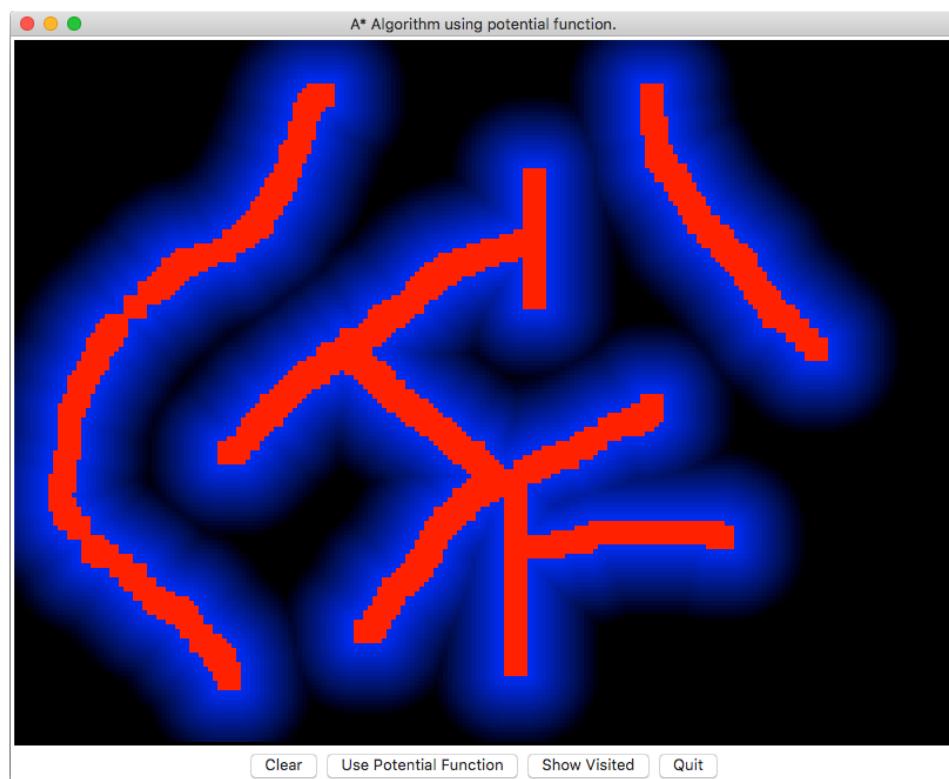


## THE POTENTIAL FIELD AROUND THE OBSTACLES



### Distance transform<sup>1</sup>

The distance transform is an operator normally only applied to **binary images**(so, binary matrices) . The result of the transform is a **graylevel image** of the **pixels** that are **inside** the **foreground regions**. The resulting image looks similar to the input image. Those graylevel intensities of the pixels that are inside the foreground regions show the **distance** to the **closest boundary** from each point (*in our case the distance from each free space node to the closest obstacle node*).

One way to think about the distance transform is to first imagine that foreground regions in the input binary image are made of some uniform slow burning inflammable material. Then consider simultaneously starting a fire at all points on the boundary of a foreground region and letting the fire burn its way into the interior. If we then label each point in the interior with the amount of time that the fire took to first reach that point, then we have effectively computed the distance transform of that region.

There are several different sorts of distance transform, depending upon which distance metric is being used to determine the distance between pixels. The most common distance metrics are: the **chessboard** distance metric, the **Euclidean** distance metric and the **city block** distance metric (aka **Manhattan** distance metric).

