The Relationship between Types of Image Retrieval and Cognitive Style in Developing Visual Thinking Skills

Waleed S. Al-halafawy, Marwa Z. Tawfiq

King Abdulaziz University (Jeddah) and Ain Shams University (Cairo), Faculty of Education, Instructional Technology Department

welhlafawy@kau.edu.sa, mzzaki@kau.edu.sa, waleed_doc@hotmail.com

Abstract: This research investigated the relationship between types of image retrieval: text based image retrieval (TBIR), content based image retrieval (CBIR), and text-content based image retrieval (T-CBIR) and students' wholist/analytic (W/A) and verbal/ imagery (V/I) cognitive styles on student visual thinking. A quasi-experimental 3x4 factorial design was employed. Independent variables were three types of retrieval and four models of cognitive styles, the dependent variables were visual thinking scores. The research sample consisted of (141) students from the Faculty of Education, Ain Shams University who were randomly assigned to groups. Analysis of variance (one and two) (ANOVA), Partial Eta Squared, and scheff'e post hoc comparison was employed to analyze data. The results confirms that T-CBIR is better than CBIR and TBIR, imagery students significantly outscored verbal students but without any difference between Wholist and Analytic students, TBIR is better than T-CBIR and CBIR to Verbal (wholist or -Analytic) students and T-CBIR is better than CBIR and TBIR to imager (wholist or -Analytic) students.

[Waleed S. Al-halafawy, Marwa Z. Tawfiq**. The Relationship between Types of Image Retrieval and Cognitive Style in Developing Visual Thinking Skills.** *Life Sci J* 2014;11(9):865-879]. (ISSN:1097-8135). http://www.lifesciencesite.com. 130

Key words: Images Search Engines, Images retrieval, text based image retrieval (TBIR), content based image retrieval (CBIR), text-content based image retrieval (T-CBIR), Cognitive Style, Visual Thinking.

1. Introduction

Within the technology of education, instructional images are very important tools and they play a major role in making the content easy to understand and retrieve. These images attract the attention of the learner and evoke his interest and help him recall its related written information (Rahim et al., 2013; Mundher et al., 2014). It also helps to reflect the meaning and the verbal practices. The image is also considered as one of the main resources of the visual learning system which aims at improving the learners' abilities in taking advantage of what is shown to him visually, and this is in order to make desired behavioral effects through a framework that allows interactions between the image and the learner. However, visual based learning doesn't only relate to extracting information from images, but goes further to include both educational design processes that can be used in learning and the theories that are based on organizing the visual learning processes (Saba and Alqahtani, 2013)

The instructional image is considered one form of learning resources that has been affected by digital technology; where image processing increase quickly and is affected by technological progress in the field of digital photographing, computer processing, storage devices, and production and retrieving processes (Lung et al., 2014; Muhsin et al., 2913; Rahim et al., 2012). No doubt, this technological progress has contributed in providing the educational digital image in great numbers through a number of web pages, database and web applications and other systems such as virtual libraries and virtual museums. However, the main problem lies in how the learner can have an access to a specific instructional image among unlimited number of images and through retrieval processes that can happen by using search engines. Digital image search engines are considered a tool to automatic inventory of the stored digital images on the web, and re-present them as output on the search engine pages based on retrieval criteria that a learner specifies while searching (Alqahtani,and Saba, 2013; Meethongjan et al., 2013).

Many literatures pointed out to the existence of three reliable basic retrieving in the retrieving processes of digital images through the search engines. The first type is the text Based Image Retrieval (TBIR) where the learner inserts a group of contextualized key words that belong to the image or characteristics ,whatever related to its components in the search engine .Based on that ,the search engine recalls the digital image that represents these text entries; whereas ,the second type is the one that is called the Content Based Image Retrieval(CBIR) (Haron et al., 2011). The word content means the graphic characteristic of the image itself where search is carried out for texture ,color ,size, shape or layout or looking for similarities of the image as one unit which is termed as search by similar. In addition to the previous two types, there is a third one which is called Text-Content Image Retrieval(TCBIR) which is the type that encompasses or integrates the two types in one form that allows the user to look for via both text and visual characteristics of the image (Joudaki et al., 2014; Rad et al., 2013; . The current research tries to identify which retrieving type is appropriate for the learners, particularly, in the light of the scientific studies that indicate every type of the retrieving has characteristics that may encourage to use it as a main type of research (Elahi, *et al.*, 2009; Zhu *et al.*, 2010; Rahim et al., 2013). No doubt identifying which type of retrieving is appropriate requires observing the specific traits and potentials of learners. The cognitive style are considered one of the most important preparations where we could explain the diversity among learners in the cognitive processes. The more individuals are distinguished in their cognitive structure, the more they will be able to respond in a distinguished manner in different situations, whereas, those less distinguished individuals in their cognitive structure have less response and more interventionist. The cognitive style is therefore the distinguished method in which learners think through in a specific problem, and then find out solution in different available methods.

In this context, Magoulas, *et al.*, (2004,); Yuan& Liu (2011) mentions that search engine depends not only on developing appropriate architectures, but also on incorporating human factors considerations. Also Clewley, *et al.*, (2010) believes that "cognitive style has been identified to be significantly influential in deciding users' preferences of search engines".

It could be said that the cognitive styles (wholist / analytic), (verbal-imagery) as one of the most important styles related to the learner aptitudes for the use of search engines via the web (Kinley& Tjondronegoro,2010,; Yuan& Liu, 2011). Learner when using search engines can be classified and described according to the pervious cognitive styles as follows: learner who located into the wholist–analytic cognitive style tend to process information in wholes or parts, while those who located into the verbaliser-imager cognitive style tend to think in words or images when they represent information. (Leem2007)

In the context of talking about scientific studies, which focused on the relationship between the search via the web and cognitive styles, Kinley, *et al.*, (2010) explained the relationship between the search via the web and cognitive styles the results indicated that a significant relation between Web search behavior and user cognitive styles..

Yuan & Liu (2011) designed a study to investigated the effect of cognitive styles on users' information-seeking task performance using an information system called Web of Science. Results demonstrated that users' cognitive styles did not impact their search performance.

The previous studies that have been presented have focused on some of the variables search tools via the web with the cognitive style (wholist-analytic) style and (verbal-imagery). Other studies have focused on the relationship between the variables of designing searches via the web and other cognitive styles as field dependent versus field independent (Magoulas, *et al.*, 2004; Kim, 2005; Faiola& Matei, 2005; Clewley, *et al.*, 2010; Ahmad et al., 2014). This shows the importance of going towards linking study structural variables of search engines and cognitive styles.

Also other studies focused on building models for image search engines such as Smith (1996) which describes a highly functional prototype system called The Visual SEEk aims at searching by visual features for images. The VisualSEEk system allows the user to perform the queries by diagramming spatial arrangements of color regions. The system picks the images that contain the most similar arrangements of similar regions. The study of Funkhouser, *et al.* (2003) has presented a web-based search engine system that supports queries based on 3D sketches, 2D sketches, 3D models, and/or text keywords. Fogarty, *et al.* (2008) study proposed an interactive system to search for images called (CueFlik) which is a Web image search application that allows end-users to quickly create their own rules for re-ranking images based on their visual characteristics. Joseph& Balakrishnan (2011) suggested system uses multiple image queries for finding desired images from database. The different queries are connected using logical operation. The proposed system is used for retrieving similar human face expressions. The findings showed that the use of multiple queries has better retrieval performance over single image queries. Finally, Gui, *et al.* (2009) proposed an improved image retrieval framework when querying with an image. This framework combines textual description of the image and features (such as color, texture and shape) that can be extracted from the images. This is all appears within the same search engine interface.

In the framework of the researcher discussion with some workers in the technological development centre and some workers in the field of designing educational web sites, disinterest was evident in designing educational image search engines on scientific basis that defines the appropriate retrieval type for the learners in the light of their potentials and readiness. The majority of search engines are build based on the digital image retrieval through the web via the use of key words without paying attention to any graphic design of the image, and without considering the intended learning outcomes which the search engines should develop in the learner as it is one of electronic learning tools that can be used as an integrated electronic system, or a sub- system for most available electronic systems. In the learning environment Search engine is a key tool in the e-cours, e-libraries, e-museums and electronic classes and other electronic learning systems. Therefore, being interested in them and ways of developing them on learning bases is considered among issues we have to cater for.

