



Teknik Presentasi

ALI RIDHO BARAKBAH

Tata Tulis Karya Ilmiah
Minggu ke-8

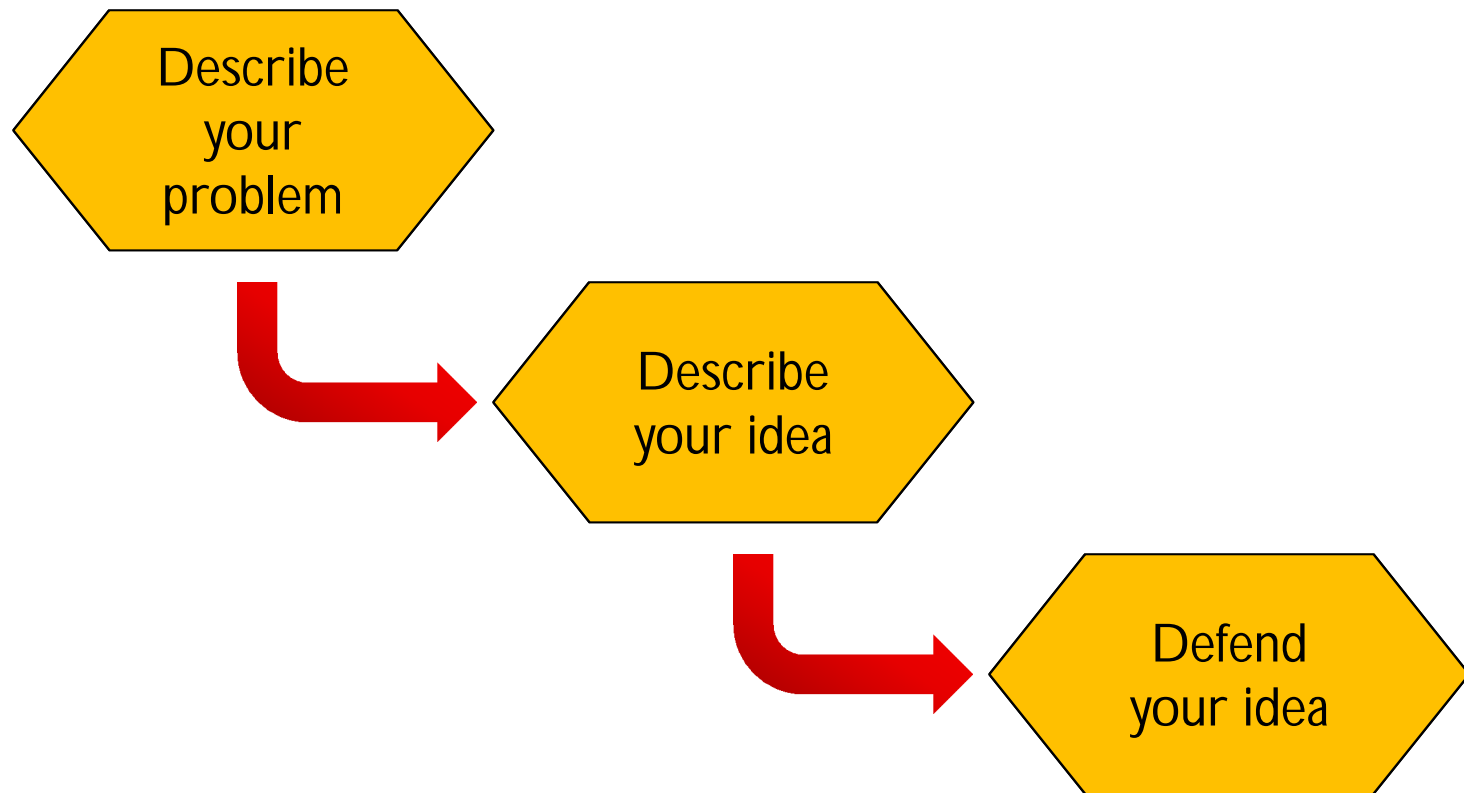
Politeknik Elektronika Negeri Surabaya
2011



Pentingnya presentasi?