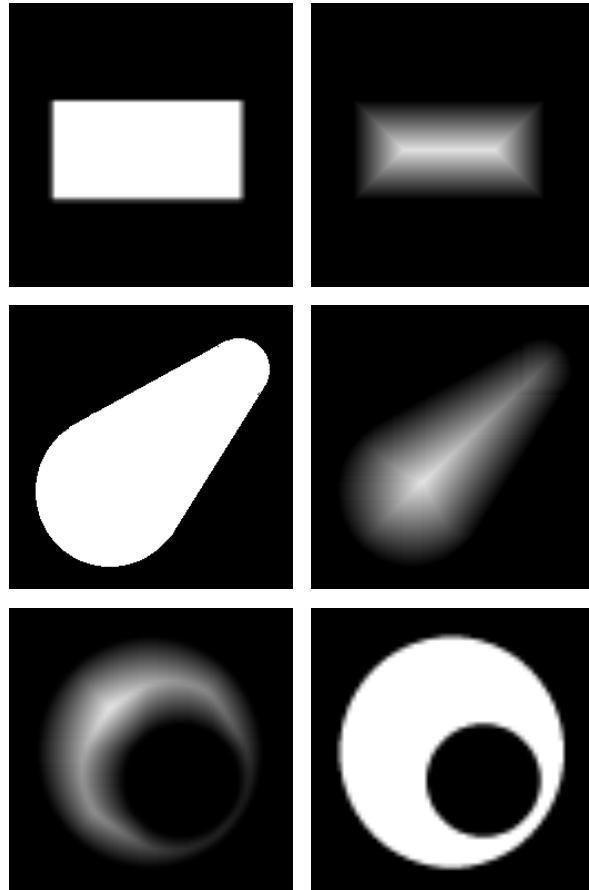


Figure 1: Euclidean distance transforms

There is a dual to the distance transform described above which produces the distance transform for the background region rather than the foreground region. It can be considered as a process of inverting the original image and then applying the standard transform as above.

---

<sup>1</sup>The previous information was gathered form: <https://homepages.inf.ed.ac.uk/rbf/HIPR2/distance.htm>

## **How it works**

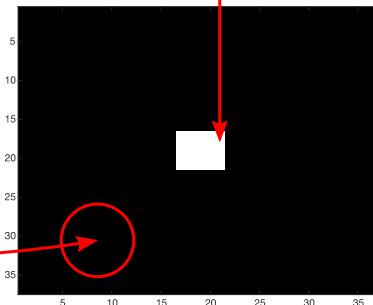
The distance transform can be calculated efficiently using clever algorithms in only two passes (e.g. Rosenfeld and Pfaltz 1968).

In python you should use:

```
scipy.ndimage.morphology.distance_transform_edt(input_binary_matrix)
```



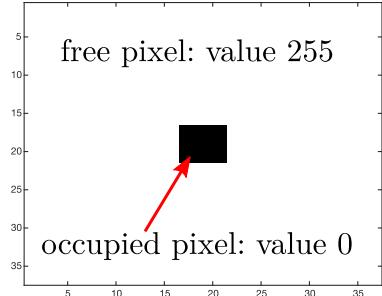
`world_obstacles`



The EDT, that is going to be used, requires that a free pixel is represented with the value 255 and an occupied pixel is represented with the value 0.

But in this lecture a free pixel is represented with the value 0 and the occupied pixel is represented with the value 255.

We invert the image → 255-world\_obstacles to use the EDT.



Example of EDT for two pixels: (7, 14) and (32, 25)

$$\sqrt{(25 - 20)^2 + (32 - 20)^2} = 13$$

$$\sqrt{(25 - 19)^2 + (32 - 20)^2} = 13.146$$

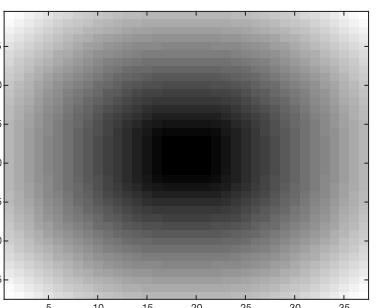
$$\sqrt{(16 - 14)^2 + (16 - 7)^2} = 9.220$$

## RESULT OF THE EDT

```
distance_transform_edt(255-world_obstacles)
// Image normalize by Matlab from 0 to 255
// imagesc(matrix); colormap(gray)
```