In addition, many courses in the area of instructional technology such as showing devices, the computer system and museums& exhibitions course need for many instructional images so that such images can assist in achieving goals of these courses. This means heading towards designing data bases for instructional images which include methods of retrieving and should be explored through scientific studies so as to help the educational process.

Thus, we conclude that the study of types of retrieving such as: TCBIR, CBIR ,and TBIR that are related to digital images through the web need more scientific studies but within the framework of interaction with wholistic/ analytic and verbal/ imagery where type of digital images that are more appropriate for the learner's cognitive style is identified by developing the visual thinking in the learner. The scientific studies in this area were scanty; and most of it was interested in retrieving processes of ordinary web pages.

Literature Review

1- Instructional Images Search Engines:

Interest in the potential of digital images has increased enormously over the last few years, fueled at least partially by advanced technology in scanning, image processing, networking, compression and have led to the generation of large online collections of images. These collections have created a need for new methods to locate specific images. Eakins& Graham (1999) assures that the Image search engines became indispensable tools for learners who look for image from a variety of images via Web. Users can inquire from these engines about any image to access it and then interact with it according to his need (Kaur, *et al.*, 2011). Based on this Wang, *et al.* (2007) defines Image search engines as tool that can "collect and index images from other sites and attempt to give access to the wide range of images available on the Internet".

Therefore, we can say that instructional image search engines are the engines that are being developed via the web to achieve the instructional goals, so that the learner can retrieve images relevant to subjects learning according to the specific activities carried out by him, and thus instructional image search engines become one of the tools in e-learning that allows the learner access sources of graphic information to serve the diverse learning situations that pass by without any Time or spatial restrictions.

Dooley, *et al.* (2005) confirms that the image search engines are the most important tools of e-learning and distance education that allow the learner access visual information that can support different learning situations. levenen, m. (2010) states that if the benefits and advantages of image search engines are significant in many applications, then they should clarify ideas from images in the learning process (images to illustrate ideas). Potter (2010) considers the image search engine as one of the important tools used for the development of thinking in general and critical thinking, in particular, the development of research skills. The researcher believes that the image search engines have many benefits in the learning process, for example, strengthening the visual learning system, facilitating comparisons among many of the visual material, provide an interactive environment where the learner can interact with the image, and get more of about size of the image, add comments, and send to a friend. This is in addition to sorting and classifying images according to image features as color, shape, size etc. No doubt that all these features support the importance of employing image search engines in the learning process, especially in light of this big growing field of digital image across the web.

2- Images retrievals types:

it can be said there are three types of image retrieval techniques. The first is text based image retrieval (TBIR), the second is content based image retrieval (CBIR). A basic difference between TBIR and CBIR is related to the values of textual and visual information in image retrieval, the third is Text and Content Based Images Retrievals (TCBIR) which combines between textual and visual information in its image (Vani& Raju,2010)

2-1- Text Based Images Retrievals (TBIR):

Text-based image retrieval (TBIR) is also known as annotation-based image retrieval (ABIR). The use of the term text-based image retrieval is to describe the process of retrieving images from databases on the basis of textual description of the image using metadata. The usual reason to annotate images (i.e. add metadata to it) is to simplify access it. The metadata can, for instance, be information like location, time, what the image is about, who is on the image and who captured it.., if the images are completely described by a textual annotation, then many image searches can be done effectively by text search techniques (Vani& Raju, 2010; Raheja & Gupta,2011).

Aarbakke (2007) confirms the need to "separate between text based image retrieval techniques that use the surrounding text of the image and text based techniques where each image or image collection is annotated. The approach that deals with surrounding text searches the keywords that are physically close to the image". This way to retrieve images is based on the assumption that the surrounding text describes the image. There might be web pages where the surrounding text has nothing to do with the image. In these cases the returned results might be irrelevant and have nothing in common with the requested image.

In TBIR, there are two major approaches to image retrieval: annotation stands for the process of describing images, and retrieval stands for the process of finding images (Styrman, 2008, 1.). The text-based technique first annotates the images with text, and then uses text-based database management systems to perform image retrieval (Fauzi & Lewis, 2008). The annotator has to write a textual description of an image using natural language. After the description has been created, it is linked to an image. To facilitate the retrieval, the annotators have to take into their account the possible use of thesauri that constrain and guide the use of vocabulary. A thesaurus is a collection of natural language words that specifies the vocabulary in some specific domain (Styrman, 2008).

Based on the above, it can be said that the goal of annotation of images is to assign semantically meaningful information to images. Text is the most common and relevant way of annotation (Aarbakke, 2007; Raheja.& Gupta, 2011). Annotation operations depend on the metadata which is structured information that describes, explains, locates, or otherwise makes it easier to retrieve, use, or manage an information resource. Metadata is often called “data about data” or “information about information” (Hodge, 2004,1).

Styrman (2008) mentions that the metadata that describes images could be roughly divided into two parts. One part is concerned with the concepts that give information about the creator of the image, and tools used in the process of creating the image and other explicit properties of that image. The other part describes what is actually there in the image, the implicit properties that can be understood by perception of the image itself. These two parts cannot be clearly separated, and both have to be taken into account when analyzing an image.

There are advantages of TBIR: It is the only way to search for the semantics of the image, it is the most commonly used technique for image retrieval and it is easy to construct queries. There is no need for tools for drawing, or audio recognition or other advanced tools for constructing queries, and finally the retrieval is fast (Aarbakke, 2007).

But In the context of talking about disadvantages of text-based image retrieval, we can say this approach can fail when: (1) image are not annotated, (2) image are annotated with a specific or derivative keywords, (3) Visually different images can have the same keywords, (4) visually similar images could be labeled by very different keywords, (5) when relevant keywords are unknown to the learner, or (5) when keywords of interest are not known at the time the image was annotated. (Funkhouser, *et al.*, 2003; Fogarty, *et al.*, 2008)

Another problem in TBIR is motivated lexically rather than conceptually. “Lexically motivated” means that TBIR operates on the word-level instead of the level of the meaning of words, and this leads to irrelevant search results in images retrieval. So some researches suggested that the idea of ontologies is that they are conceptually motivated, i.e., can be used to express the intended meaning of things, and not just words as textual strings. (Styrman, 2008)

2-2- Content Based Images Retrievals (CBIR):

Content-based image retrieval (CBIR) is also known as query by image content (QBIC) and content-based visual information retrieval (CBVIR).Content-based image retrieval (CBIR) is known as query by image content (QBIC) and content-based visual information retrieval (CBVIR). The term of content-based image retrieval is using to describe the process of retrieving images on the basis of features (such as color, texture and shape) that can be extracted from the images themselves (Vijay& Anitha, 2008; Vani& Raju, 2010).

Thus as mentioned above, representation of images needs to consider which features or Content Comparison Techniques are most useful for representing the contents of images, in this section some of the more commonly used types of feature used for image retrieval are described below.

- **Color retrieval:** Retrieving images based on color similarity is achieved by computing a color histogram for each image that identifies the proportion of pixels within an image holding specific values. The color histogram for each image is then stored in the database (Vijay & Anitha, 2008).
- **Texture retrieval:** Sakhar.& Nasre (2011) define Texture as "a feature that describes the distinctive physical composition of a surface". Textures are represented by pixels which are then placed into a number of sets, depending on how many textures are detected in the image. These sets not only define the texture, but also where in the image the texture is located (Eakins& Graham, 1999; Vijay& Anitha, 2008).
- **Shape retrieval:** The shape representations can be divided into two categories, boundary-based (or edge detection) and region-based (Tsai & Hung, 2008). The former considers the shape being composed of a set of two-dimensional regions, while the latter presents the shape by its outline (Partio, 2002; Elarbi-Boudihir et al., 2011; Haron et al., 2011, 2012).