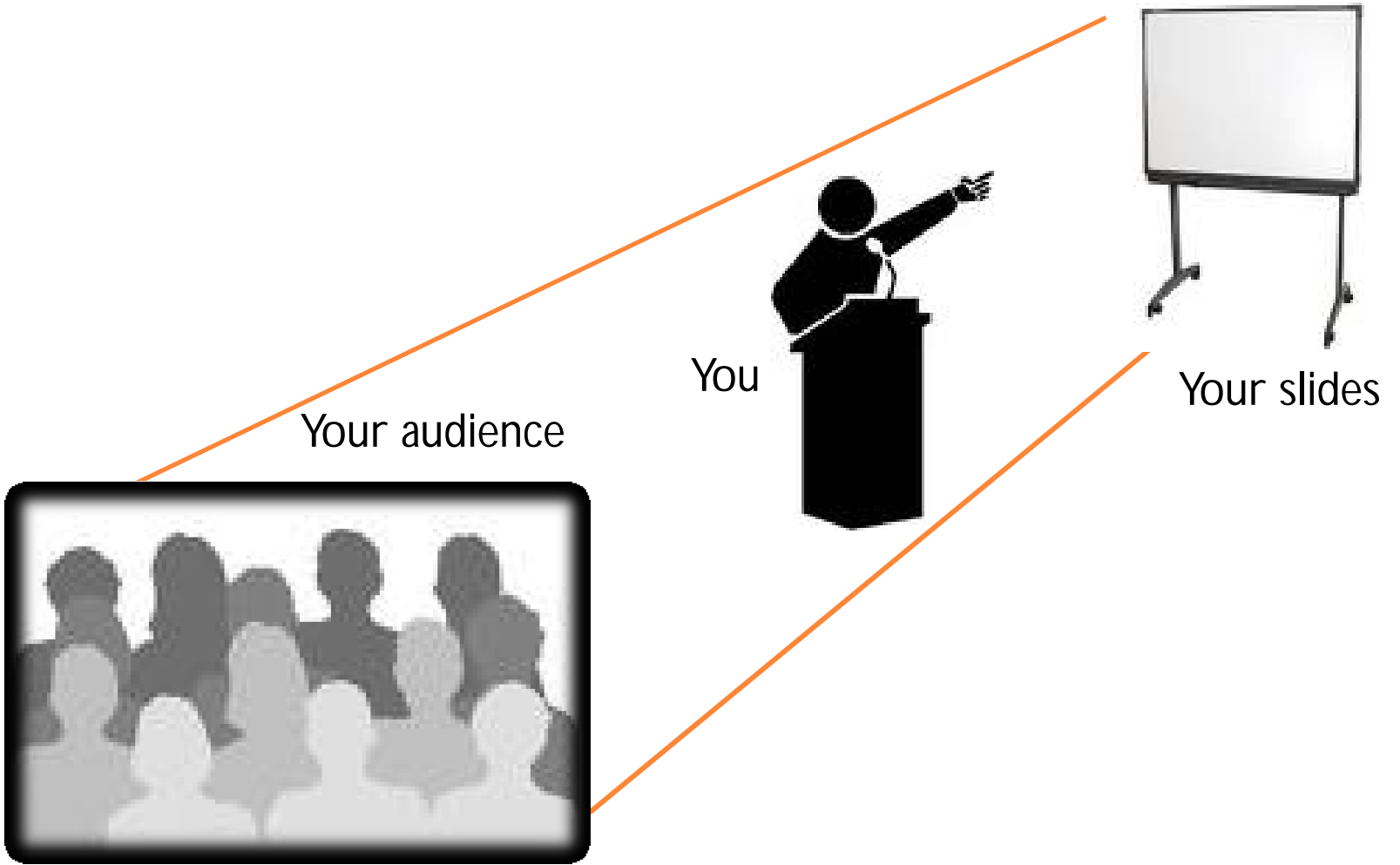
- Sarana penyampaian ide dengan lebih komunikatif
- Dapat mengikuti dan memastikan pemahaman dari pendengar
- Memberikan tingkat kepercayaan kepada pendengar tidak hanya melalui bahasa visual tetapi juga bahasa verbal

Alur presentasi



Isi presentasi

Latar belakang	1 hal
Perumusan masalah	1 hal
Related works	1 hal
Ide dasar solusi pendekatan (originality/uniqueness)	1 hal
Dasar teori	1-2 hal
Pembahasan detil pendekatan	~ hal (d disesuaikan durasi)
Hasil eksperimen dan analisa	1 hal
Kontribusi	1 hal
Referensi	1 hal