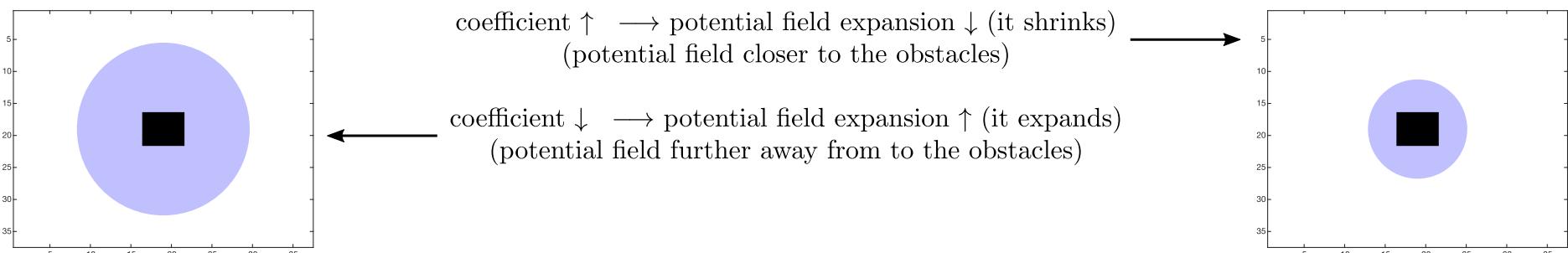
The previous matrix is so dark that if the range of gray colors is not expanded from 0 to 255 we won't see any difference when plotting that matrix.

$$\frac{\text{matrix}[i, j]}{\max(\text{matrix})} \quad 255$$

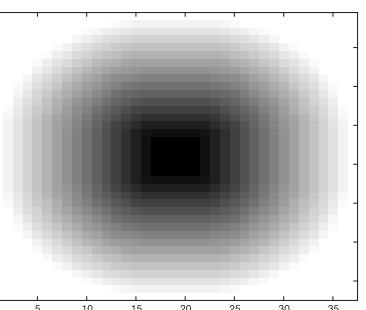


Important coefficient: This coefficient controls how big the potential field is around the obstacle

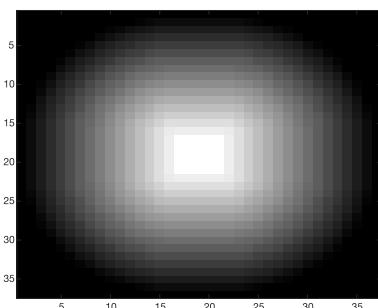
→ `16 * distance_transform_edt(255 - world_obstacles)`



```
np.minimum(16*distance_transform_edt(255-world_obstacles), 255)
```



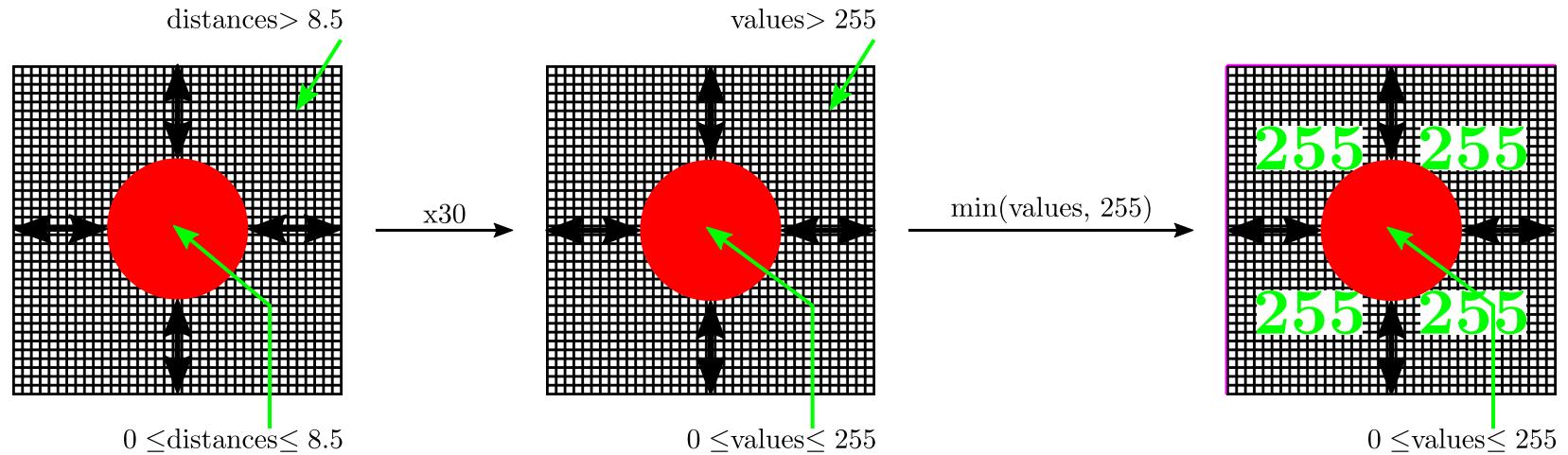
```
dist_transform = 255-np.minimum(16*distance_transform_edt(255-world_obstacles), 255)
```



```
m = max(np.max(dist_transform), 1) # Prevent m==0.
world_obstacles = np.uint8((dist_transform * 255) / m)
```