Several advantages have been cited in using CBIR for image analysis and retrieval such as ease in extracting features from the image, ability to change extracted features to other form such as histogram, and ease in building an automatic process. However, disadvantages of CBIR include that most techniques to retrieve images based on their content require the user to query based on image concepts like color or texture, which most people are not familiar with (Jeon, *et al.,* 2003). These visual contents do not allow users to query images by semantic meanings (Tsai & Hung, 2008).

There are also other three shortcomings with CBIR which restrict its practicability. Firstly, the precision of CBIR is usually unsatisfactory because of the semantic gap between user's comprehension of the image and machine capability to understand the semantics of images. Secondly, the efficiency of CBIR is usually low due to the high dimensionality of visual features. Thirdly, because the user must have a similar image at hand the query form of CBIR is unnatural for image search owing to the possible absence of appropriate example images (Elahi, *et al.,* 2009; Zhu, *et al.,* 2010). In contrast, TBIR depends on the text information to carry through the image indexing and search. Compared with the visual information, text is essentially a kind of representation for image content from the view of human-being concepts and provided with the characteristics in terms of low dimension and easy description. Therefore, TBIR is a straightforward solution to conquer the disadvantages of CBIR (Zhu, *et al.,* 2010; Saba et al., 2011; Katuka et al., 2014).

2-3- Text-Content Based Images Retrievals (TCBIR):

Text and Content Based Images Retrievals (TCBIR) also known as Visuo-textual fusion, which is a Composite system to search images from databases based on textual description of the image and features (such as color, texture and shape) that can be extracted from the images themselves. This style of retrieval depends on the combination of characteristics (TBIR) and (CBIR), and so the user can use these characteristics and interact with it through the same search engine interface (Barnard, *et al.,* 2003; Tollari& Glotin, 2007)

In this context, Clewley, *et al.,* (2010) mentions that "Content-based (using only visual features) and text-based (using only textual features) image retrieval are two different approaches to retrieve images. A middle approach exists to combine text and visual information in the same framework. Many previous works show that combining text and visual information improves image retrieval".

TCBIR is a composite processing that may involve both visual features and text in varying proportions, and may be the composite system for image retrieval: Interactive-Simple (User interaction using a single modality needs to be supported by a system) or Interactive-Composite (he user may interact using more than one modality (e.g., text and images).

3- Who list–analytic and verbal–imagery cognitive style models:

The term “cognitive styles” refers to the actual way an individual perceives and processes information. In this study we focus on the Wholist–analytic and verbal–imagery cognitive style because user preference for any type of retrieval may be related to cognitive style and characteristics of this type of retrieval that provides user easy access to the images that are looking for. So lewandowski (2006) confirms that it is essential to know how users interact with information retrievals systems in general and with search engines in particular. Based on this, Yuan& Liu (2011) believed that Wholist–analytic and verbal–imagery cognitive style is related to the learner aptitudes for the use of search engines via the web (Yuan& Liu, 2011).

"Wholists are thought to have an overall perspective on things and are able to see the whole picture relatively easily when presented with information. Analytics see the information as a collection of parts rather than as a whole and may select certain parts to focus upon. Consequently, both styles have strengths and weaknesses. Wholists are strong in drawing together fragmented information to see the whole picture, whereas analytics are good at breaking information down into its integral parts and analyzing each part separately. The wholist will have difficulty seeing beyond the whole and will find it difficult to separate information out into its integral parts and the different parts may blur into one. Analytics on the other hand will have difficulty drawing the parts together to see the whole picture and may concentrate on only one or two parts of the information at any one time" (Grimley, 2007)

The Verbal-Imagery dimension affects the modes in which individuals represent information during thinking. Verbalisrs prefer verbal, abstract material whereas imagers prefer concrete pictorial information that can be visualised. The implication of this is that if there is a mismatch between the information presented and the style of the individual then learning is reduced (Grimley, 2007)

In the context of talking about the relationship of information retrieval systems via the search engines and cognitive style, Kinley, K., et al (2010, 340-343) explains this relationship by the results of their study, which confirmed that the cognitive style of a user (Wholist–analytic and verbal–imagery style) was observed to have a greater influence on a Web user’s search behavior. A series of actions take place around the user during user interactions with search engine, which are affected by the user's cognitive style domain (Wholist–analytic and verbal–imagery style). The efficiency and completion of a user's search task depends on how he or she coordinates and processes mental information, which is determined by the cognitive style.

Therefore Kinley& Tjondronegoro (2010) mentions that in order to investigate users‘ issues and problems in retrieving information from the Web, it is imperative to understand information searching and retrieving processes, and cognitive factors, such as users‘ cognitive styles- Wholist–analytic and verbal–imagery style- that influence these processes.

4- Visual Thinking:

Visual thinking is organizing mental images around shapes, lines, colors, texture, and composition (Wileman, 1980). Mckim(1980) also defines visual thinking as "the interaction of seeing, drawing, and imagining". Dispezio (1998) confirms that Visual thinking is a powerful element that defines the way in which we process all sorts of information. "Visual Thinking is Processing information through images instead of words" (Plough, 2004). Wileman (1993) described visual thinking as "the ability to turn information of all types into pictures, graphics, or forms that help communicate the information".

Visual Thinking involves five basic skills. These include observation, recognition, perception, interpretation, and self-expression. A learner who has mastered all these is well on the way to visual thinking (Murphy, 2009):

We can say that Image search engines are one of the visual thinking tools, they are simply visualization and dependable in the development of visual thinking. Image search engines are particularly one of the visual thinking tools "that empower learners in solving complex problems by engaging them in the entire resolution process, suggesting appropriate actions with visual cues, and reducing their cognitive load with visual representations of their tasks". (Pu& Lalanne, 2002). Also Buijs& Lew, 1999) confirms that visual thinking is "an important tool for automatic annotation and visual querying of networked multimedia databases. It allows the user to express queries in his own vocabulary instead of using the computer's vocabulary".

The Theoretical Framework

The theoretical framework of this research is based on the Cognitive Load Theory, Multimedia Learning Theory, Dual Coding Theory, and conjoint retention theory. From a cognitive-load theory perspective, the presentation of content in a manner inconsistent with the cognitive style of the learner may represent a cognitive overload on the learner(Sweller, 1989; Pillay, wilss, 1996; Pillaym *et al.*, 1998).

Based on that, if the retrieving type used in the search engine (TBIR, CBIR and TCBIR) is inappropriate to the learner's cognitive style (holistic-analytic and verbal imagery) this could hinder him from using a search engine to reach the images and contents he is searching for. Moreover, this can add an extra cognitive burden on the learner as a result to the effort he exerts to translate search vocabulary he uses so that they become compatible with the used retrieving system in the search engine .For example, if the learner's cognitive style is verbal and the retrieving available pattern is based on visual content ,this could result in problems and the learner has to exert extra efforts so that he could change the verbal terms he is thinking of into visual features stimuli that are related to image such as color , size and texture.

But the theory of multimedia learning posits that optimal learning occurs when the learner engages in the appropriate combination of visual and verbal thinking. According to multimedia learning theory, optimal learning is not purely verbal or visual, but combines both types of information in the most effective way (Morett, *et al.,* 2009). In addition, cognitive-load theory emphasizes that more cognitive capacity is available when information split between the auditory system and the visual system (Jeffrey, 2009).

In this framework, the Dual Coding Theory affirms that memory consists of two systems of information processing: The Iconic System which is specific for representing and treating (coding) Non verbal stimuli and the Symbolic system which is related to coding verbal stimuli. The theory confirms the integration of the two information coding systems through its main principle which is based on imposing integrated dual coding hypothesis (Paivio, 1991), which means that an integration between TBIR and CBIR in one system called TCBIR may ease the treatment process and increase its effectiveness. , and make the learning process an ideal one.

No doubt, these principles that the multimedia learning theory depends on may contribute greatly in designing the retrieving system designing that are used in the search engine. For example, when designing TCBIR, this system should give the learner freedom to integrate among the text research stimuli, and the visual research stimuli to reach specific research findings such as the learner looks for an image by a key word in addition to identifying specific color for the images that appear as a result of the research. For example, looking for an image of a computer set but in black based on the premise that search using correspondent text and image may be better than searching via text only to reach specific research findings. Moreover, designing an interface of retrieving system should take into consideration the special contiguity, and temporal contiguity, that is the interface should put the text research fields in adjacent places to fields of searching that use the visual characteristics. These fields should be used concurrently and not consecutively, that is search should not be carried out using text first then filtering stage or consecutive research using visual characteristics because it is considered a consecutive one. Research system should be concurrent visual and text components in the light of multimedia learning theory.