Your slides

- Berikan ilustrasi menarik dalam slide (Jangan terlalu banyak kalimat dalam slide)
- Jangan membahas terlalu detail tanpa disertai ide/maksud/motivasi dasarnya.
- Pointer sangat membantu untuk memfokuskan bagian yang kita maksudkan dalam presentasi
- Klaim originality/uniqueness anda - slide
- Pertegas kontribusi

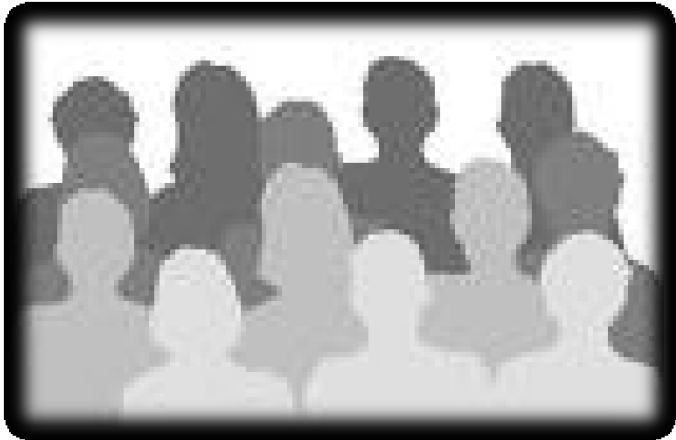


You



- Atur waktu dengan baik
- Gaya penyampaian harus convincing
- Jangan terlalu banyak melihat konten presentasi
- Terimalah kekurangan dan ubahlah sebagai kelebihan

Your audience



- Tujuan anda adalah pendengar. Jangan membelakangi pendengar.
- Perhatikan ekspresi pendengar
- Dengarkan dengan seksama pertanyaan dari pendengar dan jawablah *to-the-point*
- Hindari debat kusir



Bahasa verbal yang harus dihindari dalam presentasi

- Berbicara terlalu pelan dan bernada datar, ataupun sebaliknya terlalu cepat dan bernada tinggi
- Membosankan
- Tidak fokus pada topik
- Hal-hal yang membuat pendengar tidak tertarik



Contoh-contoh

K-means Algorithm

Let $A=\{a_i \mid i=1,\dots,f\}$ be attributes of f -dimensional vectors and $X=\{x_i \mid i=1,\dots,N\}$ be each data of A . The K-means clustering separates X into k partitions called clusters $S=\{s_i \mid i=1,\dots,k\}$ where $M \in X$ is $M_i=\{m_{ij} \mid j=1,\dots,n(s_i)\}$ as members of s_i , where $n(s_i)$ is number of members for s_i . Each cluster has cluster center of $C=\{c_i \mid i=1,\dots,k\}$. K-means clustering algorithm can be described as follows:

1. Initiate its algorithm by generating random starting points of initial centroids C .
2. Calculate the distance d between X to cluster center C . Euclidean distance is commonly used to express the distance.
3. Separate x_i for $i=1..N$ into S in which it has minimum $d(x_i, C)$.
4. Determine the new cluster centers c_i for $i=1..k$ defined as:

$$c_i = \frac{1}{n_i} \sum_{j=1}^{n(s_i)} m_{ij} \in S_i$$

5. Go back to step 2 until all centroids are convergent.

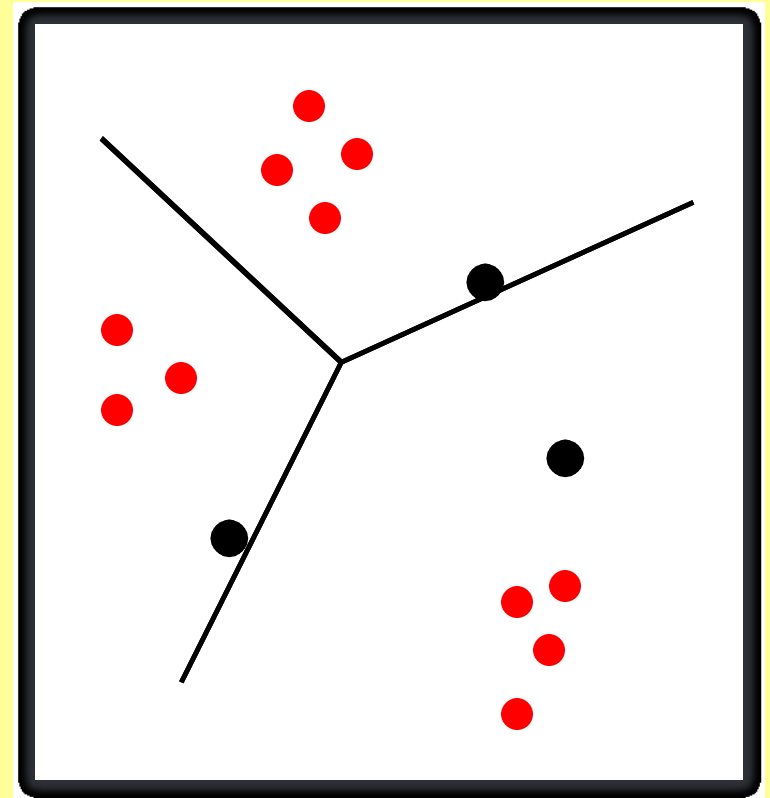
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The Algorithm of Pillar

Let $X=\{x_i \mid i=1,\dots,n\}$ be data, k be number of clusters, $C=\{c_i \mid i=1,\dots,k\}$ be initial centroids, $SX \subseteq X$ be identification for X which are already selected in the sequence of process, $DM=\{x_i \mid i=1,\dots,n\}$ be accumulated distance metric, $D=\{x_i \mid i=1,\dots,n\}$ be distance metric for each iteration, and m be the grand mean of X . The following execution steps of the proposed algorithm are described as:

1. Set $C=\emptyset$, $SX=\emptyset$, and $DM=[]$
2. Calculate $D \leftarrow \text{dis}(X,m)$
3. Set number of neighbors $nmin = \alpha \cdot n / k$
4. Assign $dmax \leftarrow \text{argmax}(D)$
5. Set neighborhood boundary $nbdis = \beta \cdot dmax$
6. Set $i=1$ as counter to determine the i -th initial centroid
7. $DM = DM + D$
8. Select $\mathcal{K} \leftarrow x_{\text{argmax}(DM)}$ as the candidate for i -th initial centroids
9. $SX=SX \cup \mathcal{K}$
10. Set D as the distance metric between X to \mathcal{K} .
11. Set $no \leftarrow$ number of data points fulfilling $D \leq nbdis$
12. Assign $DM(\mathcal{K})=0$
13. If $no < nmin$, go to step 8
14. Assign $D(SX)=0$
15. $C = C \cup \mathcal{K}$
16. $i = i + 1$
17. If $i \leq k$, go back to step 7
18. Finish in which C is the solution as optimized initial centroids

The Algorithm of Pillar

Let $X = \{x_i \mid i=1, \dots, n\}$ be data, k be number of clusters, $C = \{c_i \mid i=1, \dots, k\}$ be initial centroids, $SX \subseteq X$ be identification for X which are already selected in the sequence of process, $DM = \{x_i \mid i=1, \dots, n\}$ be accumulated distance metric, $D = \{x_i \mid i=1, \dots, n\}$ be distance metric for each iteration, and m be the grand mean of X . The following execution steps of the proposed algorithm are described as:

Initial settings

1. Set $C = \emptyset$, $SX = \emptyset$, and $DM = []$
2. Calculate $D \leftarrow \text{dis}(X, m)$
3. Set number of neighbors $nmin = \alpha \cdot n / k$
4. Assign $dmax \leftarrow \text{argmax}(D)$
5. Set neighborhood boundary $nbdis = \beta \cdot dmax$