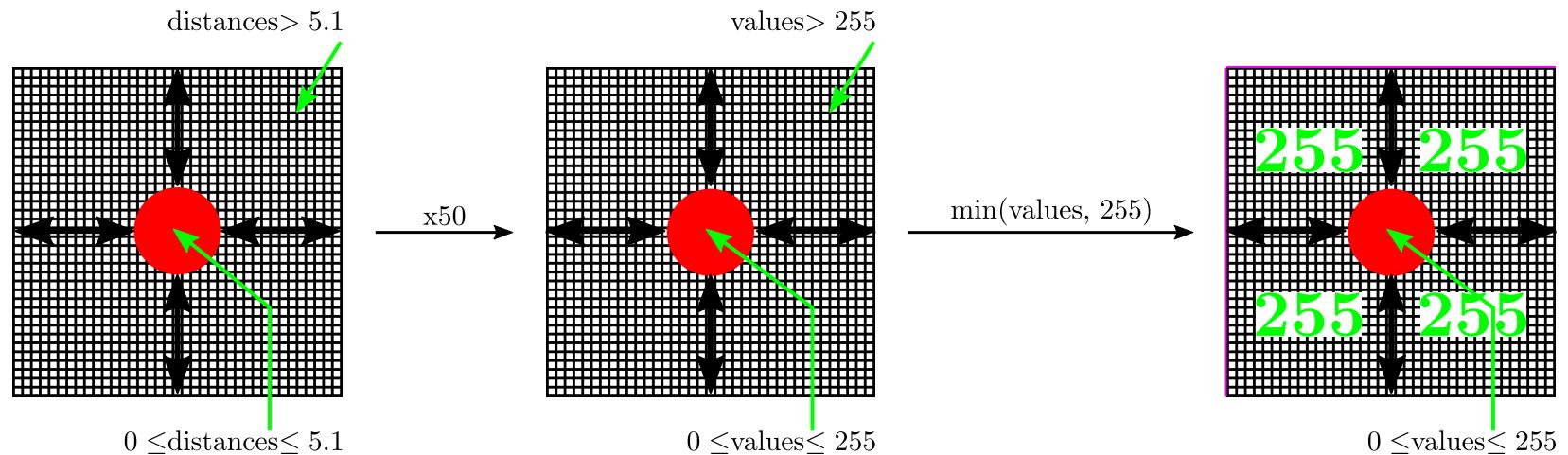
If coefficient = 30, then  $255/30 = 8.5$ .

All the distances greater or equal 8.5 give values greater or equal 255.



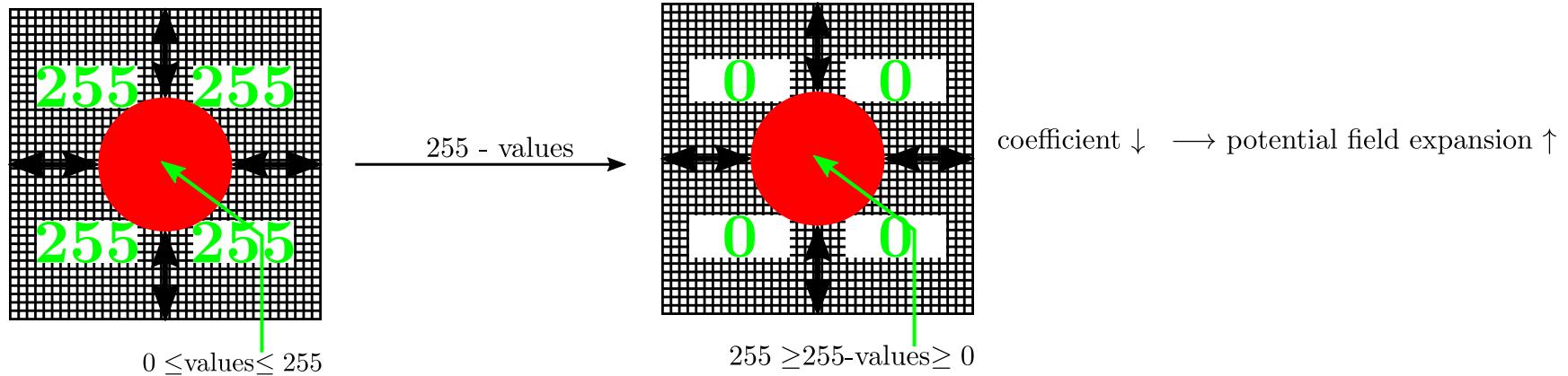
If coefficient = 50, then  $255/50 = 5.1$ .

