \leftarrow \mathbf{true}$ $weight \gets 1 - ((i - start + n) \text{ MOD } n)/n$ 12: $sum \gets sum + weight \cdot min$ 13: $i \leftarrow (i+1) \text{ MOD } n$ 14:15: **until** i = start // all points are processed16: return sum

The following pseudocode addresses gesture preprocessing (or normalization) which includes resampling, scaling with shape preservation, and translation to origin. The code is Jacob O. Wobbrock Information School | DUB Group University of Washington Seattle, WA 98195-2840 USA wobbrock@uw.edu

similar to \$1 and \$N recognizers^{1,2} and we repeat it here for completeness. We highlight minor changes.

- Gesture normalization. Gesture points are resampled, scaled with shape preservation, and translated to origin. NORMALIZE (POINTS points, int n) 1: $points \leftarrow \text{Resample}(points, n)$ 2: Scale(points) 3: TRANSLATE-TO-ORIGIN(points, n) **Points resampling**. Resample a *points* path into *n* evenly spaced points. We use n = 32. RESAMPLE (POINTS points, int n) 1: $I \leftarrow PATH-LENGTH(points) / (n-1)$ 2: $D \leftarrow 0$ 3: $newPoints \leftarrow points_0$ 4: for each p_i in points such that $i \ge 1$ do 5: if p_i .strokeId == p_{i-1} .strokeId then $d \leftarrow \text{Euclidean-Distance}(p_{i-1}, p_i)$ 6: $\overline{7}$: if $(D+d) \ge I$ then $q.\mathbf{x} \leftarrow p_{i-1}.\mathbf{x} + ((I-D)/d) \cdot (p_i.\mathbf{x} - p_{i-1}.\mathbf{x})$ 8: 9: $q.y \leftarrow p_{i-1}.y + ((I-D)/d) \cdot (p_i.y - p_{i-1}.y)$ 10: $q.strokeId \leftarrow p_i.strokeId$ $\frac{1}{\text{APPEND}(newPoints, q)}$ 11: INSERT(points, i, q) /// q will be the next p_i 12:13: $D \leftarrow 0$ else $D \leftarrow D + d$ 14: 15: return newPoints PATH-LENGTH (POINTS points) 1: $d \leftarrow 0$ 2: for each p_i in points such that $i \ge 1$ do 3: if p_i .strokeId == p_{i-1} .strokeId then
 - 4: $d \leftarrow d + \text{EUCLIDEAN-DISTANCE}(p_{i-1}, p_i)$ 5: return d

Points rescale. Rescale *points* with shape preservation so that the resulting bounding box will be $\subseteq [0..1] \times [0..1]$. SCALE (POINTS *points*)

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1: 2.	$x_{min} \leftarrow \infty, x_{max} \leftarrow 0, y_{min} \leftarrow \infty, y_{max} \leftarrow 0$	
2: 3:	$x_{min} \leftarrow MIN(x_{min}, p.x)$	
4:	$y_{min} \leftarrow \operatorname{MIN}(y_{min}, p.\mathrm{y})$	
5: 6.	$x_{max} \leftarrow MAX(x_{max}, p.x)$	
0. 7:	$g_{max} \leftarrow MAX(g_{max}, p.y)$ $scale \leftarrow MAX(x_{max} - x_{min}, y_{max} - y_{min})$	
8:	for each p in points do	
9:	$p \leftarrow ((p.x - x_{min})/scale, (p.y - y_{min})/scale, p.strokeId)$	
Points translate . Translate <i>points</i> to the origin $(0, 0)$.		
FRANSLATE-TO-ORIGIN (POINTS <i>points</i> , int n)		
1:	$c \leftarrow (0,0) //$ will contain centroid	
2:	for each p in points do	
3:	$c \leftarrow (c.\mathbf{x} + p.\mathbf{x}, c.\mathbf{y} + p.\mathbf{y})$	
4: 5.	$c \leftarrow (c.x/n, c.y/n)$	
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¹http://depts.washington.edu/aimgroup/proj/dollar/index.html
²http://depts.washington.edu/aimgroup/proj/dollar/ndollar.html

 $p \leftarrow (p.x - c.x, p.y - c.y, p.strokeId)$

6:

This pseudocode is modified slightly from that which appears in the original ACM ICMI 2012 publication by Vatavu, Anthony, and Wobbrock (http://dx.doi.org/10.1145/2388676.2388732) to better highlight the use of the *strokeId* property and to provide a normalized matching score. It also contains more comments to assist the implementation. This algorithm's logic remains unchanged.