The conjoint retention theory was to introduce a general a researchers' reliable framework that can be used when arranging the visual and verbal stimuli through a search engine interface with regard to successive search icons that the learner uses when inputting research variable related to the image he needs. Will the search engine arrange his search icons in a way where the verbal search icons appears first followed, in sequence, by the icons with visual characteristics of the images or is it vice versa. The conjoint retention theory solved this argument for the benefit of specific research icons of the image visual characteristics which were then followed by text search icons.

Research questions

The major aim of the present research was to investigate the possible interactions among the image retrieval type (text based Image retrieval/ content based image retrieval/ text-content based image retrieval) and cognitive style (Wholist-Analytic and the Verbal-Imager cognitive styles) on the visual thinking skills. More specifically, the aim was developed to address the following questions:

- What is the effect of image retrieval type (TBIR/ CBIR/ T-CBIR) on the visual thinking skills?
- What is the effect of cognitive style (W-A and the V-I cognitive styles) on the visual thinking skills?
- What is the effect of the interaction between the image retrieval approach variable type (TBIR/ CBIR/ T-CBIR) and cognitive approach variable type (W-A and the V-I cognitive styles) on the visual thinking skills?

Research hypotheses

- **H1**: there are no significant statistical differences at 0.05 level among student average scores for the experimental groups in the visual thinking skills related to the change in image retrieval type variable (TBIR/ CBIR/ T-CBIR).
- **H2**: there are no significant statistical differences at 0.05 level among student average scores for the experimental groups in the visual thinking skills related to the change in cognitive style variable (W-A and the V-I cognitive styles).
- **H3**: there are no significant statistical differences at 0.05 level among student average scores for the experimental groups in the visual thinking skills related to the interaction between the image retrieval type variable (TBIR/ CBIR/ T-CBIR) and cognitive style variable (W-A and the V-I cognitive styles).

Methodology

1- Design:

The design of the research was based on a quasi-experimental research that employed a 3x4 factorial design. It was designed to examine the effects of independent variables on the dependent variables (See Figure 5). The independent variables were the three modes of the image retrieval and the dependent variable was the student's visual thinking.

Fig.5. The 3x4 Quasi-Experimental Design of the research

	WI	AI	WV	AV
TBIR	TBIR+ WI	TBIR+ AI	TBIR+WV	TBIR+AV
CBIR	CBIR+ WI	CBIR+ AI	CBIR+ WV	CBIR+ AV
T-CBIR	T-CBIR+ WI	T-CBIR+ AI	T-CBIR+ WV	T-CBIR+ AV

TBIR, text based Image retrieval; CBIR, content based image retrieval; T-CBIR, text-content based image retrieval; WI, Wholist- Imager; Analytic - Imager; Wholist- Verbal; Analytic – Verbal.

1-1 Independent variables:

There are two independent variables in the present research. The first independent variable consists of three types of image retrieval: (1) text based Image retrieval (TBIR), (2) content based Image retrieval (CBIR), (3) text-content based Image retrieval (T-CBIR) .

The second independent variable consists of four types of cognitive styles: wholist-imager (WI), analytic-imager (AI), wholist-verbalizer (WV) and analytic-verbalizer (AV).

1-2 Independent variables:

One dependent variables is examined in the present research that is **visual thinking skills in computer system.**

2- Sample:

The research final sample contains 141 students from the second and third year, first semester of the academic year 2010/2011 at the Department of Instructional Technology at College of Education at Ain Shams University; in addition, 10 students as a pilot study to verify the validity of the tools as well as the experimental processes. Students of the final sample were assigned to 12 experimental groups according to the three retrieving patterns (TBIR, CBIR, T-CBIR), together with the four cognitive style (WI, AI, WV, AV). This is shown in figure (5):

3- Instrumentation:

3-1 Test of cognitive style:

The computer-based Cognitive Style Analysis Wholist/Analytic& verbal/imagery test (CSA-WA-VI) was administered to determine students' cognitive styles in terms of the wholist–analytic and verbal–imagery dimensions. Riding’s CSA test was chosen because it is relatively new compared to any other cognitive style tests (Peterson, 2005); a good number of studies in search engine design have used it (for example: Ford, *et al.*, 2005; Kinley, K., Tjondronegoro& Partridge, 2010; Yuan& Liu, 2011).

3-2 Test of visual thinking:

The researcher builds up a visual-thinking test in order to measure the sample students’ ability to understand and translate the visual image into verbal output within the content of the pc system. The researcher identified the main skills of the visual thinking in order to build up the test, which also were theoretically shown in advance and it included (observation, recognition, perception, interpretation, and self-expression). The researcher also revised a variety of practical Arabic studies which, in turn, designed tests to measure the visual thinking skills. The researcher, however, concluded that these tests include similar previously occurred skills but with different titles; these skills were as follow: (skills that relate to the ability of identifying the shape and giving a description to it, a skill of analyzing the shape, skills of making connection, interpreting ambiguity, skills of extracting meaning. The researcher surveying some specialists within the field of instructional technology and curriculum then settled on four skills including the visual thinking test; these skills are (observation recognition, perception and interpretation). The test was in the form of multiple-choice and it was based on the objectives, aims of its content, and the skills included. The test contains 35 Questions, 5 were omitted after being verified by the arbitrators and however reduced to 30 Questions that included the four main skills as follow: (observation (33.3%), recognition (26.7%), perception (23.3%), and interpretation (16.7%))- the visual thinking test , appendix 4-.

4- The statistical method:

To ensure homogeneity of the experimental groups with respect to visual thinking, one-way analysis of variances “ANOVA” was used. The two-way ANOVA conducted on the students' visual thinking scores according to the retrieval style (TBIR, CBIR and T-CBIR(and Cognitive styles (WI, AI, WV, and AV) and that is to identify significant differences between groups. This was followed by estimating the effect size (Partial Eta Squared) to quantify and explain how much better the effect was. Finally, scheff'e posts hoc comparison to compare between multi groups.

5- Procedures:

Procedures of the research were followed through an instructional design model (The ADDIE Model) which includes five main stages. The researcher modified the minor steps of the main stages. These procedures could be shown as follow:

5 – 1: The Analysis Phase:

Each of the four main groups that are classified according to the cognitive style was divided into three minor groups, one for each retrieving model. However, students’ number was as follow: WI (12, 11, 12), AI (12, 12, 12), WV (11, 11, 10), AV (13, 13, 12).

Within this stage, the researcher conducted a prospective study with some of the research sample students – appendix 2 – so that one become acquainted with the context in which they use image search engines through the internet and it was obvious that the most frequently used one is the Google image with a percent (97.7%), then came Yahoo image next with a percent (88.7%), then Bing (77.9%). The researcher also discussed the strategy of search they use and concluded that Key words were prioritized then text and finally the visual properties of the image like color and size. The research sample students necessitate the importance of comprising different strategies for the image search engines so that it allow easy and quick access for the instructional images.

The content of PC system was also identified as essential to all experimental processes that relate to the current research. The content here entails a variety of instructional images that illustrate the main components of the PC and this meets the requirements of the students of Instructional Technology. However, this gives the possibility of converting a large portion of this content into digital images that students do search for through search engines of the current study.

5 – 2: The Design Phase:

Objectives are identified here according to the specified content of the previous phase – appendix (3), and based on these objectives, 665 digital instructional images were presented to meet the requirements of these objectives. This was followed by a design to three retrieving systems as defined in this researcher. The first system is (TBIR) through which students search digital images which are available within the databases through only text and vocabulary in order to achieve the desired image. Database was specially designed to this system in the light of Dublin Core metadata which include a detailed written description to all the details and content of the image and what relates to it. The second system is (CBIR) through which students search for instructional images by finding similar images or example where they upload it on the search engine which analyzes its content and the color parts to find out the similar image on the results page. Students can also search for any image within the database using specific colors or sizes of the image through the interface of the search engine. Using these options, images will be shown according to their previously specified size and color. The third system is (TCBIR) through which students search any image according to the textual and visual stimuli in which student can specify key words related to the targeted image specifying a color, which means that the results will only show images that contains these keywords and with only the color that has been specified, figure (1) illustrated these three retrieving systems used in this research.

