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Algorithm 1 Marie Curie Genetic Algorithm Overview

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1: Let  $NUM\_GENS = 100$  represent the number of generations to evolve
2: Let  $POP\_SIZE = 100$  represent the size of the total population
3: Let  $NBPG = 50$  represent the number of new candidates to breed every generation
4: Let  $\mathbf{S}_{min}$  and  $\mathbf{S}_{max}$  represent the vectors of servo limits
5: Let  $L_R$  represent the landmarks in the reference image
6: Let  $P = \{C_i, i \in \{0, 1, \dots, POP\_SIZE\}\}$  where each  $C_i$  is a candidate expression
7: for  $i \in \{0, 1, \dots, POP\_SIZE - 1\}$  do
8:   Initialize  $\mathbf{C}_i.\mathbf{chromosome}$  to  $\mathcal{U}(\mathbf{S}_{min}, \mathbf{S}_{max})$ 
9:   Score each candidate s.t.  $C_i.score = mc\_score()$ 
10: end for
11: for  $g \in \{0, 1, \dots, NUM\_GENS\}$  do
12:   Let  $N = \{N_i, i \in \{0, 1, \dots, NBPG\}\} = mc\_breed\_new(NBPG)$  be the set of new candidates for this gen
13:   Score  $N$  s.t.  $N_i.score = mc\_score(\mathbf{N}_i.\mathbf{chromosome}, L_R)$ 
14:   Set  $C = C \cup N$ 
15:   Remove the  $NBPG$  elements with the worst score from  $C$ 
16: end for
17: return  $C_{opt} = C_i$  where  $i = \underset{i}{\operatorname{argmin}}\{C_i.score\}$ 

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Algorithm 2 MC Breed New ($mc_breed_new(N_C, N_{CpP})$)

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1: Let  $N_C$  be the number of new candidates to breed
2: Let  $N_{CpP}$  be the maximum number of candidates to breed for a single set of parents
3: Calculate the number of pairs of parents  $N_{pP}$ 
4: Get the mating pool  $M$  which is comprised of the best (lowest) scoring  $2N_{pP}$  candidates in  $C$ 
5: Create  $N_{pP}$  pairs of parents,  $P_p$ , by pairing the highest scoring parents together (i.e.  $P_p = \{\{M_0, M_1\}, \{M_2, M_3\}, \dots\}$ )
6: Initialize  $N = \emptyset$  where  $N$  is the set of all new candidates bred this generation.
7: for  $p \in P_p$  do
8:   for  $j \in \{0, 1, \dots, N_{CpP} - 1\}$  do
9:     Let  $C_N$  represent the new candidate
10:    Randomize order of  $p$ 
11:    Randomly select location  $i$  in which to perform crossover of chromosomes
12:    Set  $\mathbf{C}_N.\mathbf{chromosome} = [p_0[:i]^T, p_1[i:]^T]^T$  representing the concatenation of the two parent chromosomes
    sliced at index  $i$ 
13:    Set  $\mathbf{C}_N.\mathbf{chromosome} = \mathcal{N}(\mathbf{C}_N.\mathbf{chromosome}, 50^2)$  representing a mutation of the inherited chromosome
    with each gene varying in a normal distribution parameterized by  $\mu = \mathbf{C}_N.\mathbf{chromosome}$  and  $\sigma^2 = 50^2$  where
    50 is the standard deviation in quarter microseconds
14:    Saturate values in  $\mathbf{C}_N.\mathbf{chromosome}$  to safe limits for servos
15:    Append  $C_N$  to  $N$  by  $N = N \cup C_N$ 
16:   end for
17: end for
18: return  $N$ 

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Algorithm 3 MC Score Algorithm ($\text{mc_score}(X, L'_R)$)

- 1: Let $M = 68$ be the number of landmarks recognized in an image (constrained by dlib landmark recognition algorithm)
 - 2: Let $D = 2$ be the dimensionality of a single landmark
 - 3: Let $L \in \mathbb{R}^{D,M}$ represent the raw pixel valued landmarks
 - 4: Let L'_R be the reference landmarks to score against
 - 5: Let X be the chromosome to score
 - 6: Actuate X on the face using the Maestro Controller
 - 7: Capture an image, I_C , of the face
 - 8: Get the bounding box B of the face
 - 9: Detect the center of a rectangular bounding box, $B_C = [x, y]^T \in \mathbb{R}^2$ of the face
 - 10: Detect raw landmarks for cand. image $L_C = \text{dlib_predictor}(I_C).landmarks$
 - 11: Calculate new "centered" landmarks $L_C^C = L_C - (B_C \otimes \mathbf{1}^T)$
 - 12: Calculate the horizontal scaling by $x_s = B_{Right} - B_{C,x}$
 - 13: Calculate the vertical scaling by $y_s = B_{Bottom} - B_{C,y}$
 - 14: Get normalized landmarks $L'_C = L_C^C \oslash ([x_s, y_s]^T \otimes \mathbf{1}^T)$
 - 15: Calculate difference in corresponding landmarks between the reference image and the candidate image $L_D = L'_C - L'_R$
 - 16: **return** $\|L_D\|_F = \sqrt{\text{tr}(L_D^T L_D)}$ where $L_D^T L_D \in \mathbb{R}^{(M,M)}$ is the Gramian matrix of L_D and the diagonal elements of $L_D^T L_D$ represent the euclidean distance error of each landmark. This can also be expressed as the square root of the sum of the squared errors.
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