6. Set $i=1$ as counter to determine the i -th initial centroid

Accumulating D to DM

[Selecting initial centroid candidate

8. Select $\mathcal{K} \leftarrow x_{\text{argmax}(DM)}$ as the candidate for i -th initial centroids

9. $SX = SX \cup \mathcal{K}$

10. Set D as the distance metric

Outlier detection

11. Set $no \leftarrow$ number of data points fulfilling $D \leq nbdis$

12. Assign $DM(x_{\mathcal{K}}) = 0$

13. If $no \geq nmin$, **Promoting the candidate to be an initial centroid**

14. Assign $C = C \cup \mathcal{K}$
15. **Iterative process until all initial centroids fulfilled**

16. $i = i + 1$

17. If $i \leq k$, go back to step 7

18. Finish in which C is the solution as optimized initial centroids

Related Works for Emotion based CBIR

- Park and Lee introduced an emotion-based image retrieval driven by users [28]. The system constructed emotion recognition by analyzing consistency feedbacks from the users.
- Solli and Lenz developed an image retrieval system involving bags of emotion [44]. The system used color emotion models derived from psychophysical experiments which are activity, weight and heat.
- Wang and He presented a survey on emotional semantic image retrieval [54]. The supervised learning techniques usually used to bridge semantic gap between image features and emotional semantics.

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**Supervised
models
connecting
user's
emotion to
the image
search system**

Motivation of this research

- This research presents a semantic image search system with an emotion oriented context recognition mechanism by connecting a series of emotion expressions to the color based impression.
- My motivation implementing an emotional context in the image search system is to express user's impressions for retrieval process
- The search system addresses a dynamic manipulation of unsupervised emotion recognition