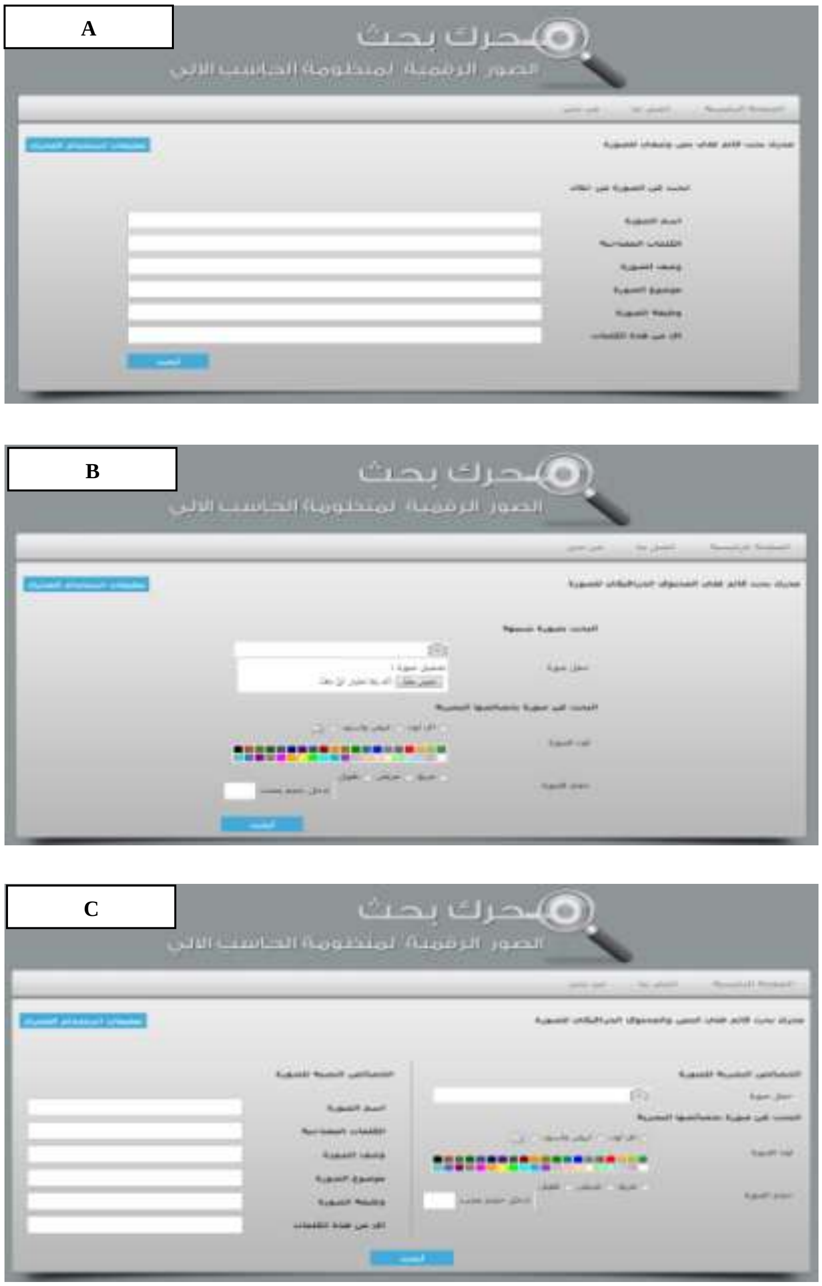

Fig.1. screenshot of (A) TBIR, (B) CBIR, (C) TCBIR

A design for the currently used instructional strategy was developed in this study, which followed the design of retrieving systems. These strategies are based on two strategies: the first is called the research learning strategy in which the attitudes towards students' continuous research are based on instructional images that correspond to the topics that have been studied using search engines, the second strategy is the visual thinking strategy in which students are required to analyze different images they already have and identify their properties and elements to provide various alternatives.

5 – 3: The development Phase:

Three databases were developed in this phase, first is (TBIR), second is (CBIR), and the third tried to include features of both bases so it becomes suitable to (TCBIR). Functions that relate to analyzing the visual properties of the digital images as represented by color and size were written and programmed in this phase. Ajax, jquery and JavaScript were also used to design the three retrieving systems; these systems were then published on (http://devegy.com/search)

5-4: The implementation phase:

Visual thinking test was pre-implemented in this phase followed by a separate meeting to the main groups in order to explain the required methods and tasks with regards to the activities and strategies that will be used through search engines. These meetings are also to discuss the methods of using each search engine and the required instructions. To ensure homogeneity of the experimental groups with respect to visual thinking one-way analysis of variances ANOVA were used, the results indicates that there was no significant difference between all groups or within groups [F=0.358, *P*=0.970]. This was followed by making the retrieving systems available to be used by students, where each four groups, classified according to the cognitive method (WI, AI, WV, AV), use one system among the three retrieving systems (TBIR, CBIR, TCBIR). The implementation process continued for 10 days within two weeks. (The implementation was coordinated with Dr Khaled Nofal, Dr Muhammad Hamdi, Department of Instructional Technology at College of Education, Ain Shams University)

5-5 The Evaluation Phase:

visual thinking post-test was implemented in this phase, in addition to monitoring results and transferring them into a program called SPSS 17.0, and then making statistical processes, analyzing and discussing results as this will be mentioned later in this study.

Findings

Results of the 12 experimental groups were analyzed with regards to visual thinking of the students of Instructional Technology. Means, standard deviations, current research variables, retrieval type (TBIR, CBIR, and T-CBIR) and cognitive types (WI, AI, WV, and AV) were all taken into consideration. Table (1) shows the results of this analysis.

Table 1. Mean scores for the three retrievals style according to four Cognitive types

Retrieval type	Cognitive style				Total
	WI	AI	WV	AV	
TBIR	Mean=20.92±2.35	Mean=21.00±2.34	Mean=23.50±1.96	Mean=25.17±1.27	Mean=22.61±2.69
	N=12	N=12	N=10	N=12	N=46
CBIR	Mean=20.10±0.70	Mean=20.42±1.24	Mean=18.00±2.53	Mean=17.69±4.37	Mean=19.02±2.90
	N=11	N=12	N=11	N=13	N=47
T-CBIR	Mean=27.90±1.16	Mean=29.90±1.31	Mean=21.73±1.27	Mean=21.08±1.98	Mean=24.73±3.76
	N=12	N=12	N=11	N=13	N=48
Total	Mean=22.77±3.53	Mean=23.50±4.34	Mean=21.00±3.02	Mean=21.21±4.17	Mean=22.13±3.93
	N=35	N=36	N=32	N=38	N=141

The two-way ANOVA conducted on the students' visual thinking scores according to the retrieval types (TBIR, CBIR and T-CBIR(and Cognitive styles (WI, AI, WV, and AV) to identify significant differences between groups. Table 2 shows the results of two-way ANOVA.

Table 2. The two-way ANOVA on the students' visual thinking scores according to the retrieval types and Cognitive styles

Source	Sum of Square	df	Mean of Square	F	Sig.	ŋ2
Retrieval style	782.26	2	391.13	86.31	0.000	0.572
cognitive style	139.55	3	46.52	10.26	0.000	0.193
Retrieval*Cognitive	639.47	6	106.58	23.52	0.000	0.522
Error	584.62	129	4.53			
Total	71245.00	141				

A summary of the main effects and interactions presented in the three sections that follow:

1- Effects of retrievals types:

The results indicates that there was significant difference on the main effect for the types of retrievals [$F_{(2, 141)}$=86.31, P=0.00]. Result of Scheff'e post hoc comparison indicated that T-CBIR students [M=24.73] significantly outscored TBIR[M=22.61] [LSD=2.12, P=0.00] and CBIR [M=19.02] [LSD=5.71, P=0.00] students in the visual thinking test. When estimating the effect size (Partial Eta Squared) to quantify and explain how much better the effect was, the results showed that the effect size was large for this interaction (η2= 0.572), and so this results has practical implications for instructional designers of search engine.