All the distances greater or equal 5.1 give values greater or equal 255.



If coefficient = 30, then  $255/30 = 8.5$ .

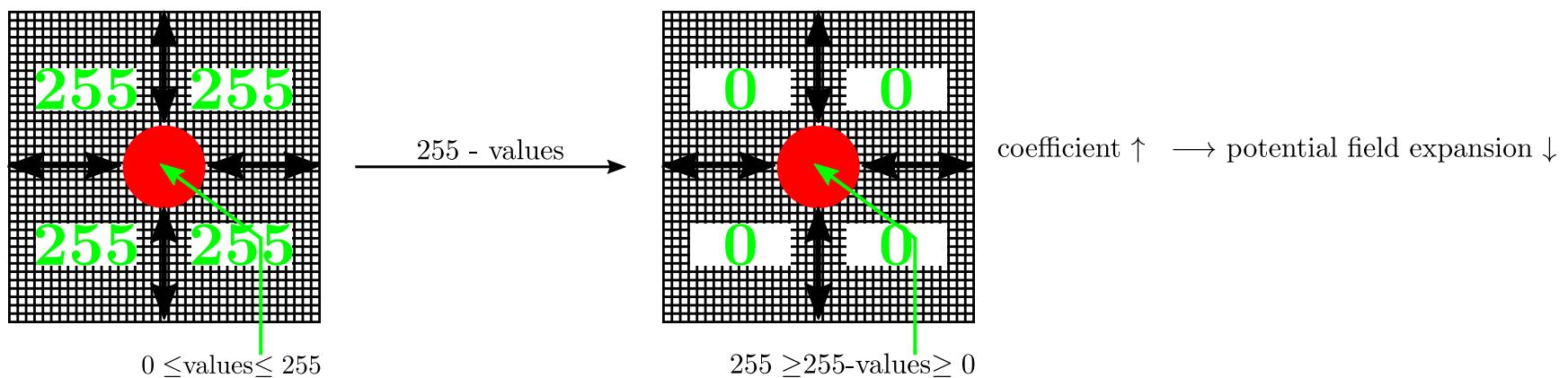
All the distances greater or equal 8.5 give values greater or equal 255.



coefficient  $\downarrow$   $\longrightarrow$  potential field expansion  $\uparrow$

If coefficient = 50, then  $255/50 = 5.1$ .

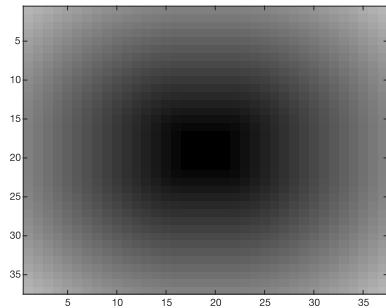
All the distances greater or equal 5.1 give values greater or equal 255.



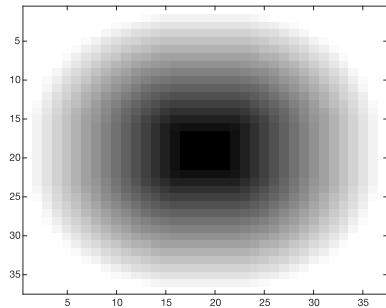
coefficient  $\uparrow$   $\longrightarrow$  potential field expansion  $\downarrow$

```
np.minimum(coeff*distance_transform_edt(255-world_obstacles), 255)
```