Motivation of this research

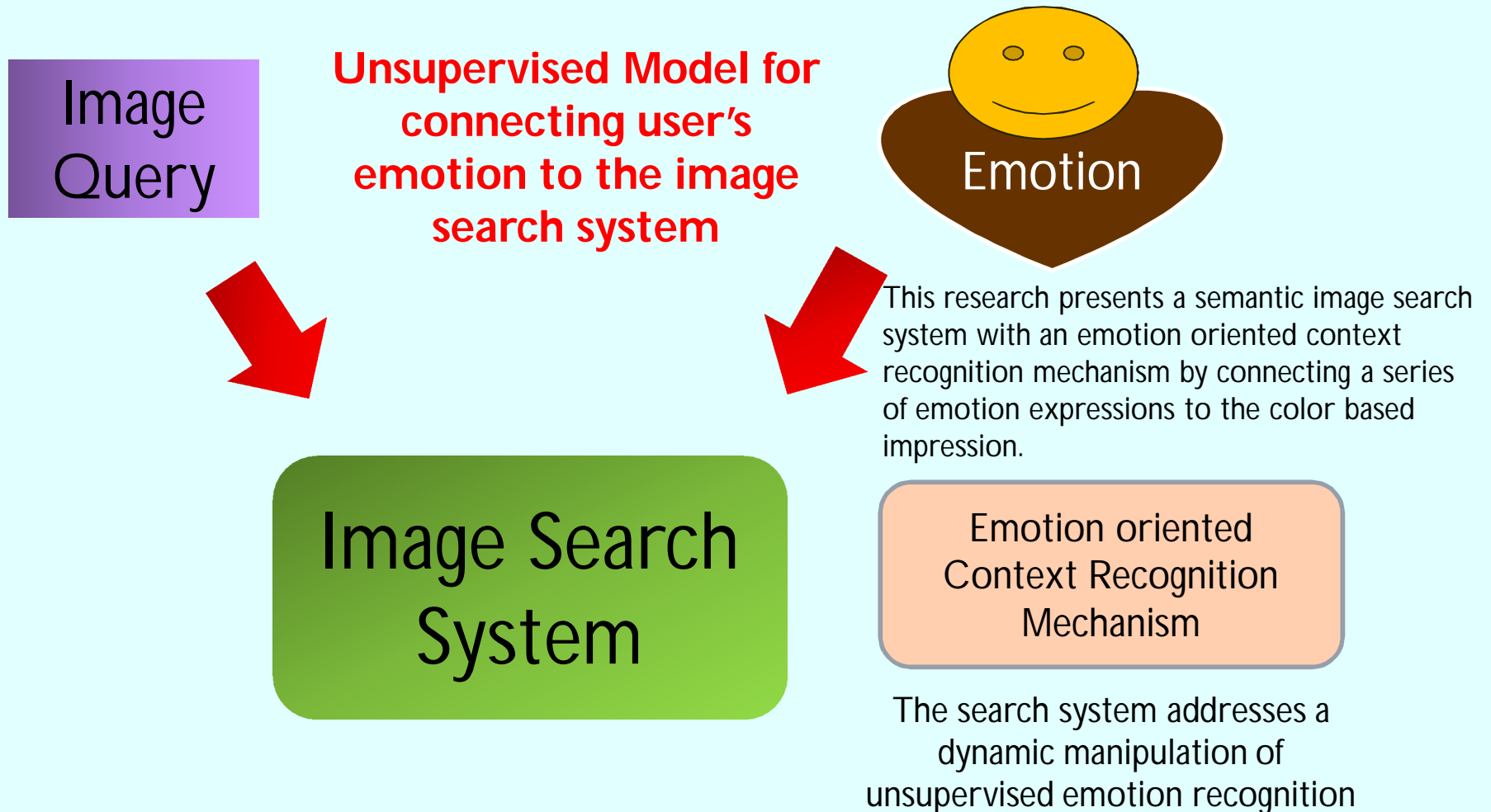
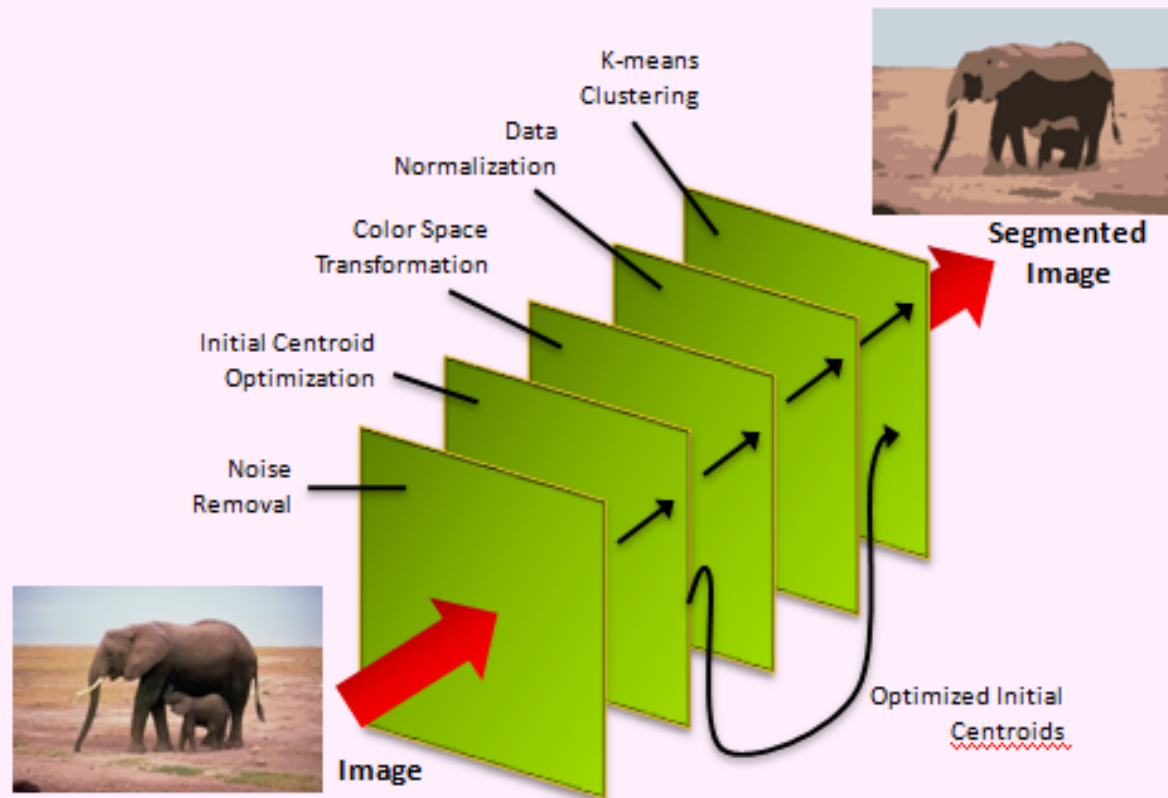


Image Segmentation for Pre-processing using Pillar Algorithm

- Noise removal
- Initial centroid optimization
- Color space transformation
- Data normalization
- K-means clustering

Image Segmentation for Pre-processing using Pillar Algorithm





Referensi

- Budi Rahardjo, *Panduan Menulis dan Mempresentasikan Karya Ilmiah: Thesis, Tugas Akhir, dan Makalah*, 2005.
- Simon Peyton Jones, *How to write a great research paper*, Microsoft Research, Cambridge