2- Effects of cognitive styles:

The results indicates that there was significant difference on the main effect for the cognitive style [$F_{(3, 141)}$=10.26, p=0.00]. Result of Scheff'e post hoc comparison indicated that WI students [M=22.77] significantly outscored WV [M=21.00] [LSD=1.77, P=0.01] and AV [M=21.21] [LSD=1.56, P=0.02] students in the visual thinking test. Also AI students [M=22.77] significantly outscored WV [M=21.00] [LSD=2.50, P=0.00] and AV [M=21.21] [LSD=2.28, P=0.00] in the visual thinking test. But no significant difference between WI and AI, also no significant difference between WV and AV in the visual thinking test. When estimating the effect size (Partial Eta Squared) to quantify and explain how much better the effect was, the results showed that the effect size was large for this interaction (η2= 0.193), and so this results has practical implications for instructional designers of search engine.

3- Effects of interaction between retrievals types and cognitive styles:

The interaction between the retrieval type and cognitive style of the students showed significant difference [$F_{(6, 141)}$=.59, p=0.00]. When estimating the effect size (Partial Eta Squared) to quantify and explain how much better the effect was, the results showed that the effect size was large for this interaction (η2= 0.522), and so this results has practical implications for instructional designers of search engine. Result of Scheff'e post hoc comparison indicated that, In the TBIR type from the LSD multiple comparison, statistically significant differences were attributable for WV students [M = 23.50] in comparison with WI [M=20.92] [LSD=2.58, p=.04] and AI students [M = 21.00] [LSD=2.50, p=.05]. and AV students [M=25.17] in comparison with WI [LSD=4.25, p =.02] and AI students [LSD =4.17, p=.03], But no significant difference between WV and AV, also between WI and AI. In the CBIR type from the LSD multiple comparison no significant difference between WI, AI, WV and AV . In the T-CBIR type from the LSD multiple comparison, statistically significant differences were attributable for WI students [M = 27.90] in comparison with WV [M=21.73] [LSD=5.36, p=.01] and AV students [M = 21.08] [LSD=6.01, p=.00], also statistically significant differences were attributable for AI students [M=29.90] in comparison with WV [LSD=7.36, p=.00] and AV students [LSD =8.01, p=.00], But no significant difference between WI and AI, also between WV and AV. Based on the results and comparisons between groups we can say that TBIR more suitable for WV and AV students, while T-CBIR more suitable for WI and AI students.

Discussion

1- Retrievals types:

Results have shown that the (T-CBIR) has got the upper hand over both (TBIR) and (CBIR) in developing visual thinking for the research sample students. This could be explained in the fact that T-CBIR brings together the features of both TBIR and CBIR, where students can flexibly use any of these features to get images they search for easily depending on the textual and visual stimuli together. This will make the results more integrated with the students' inquiries and will reflect the other two types where each of them rely only on one of the features or stimuli; TBIR relies on textual variable while CBIR relies only on visual features and this will limit students' use of these stimuli and inputs, which in turn reflect his/her inner thinking. This result matches Funkhouser, *et al.* (2003); Gui, *et al.* (2009) which assures the effectiveness of retrieving hybrid forms that are based on text and visual features in the processes of retrieving digital images.

This result could be explained according to some learning theories like multimedia learning theory, which believes that learning as dependant on both verbal and visual stimuli together, not separately, is an ideal one. This means that T-CBIR is the best type because it relies on both verbal and visual stimuli together and this is compatible with cognitive-load theory and the dual coding theory. These theories believe that individual cognitive abilities becomes at their best when processing information occurs through both auditory and visual channels. This entails that integrating both CBIR and TBIR in one system would facilitate and improve the treatment processes and make the learning process ideal. However, it reduces the cognitive load which learner might confront when relying on one stimulus, textual or visual (Paivio, 1991; Mayer, 2001; Jeffrey, 2009).

The design of the interface for TCBIR system as based on multimedia learning theory took both the Spatial Contiguity and the Temporal Contiguity into consideration. Textual search icons were placed close to the search icons that use visual features. These icons, being shown simultaneously and not successively, would facilitate the visual thinking process which is associated with both verbal and visual stimuli. Moreover, arranging search icons through the interface placed visual icon on the right then the textual icon on the left. This way helps students attain verbal representations that suit the previously specified visual ones. Conjoint retention theory assures that visual representations require less effort than verbal ones in students' attempt to process things. Visual representation becomes like a prompt and guide to the verbal ones. Thus, a verbal description becomes meaningful when it can be associated with a visual representation (Mayer, 2001; Morett, *et al.* 2009) .

We could therefore say here that T-CBIR offered textual and visual tools for students to encourage learners to practice visual thinking skills by making the search icons that have visual features and textual description available for them to make processes like observation, recognition, perception, and interpretation. These all make the components of the visual thinking skill.

2- Cognitive styles:

The cognitive imagery style has great influence on whether analytic or wholistic when compared with the verbal cognition style. This is due to the nature of this type which allows learners to produce visual representations that suit everything learners have in mind whether analytical or wholistic. Thus, the cognitive imagery style helps matching visual representations with the scientific material that students search for on search engines like instructional digital images. What you process in your mind is translated into visual images that might be related to color, shape or size or even a similar image. This helps students with visual cognitive approach in the study sample identify image stimuli that they look for more actively than students with verbal cognitive approach whose ideas are translated into words or verbal output that might not be accurately expressing the image they search for. It hinders them from visualizing the nature of the learning material and its frame, which of course affects the visual thinking processes that are related to the features of the learners' available image. One could also say that the absence of referring differences between the Analytic and the wholistic styles relates to the fact that this style, being coupled with the imagery or visual style provides students in the study sample with research vocabulary that facilitate access to a desired results, whether they express the image holistically or analytically. These are all like evidence that help learners practicing the visual thinking skills associated with the presented visual material. For example, when students with wholistic cognitive approach think of describing an image, they do that through wholistic visual representation which expresses the image that the student tries to get. Here, the student specifies an image similar to the image that he is searching for, while the analytic cognitive approach describes the image depending on the partial components of the image like color, shape or texture. However, both approaches, analytic and wholistic, help producing representations that facilitate targeting the image and processing it visually. When students download an image to search for a similar one, they do observation, recognition, perception and interpretation through comparing the downloaded image and the one that appears on the results page. Moreover, when students use special features like color and size, they make visual thinking processes though comparing the specified visual elements as inputs in the search and image icons that appear on the results page. The same applies when the wholistic-analytic approach is coupled with the verbal approach, where students use either words to describe the entire image or words to describe elements and parcel of the image. This result agrees with Yuan's& Liu (2011) study which demonstrated that users' cognitive styles Wholist-Analytic did not affect their search performance.

3- Interaction between retrievals types and cognitive styles:

The results confirmed that the TBIR kind of retrieving was more suitable for students with cognitive type AV, WV than other retrieving types (T-CBIR, CBIR) in developing the visual thinking for the sample students of the research. This result can be explained in the fact that TBIR was compatible with the cognitive features of the verbal approach, whether wholistic or analytical. TBIR however gave students of the research the chance to retrieve digital images similar to the way of their thinking, that is, the verbal method. They can describe images using words or sentences, and can describe it as one unit or partially providing a description to the elements or features of these images; while, on the other hand, the components of other retrieving forms like T-CBIR and CBIR depend on the features and visual stimuli that verbal learners find it difficult suit them with visual representations. This is because the learner in this way thinks verbally and not visually or visionary. This result agrees with the cognitive load theory which confirms that learners learn better when the context is suitable to their cognitive characteristics. T-CBIR was also more suitable for students with cognitive style AI, WI than other retrieving forms like TBIR and CBIR in developing the visual thinking of the students research sample, and this is due to the fact that T-CBIR type was compatible with the cognitive features of the imager style (wholistic and analytic). It also provides search icons based on the visual features of the image as a whole. Students here can download similar image that can express their wholistic thinking about the image, or partially like when students specify a color, shape or size for the image to make it a standard to the image that they retrieve. In addition, this type of retrieving left the door open for using textual stimuli hand in hand with the visual ones, which helps in reducing the cognitive load on the visual channels of the learners. Integrating visual stimuli with verbal ones allow students to put on verbal representations that suit the image being based on the visual representations that students have in mind. Therefore, the arrangement of textual research icons comes prior to the visual search icons and this corresponds with the conjoint retention theory. No doubt, this is all reflected on the learner through providing various alternatives that facilitate his practice to the visual thinking skills through an integration between visual and verbal stimuli in analyzing and recognizing the digital image.