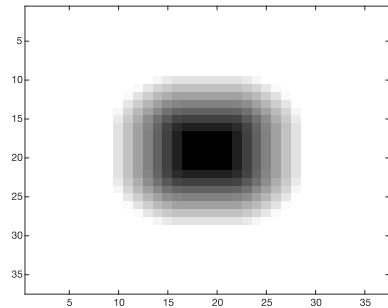
x8



x16



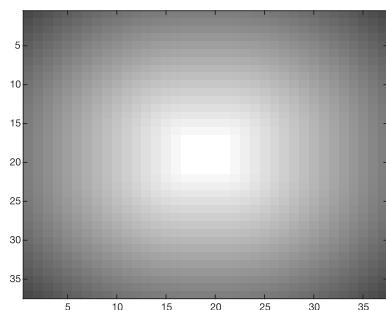
x32



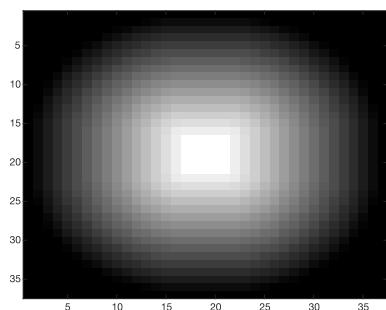
### Matrix with obstacles, free spaces and the potential field

```
255 - np.minimum(coeff*distance_transform_edt(255-world_obstacles), 255)
```

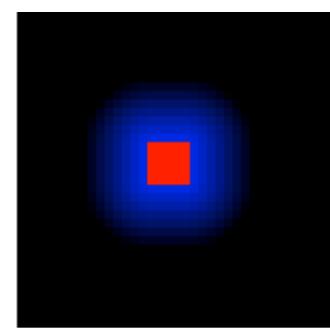
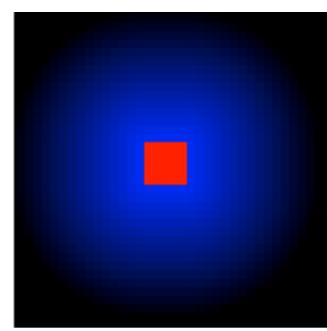
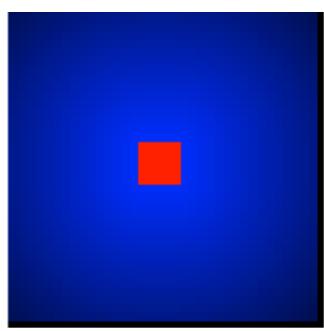
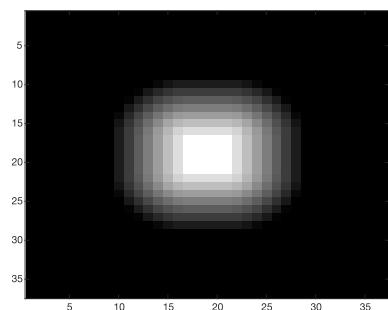
x8



x16



x32



```
np.minimum(8*edt(255-world_obstacle), 255)
```

```
255 - np.minimum(8*edt(255-world_obstacle), 255)
```

73	79	84	90	95	99	104	108	111	115	118	120	123	124	126	126	127	127	127	127	127	126	126	124	123	120	118	115	111	108	104	99	95	90	84	79									
79	85	90	96	101	106	110	115	119	122	125	128	130	132	133	134	135	135	135	135	135	134	133	132	130	128	125	122	119	115	110	106	101	96	90	85	79								
84	90	96	102	107	112	117	121	126	129	133	136	138	140	141	142	143	143	143	143	143	142	141	140	138	136	133	129	126	121	117	112	107	102	96	90	84	79							
90	96	102	107	113	118	123	128	132	136	140	143	146	148	149	150	151	151	151	151	150	150	149	148	146	143	140	136	132	128	123	118	113	107	102	96	90	84	79						
95	101	107	113	119	124	130	135	139	143	147	151	153	156	157	158	159	159	159	159	158	157	156	153	151	147	143	139	135	130	124	119	113	107	101	95	90	84	79						
99	106	112	118	124	130	136	141	146	150	154	158	161	163	165	166	167	167	167	167	167	166	165	163	161	158	154	150	146	141	136	130	124	118	112	106	95	90	84	79					
104	110	117	123	130	136	141	147	152	157	161	165	168	171	173	174	175	175	175	175	175	174	173	171	168	165	161	157	152	147	141	136	130	123	117	110	104	98	92	86	80				
108	115	121	128	135	141	147	153	158	163	168	172	176	179	181	182	183	183	183	183	182	181	179	176	172	168	163	158	153	147	141	135	130	124	118	112	106	95	90	84	79				
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115	122	129	136	143	150	157	163	169	175	181	186	190	194	196	198	199	199	199	199	198	196	194	190	186	181	175	169	163	157	150	143	136	129	122	116	110	104	98	92	86	80			
118	125	133	140	147	154	161	168	175	181	187	192	197	201	204	206	207	207	207	207	206	204	201	197	192	187	181	175	168	161	154	147	140	133	125	116	108	100	94	88	82	76			
120	128	136	143	151	158	165	172	179	186	192	198	203	208	211	214	215	215	215	215	214	211	208	203	198	192	186	179	172	165	158	151	143	136	128	120	112	104	96	90	84	79			
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126	134	142	150	158	166	174	182	190	198	206	214	222	229	237	243	247	247	247	247	247	243	237	229	222	214	206	198	190	182	174	166	158	150	142	134	126	118	110	102	96	90	84	79	
126	133	141	149	157	165	173	181	189	196	204	211	219	226	232	237	239	239	239	239	237	232	226	219	211	204	196	189	181	173	165	157	149	141	133	125	117	109	101	95	89	83	77		
124	132	140	148	156	163	171	179	186	194	201	208	215	221	226	229	231	231	231	231	231	229	226	221	215	208	201	194	186	179	171	163	156	148	140	132	124	116	108	100	94	88	82	76	
123	130	138	146	153	161	168	176	183	190	197	203	209	215	219	222	223	223	223	222	219	215	209	203	197	190	183	176	168	161	153	146	138	130	122	114	106	100	94	88	82	76			
120	128	136	143	151	158	165	172	179	186	192	198	203	208	211	214	215	215	215	215	214	211	208	203	198	192	186	179	172	165	158	151	143	136	128	120	112	104	98	92	86	80			
118	125	133	140	147	154	161	168	175	181	187	192	197	201	204	206	207	207	207	207	206	204	201	197	192	187	181	175	168	161	154	147	140	133	125	116	108	100	94	88	82	76			
115	122	129	136	143	150	157	163	175	181	187	198	204	196	198	199	199	199	199	198	196	194	190	186	181	175	169	163	157	150	143	136	129	122	114	106	100	94	88	82	76				
111	119	126	132	139	146	152	158	164	169	175	179	183	186	189	190	191	191	191	190	189	186	183	179	175	169	164	158	152	146	139	132	126	119	113	107	101	95	90	84	79				
108	115	121	128	135	141	147	153	158	163	168	172	176	179	181	182	183	183	183	182	181	179	176	172	168	163	158	153	147	141	135	128	121	115	107	101	95	90	84	79					
104	110	117	123	130	136	141	147	152	157	161	165	168	171	173	174	175	175	175	175	174	173	171	168	165	161	157	152	147	141	136	130	123	117	110	104	98	92	86	80					
99	106	112	118	124	130	136	141	146	150	154	158	161	163	165	166	167	167	167	166	165	163	161	158	154	150	146	141	136	130	124	118	110	104	98	92	86	80							
95	101	107	113	119	124	130	135	139	143	147	151	153	156	157	158	159	159	159	159	158	157	156	153	151	147	143	139	135	130	124	119	113	107	101	95	90	84	79						
90	96	102	107	113	118	123	128	132	136	140	143	146	148	149	150	151	151	151	151	150	149	143	140	136	132	128	123	118	113	107	102	96	90	84	79									
84	90	96	102	107	112	117	121	126	129	133	136	138	140	141	142	143	143	143	143	142	141	140	138	136	133	129	126	121	117	112	107	102	96	90	84	79								
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73	79	84	90	95	99	104	108	111	115	118	120</td																																	

```
np.minimum(16*edt(255 - world_obstacles), 255)
```

```
255 - np.minimum(16*edt(255-world_obstacles), 255)
```

```
np.minimum(32*edt(255-world_obstacles), 255)
```

```
255 - np.minimum(32*edt(255-world_obstacles), 255)
```

The cost associated to the node  $world\_map(i, j)$  due to the presence of a potential field around the obstacles is:

$$cost_{PF}(i, j) = \frac{world\_map(i, j)}{64}$$

where  $(i, j)$  are the i-th row and the j-th column in the `world_map` matrix. The above equation uses values of the `world_map` between 0 and 254.