Conclusion

This research produced important findings not only regarding types of image retrieval, but also provided important insights on the effects of students' cognitive styles on using types of image retrieval. The results showed that T-CBIR is better than CBIR and TBIR, imagery students significantly outscored verbal students but no difference between Wholist and Analytic students, TBIR is better than T-CBIR and CBIR to Verbal (wholist or -Analytic) students and T-CBIR better than CBIR and TBIR to imager (wholist or -Analytic) students.

These results imply the need for more interest in cognitive styles of the learner when designing search engines retrieval systems, also a need to take into account that the image search engines should include text and visual fields to accommodate all of the text and visual features to image.

This research investigated the relationship between users' wholist/analytic and verbal/ imager cognitive styles and types of image retrieval: text based image retrieval (TBIR), content based image retrieval (CBIR), and text-content based image retrieval (T-CBIR). The next step is to investigate the effects of Dependent/Independent Cognitive Styles on the design of search engine Interfaces.

References

1. Aarbakke,A.S. (2007). M2S AND CAIR: Image based information retrieval in mobile environments, Master's Thesis, Faculty of Science, University of Troms.
2. Alqahtani,F.A. Saba, T. (2013) Impact of Social Networks on Customer Relation Management (CRM) in Prospectus of Business Environment, Journal of American Sciences, vol. 9(7), pp.480-486.
3. Ahmad, A.M., Sulong, G., Rehman, A., Alkawaz,MH., Saba, T. (2014) Data Hiding Based on Improved Exploiting Modification Direction Method and Huffman Coding, Journal of Intelligent Systems, vol. 23 (4), pp. 451-459, doi. 10.1515/jisys-2014-0007.
4. Barnard, K., Duygulu, P., de Freitas, N., Forsyth, D., Blei, D., Jordan, M.I. (2003). Matching words and pictures, Machine Learning Research, 3, 1107–1135.
5. Clewley,N., Chen.S., Liu, X., (2010). Cognitive styles and search engine preferences: Field dependence/independence vs holism/serialism, Journal of Documentation, 66 (4), 585 - 603
6. Dispezio, M.A. (1998). Visual Thinking Puzzles, new York, Sterling Publishing Company, Inc.
7. Dooley, K.E., Lindner, J. & Dooley, L. (2005). Advanced methods in distance education: applications and practices for educators, trainers and learners, Idea Group Inc, London.
8. Elahi, N.; Karlsen, R.& Akselsen, S.(2009). A Context Centric Approach for Semantic Image Annotation and Retrieval, proceeding Future Computing, Service Computation, Cognitive, Adaptive, Content, Patterns, IEEE Computer Society Washington, DC, USA, Computation World, 15-20 Nov, 665-668.
9. Faiola, A., & Matei, S. A. (2005). Cultural cognitive style and web design: Beyond a behavioral inquiry into computer-mediated communication. Journal of Computer-Mediated Communication, 11(1), article 18.
10. Fauzi, M.F.A.& Lewis, P.H. (2008). A multiscale approach to texture-based image retrieval, Pattern Analysis & Applications, 11 (2), May, 141-157.
11. Fogarty,J., Tan,D., Kapoor,A.& Winder,S. (2008). CueFlik: Interactive Concept Learning in Image Search, CHI '08 Proceedings of the twenty-sixth annual SIGCHI conference on Human factors in computing systems, Florence, Italy, April 5–10, 29-38.
12. Ford, N., Miller, D. &Moss, N. (2005). Web Search Strategies and Human Individual Differences: Cognitive and Demographic Factors, Internet Attitudes, and Approaches, Journal of the American Society for Information Science and Technology, 56 (7),741-756.
13. Funkhouser,T. , Min,p. , Kazhdan,M. , Chen,J. , Halderman,A., &Dobkin,D (2003). A Search Engine for 3D Models. ACM Transactions on Graphics, 22(1).83-105, January.
14. Grimley, M. (2007). Learning from Multimedia Materials: The Relative Impact of Individual Differences, Educational Psychology, 27 (4), 465-485.

15. Gui,C., Liu,J., Xu,C.& Lu,H.(2009). Web image retrieval via learning semantics of query image, Proceedings of the 2009 IEEE international conference on Multimedia and Expo (ICME'09), IEEE Press Piscataway, NJ, USA, 1476-1479.
16. Hodge,G. (2004). Understanding Metadata, a guide for libraries , NISO Press , Bethesda Avenue, USA.
17. Haron, H. Rehman, A., Wulandhari, L.A., Saba, T. (2011) Improved vertex chain code based mapping algorithm for curve length estimation, Journal of Computer Science vol. 7(5), pp. 736-743.
18. Jeffrey, L.M. (2009). Learning orientations: Diversity in higher education, Learning and Individual Differences, 19, 195–208.
19. Jeon, J., Lavrenko, V., Manmatha, R. (2003). Automatic image annotation and retrieval using cross-media relevance models, Proceedings of the 26th annual international ACM SIGIR conference on Research and development in information retrieval (SIGIR '03), ACM New York, NY, USA, 119-126.
20. Jing,Y. & Baluja.S (2008). PageRank for Product Image Search, WWW '08 Proceedings of the 17th international conference on World Wide Web, Beijing, China, April 21–25, 307-315.
21. Joseph,S.& Balakrishnan,K. (2011) . Multi-Query Content Based Image Retrieval System using Local Binary Patterns. International Journal of Computer Applications, 17(7), March,1-5.
22. Joudaki, S. Mohamad, D. Saba, T. Rehman, A. Al-Rodhaan, M. Al-Dhelaan, A. (2014) Vision-based sign language classification: a directional Review, IETE Technical Review, Vol.31 (5), 383-391, doi. 10.1080/02564602.2014.961576
23. Katuka, J.I. Mohamad, D. Saba, T. El-Affendi,M., Mohamed, A.S. (2014) An Analysis of Object Appearance Information and Context Based Classification, 3D Research 5 (3), 24.
24. Kaur,M., Bhatia,N.& Singh,S. (2011). WEB SEARCH ENGINES EVALUATION BASED ON FEATURES AND END-USER EXPERIENCE, International Journal of Enterprise Computing and Business Systems, 1 (2), July.
25. Kim, K.S. (2000). Effects of Cognitive Style on Web Search and Navigation. In J. Bourdeau & R. Heller (Eds.), Proceedings of World Conference on Educational Multimedia, Hypermedia and Telecommunications, Chesapeake, VA, 531-536.
26. Kim, K.S. (2005). Individual differences in Web search behavior: Impacts of users' cognitive style, search experience and self-assessed problem-solving ability. Advances in Psychology Research, 35, 29-49.
27. Kinley, K. & Tjondronegoro, D. (2010). The impact of users' cognitive style on their navigational behaviors in web searching. In Judy, Kay, Thomas, Paul, & Trotman, Andrew (Eds.) Proceedings of 15th Australasian Document Computing Symposium (ADCS), School of Computer Science and IT, RMIT University, University of Melbourne, Melbourne, Victoria, 68-75.
28. Kinley, K.& Tjondronegoro, D. (2010). User-Web Interactions: How Wholistic/ Analytic Web Users Search the Web?, OZCHI '10 Proceedings of the 22nd Conference of the Computer-Human Interaction Special Interest Group of Australia on Computer-Human Interaction, Australian National University, Canberra, Australia, 344-347.
29. Lee,J. (2007). The effects of visual metaphor and cognitive style for mental modeling in a hypermedia-based environment, interacting with Computers, 19, 614-629.
30. Lung, J.W.J., Salam, M.S.H, Rehman, A., Rahim, M.S.M., Saba, T. (2014) Fuzzy phoneme classification using multi-speaker vocal tract length normalization, IETE Technical Review, vol. 31 (2), pp. 128-136, doi. 10.1080/02564602.2014.892669
31. levenen,m. (2010). an introduction to search engines and web navigation, john wiely, sons, inc, Hoboken, new jersey.
32. lewandowski, D. (2006).Query types and search topics of German Web search engine users, Information Services & Use, 26, 261–269.
33. Meethongjan, K. Dzulkifli, M. Rehman, A., Altameem, A., Saba, T. (2013) An intelligent fused approach for face recognition, Journal of Intelligent Systems, vol. 22 (2), pp. 197-212, doi. 10.1515/jisys-2013-0010.
34. Magoulas, G.D., Chen, S.Y., Dimakopoulos, D. (2004). A Personalised Interface for Web Directories Based on Cognitive Styles. In User Interfaces for All, LNCS 3196, 159-166.
35. Mundher, M. Muhamad, D. Rehman, A. Saba, T. Kausar, F. (2014) Digital watermarking for images security using discrete slantlet transform, Applied Mathematics and Information Sciences, vol 8(6), pp. 2823-2830, doi.10.12785/amis/080618.
36. Muhsin; Z.F. Rehman, A.; Altameem, A.; Saba, A.; Uddin, M. (2014). Improved quadtree image segmentation approach to region information. the imaging science journal, vol. 62(1), pp. 56-62, doi. http://dx.doi.org/10.1179/1743131X13Y.0000000063.
37. Murphy, Stuart J. (2009). The Power of Visual Learning in Secondary Mathematics Education: How does visual learning help high school students perform better in mathematics?, Research Into Practice Mathematics, PearsonSchool, 1-8.(http://assets.pearsonschool.com/asset_mgr/legacy/200916/MatMon092291HS2011StuMur_LR_20702_1.pdf)
38. Partio, M. (2002). Content-based Image Retrieval using Shape and Texture Attributes, Master of Science Thesis, Institute of Signal Processing, Tamper university OF Technology.

39. Peterson, E.R., Deary, I.J.& Austin, E.J. (2005). Are intelligence and personality related to verbal-imagery and wholistic-analytic cognitive styles?, Personality and Individual Differences, 39, 201–213.
40. Pillay, H. K., Boles, W.W., & Raj, L. (1998) Personalizing the design of computer-based instruction to enhance learning, The journal of the association for learning technology (ALT), 6(2), pp. 17-31.
41. Pillay, H. K., wilss, l. (1996). Computer Assisted Instruction & Individual Cognitive Styles Preferences, Australian Educational Computing, 11 (2), 28-33.
42. Plough, J.M. (2004).Students Using Visual Thinking to Learn Science in a Web-based Environment, Doctoral Thesis, Drexel University.
43. Potter, M.L. (2010). From Search to Research: Developing Critical ThinkingThrough Web Research Skills, Microsoft Corporation. 1-39.
44. Pu, P.& Lalanne, D. (2002). Design Visual Thinking Tools for Mixed Initiative Systems, Proceedings of the 7th international conference on Intelligent user interfaces (IUI '02), ACM, New York, 119-126.
45. Rad, A.E. Rahim,M.S.M, Rehman, A. Altameem, A. Saba, T. (2013) Evaluation of current dental radiographs segmentation approaches in computer-aided applications IETE Technical Review, vol. 30(3), pp. 210-222.
46. Rahim,MSM, Isa,SAM, Rehman, A., Saba, T (2013) Evaluation of adaptive subdivision method on mobile device, 3D Research vol. 4(4), pp. 1-10, doi:10.1007/3DRes.02(2013)4.
47. Rahim, M.S.M, Rehman, A. Kumoi, R. Abdullah, N. Saba, T. (2012) FiLeDI framework for measuring fish length from digital images, International Journal of Physical Sciences, vol.7(4), pp.607-618
48. Rehman, A. (2012) Machine learning based air traffic control strategy Int. J. Mach. Learn. & Cyber. https://doi.org/10.1007/s13042-012-0096-6.
49. Raheja, K.& Gupta, D. (2011). To Study the Ways to Annotate Images Manual, Semi-Automatic and Fully Automatic in M2S and CAIR, International Journal of Computer Science and Information (IJCSIT), 2 (4),1725-1728.
50. Rahmani, R., Goldman, S., Zhang, H., Cholleti, S. & E. Fritts, J. (2008). Localized Content Based Image Retrieval, IEEE Transactions on Pattern Analysis and Machine Intelligence, Special Issue, 30 (11), November, 1902-1912.
51. Rao, m., Rao, p., Govardhan, a. (2011). Content Based Image Retrieval using Dominant Color, Texture and Shape, International Journal of Engineering Science and Technology (IJEST), 3(4), 2887-1896.
52. Saba, T., Alqahtani, F.A (2013) Semantic analysis based forms information retrieval and classification, 3D Research, vol. 4(3), doi.org/10.1007/3DRes.03(2013)4
53. Sakhare,S.V.& Nasre,V.G. (2011). Design of Feature Extraction in Content Based Image Retrieval (CBIR) using Color and Texture, International Journal of Computer Science & Informatics, 1(2), 57-61.
54. Smith, C., (1996). VisualSEEk: a fully automated content-based image query system, World Wide Web Internet And Web Information Systems,ACM Multimedia 96, Boston,November 20, 87-98.
55. Styrman, A. (2008). Ontology-Based Image Annotation and Retrieval, Master Thesis, Computer Science, University of Helsinki, May.
56. Sweller, J. (1989). Cognitive technology: Some procedures for facilitating learning and problem-solving in maths and science, Journal of Educational Psychology, 81, 457-466.
57. Tollari, S.& Glotin, H. (2007). Web image retrieval on ImagEVAL: Evidences on visualness and textualness concept dependency in fusion model, Proceedings of the 6th ACM international conference on Image and video retrieval (CIVR '07), ACM, New York, USA, 65-72.
58. Tsai, C. & Hung,C. (2008). Automatically Annotating Images with Keywords: A Review of Image Annotation Systems, Recent Patents on Computer Science , 1, 55-68.
59. Vani,V.& Raju,S. (2010). A detailed survey on query by image content techniques, ICNVS'10 Proceedings of the 12th international conference on Networking, VLSI and signal processing, World Scientific and Engineering Academy and Society (WSEAS), Wisconsin, USA, 204-205.
60. Vijay, K.& Anitha, R. (2008). A Content-Based Approach to Image Database Retrieval, Journal of Computer Applications, Vol 1 (4), Oct – Dec, 15-17.
61. Zhu ,G., Yan, s.& Ma, y. (2010).Image Tag Refinement Towards Low-Rank, Content-Tag Prior and Error Sparsity , Proceedings of the international conference on Multimedia (MM '10), October 25-29, Firenze, Italy, 461-470.
62. Elarbi-Boudihir, M. Rehman, A. Saba, T. (2011) Video motion perception using optimized Gabor filter, International journal of physical sciences, vol.6(12),pp. 2799-2806.
63. Haron,H. Rehman, A., Wulandhari, L.A., Saba, T. (2011) Improved vertex chain code based mapping algorithm for curve length estimation, Journal of Computer Science vol. 7(5), pp. 736-743.
64. Haron, H. Rehman, A. Adi, DIS, Lim, S.P. and Saba, T.(2012). Parameterization method on B-Spline curve. Mathematical problems in engineering, vol. 2012, doi:10.1155/2012/640472.
65. Saba, T., Rehman, A., and Sulong, G. (2011) Improved statistical features for cursive character recognition" International Journal of Innovative

Computing, Information and Control (IJICIC) vol. 7(9), pp. 5211-5224
66. Katuka, J.I. Mohamad, D. Saba, T. El-Affendi,M., Mohamed, A.S. (2014) An Analysis of Object Appearance Information and Context Based Classification, 3D Research 5 (3), 24.