Remember:

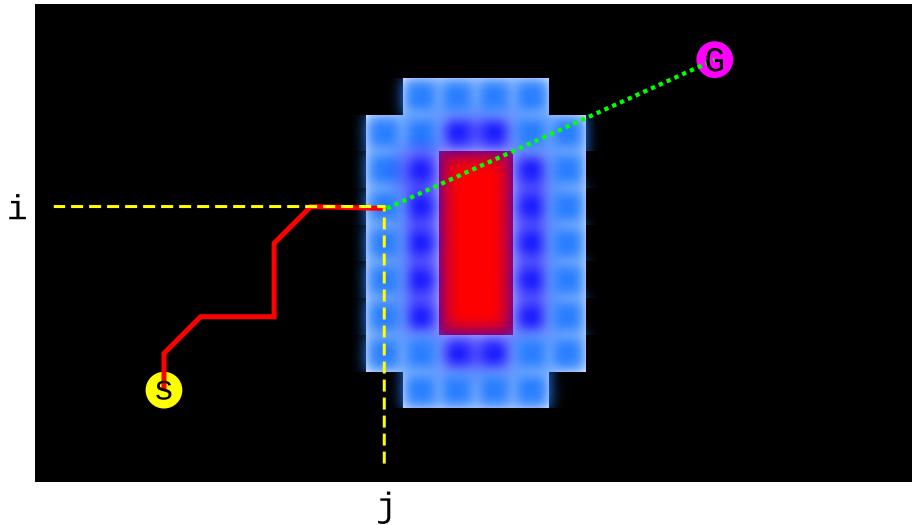
- The value  $world\_map(i, j) = 0$ , in these path planning lectures, represents a free space node and any path can pass through that node.
- The value  $world\_map(i, j) = 255$ , in these path planning lectures, represents an obstacle node and no one path can pass through that node. This value can't be used in the above equation.

The total cost associated to the node  $world\_map(i, j)$  is:

$$total\_cost(i, j) = A + B + C + D$$

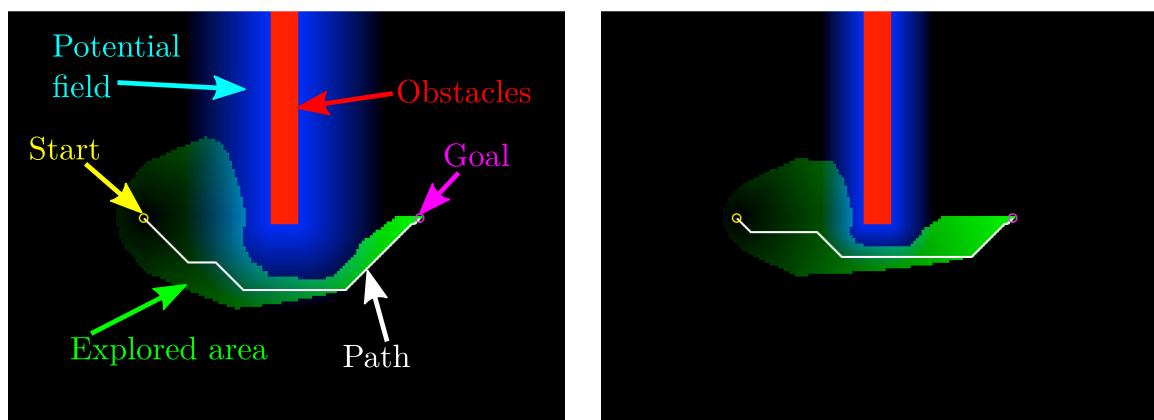
where:

- A is the total cost of the previous node in the path.
- B is the cost of the transition between the previous node in the path and the current node ( $world\_map(i, j)$ ).
- C is the cost associated to the node  $world\_map(i, j)$  due to the presence of a potential field around the obstacles,  $cost_{PF}(i, j)$ .
- D is the estimated Euclidean distance between the current node ( $world\_map(i, j)$ ) and the goal node.



x8

x16



x32

