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# A CONCEPT FOR BUILDING MORE HUMANLIKE SOCIAL ROBOTS AND THEIR ETHICAL CONSEQUENCE

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**ABSTRACT**

Human – computer interaction is a vast area of research that targets two very different groups of subjects: the humans as a biology originated group, and the machines – as human made products. One specific part of this interaction is the human – robot interaction. This paper discusses the challenges that arise in the human – robot interaction. Special accent is put on creating social robots, in particular on creating more human-like empathic robots. Here a concept for creating such robots is proposed, where data from human-human interaction is used for feature selection. As an example of the stated concept a robot has been added the ability to perceive human emotions. In this research the robot uses human sound data as source for perceiving human emotions. Additionally, a biologically driven custom algorithm is used in this research for emotion evaluation classification. The proposed approach is analyzed and evaluated using experimental results done from real data. Also, the influence of the emotion aware robots on humans is explained in more detail. At the end, a discussion about the importance of sharing life with these emotion aware robots today and in the future is argued.

**KEYWORDS**

human-robot interaction, social robots, robotics, emotion classification.

## 1. INTRODUCTION

Human – computer interaction is a computers science research area that has a great impact on humans and their social interaction with other humans and machines. One aspect of human – computer interaction is the newly evolved discipline of human – robot interaction.

Today many robots are built for all kinds of different purposes. There are industrial robots, military robots, educational robots, social robots and many others. Some robots, for example social robots, are built to be used in interaction with humans. So, robots are becoming part of our everyday life. Human-robot interaction is an attractive research field that involves studies about the interaction between robots and humans. The way the interaction is performed is changing through the years. The interaction differs in the way communication is performed. On the lowest level of interaction, humans communicate with robots using physical impression on input devices, like buttons. At higher level, human movement and speech are "seen" and "listened" by robots. For example, a picture is processed using different kinds of algorithms in order to detect a color, shape or human on a picture. A sound is processed to detect some sound characteristic, to recognize humans or their speech. A robot could behave based on these recognized features and other information that can be derived from both picture and sound. At the highest level, robots can even express and perceive social behavior. Therefore, a specific part of human - robot interaction are, so called, social robots and their primary task is to maintain successful interaction with humans. Social behavior is the highest level of communications between humans, and a challenging one for robots.

According to the main characteristics of the interaction, human-robot interaction can be robot-cantered, human-centered or robot cognition-centered (Dautenhahn, 2007). Robot-centered interaction puts the robots at the focus. The goal is the robot to be satisfied according to its internal state. In the human-centered interaction the goal of the robot is to accomplish the tasks given by humans. The last interaction type emphasizes the robot as an intelligent system that performs some cognitive tasks. In this interaction the robot could make its own decisions and solve complex problems. One cognitive task is the task of perceiving human emotions. This task is one of the most important tasks for the social robots and it is the main research interest of this paper.

## 1.1 Social Robots

The development of social robots is one of the challenges today in the domain of human-robot interaction (Feil-Seifer & Matarić, 2009). Social robots should have some human characteristics, like verbal and nonverbal communication, they should have their own body and they should perceive and express emotions. As defined, a special condition for one robot to be social is the inclusion of the concept of emotion. The reason is that emotions give and present some additional information that differs from the information from verbal or nonverbal communication. As a result, emotions make the communication more human-like.

There are many examples where social robots are included in the real life due to their specific usage (Kirandziska & Ackovska, 2013). There are social robots included in education in helping human learning activity, robots that are caregivers to older people, people with cognitive disabilities and people with some physical disabilities. The usage of social robots for autistic people, especially children, has been proven successful in many robot applications (Dautenhahn, 2003). Robots are also used in rehabilitation process where robots motivate and help people in their rehabilitation exercises. Robots can also be just companions to humans. Besides socially interacting, robots can do some specific domestic task like vacuum cleaning, lawn-mowing and window cleaning.

Today not all social robots support emotions, since this task is hard to implement. A social robot that perceives emotions is called emotion aware robot. However, emotion perception is one important feature of social robots and makes them more human- like. In general, there are several aspects of emotions that have to be considered when creating emotion aware robots. These aspects make the problem of emotion perception a difficult one.

## 1.2 Emotions are Difficult to define and implement

The concept of emotion itself is very difficult to explain precisely. Many different definitions of emotion exist. One defines emotion as a conscious mental reaction, other as a mental state and another as subjective experience [Dixon, 2012]. This variety in the definition of emotion makes it really hard to understand what emotions truly are, how they are shown and expressed.

Since emotions are difficult to define, it is very challenging to find a proper representation modus. One possibility is to represent the emotions by listing all possible emotions. However, this is not an easy task. There are more than twenty different emotions. Many researchers have defined different lists of emotions. For example, Plutchik created a wheel of emotions (Fig. 1) where 32 emotions are represented. This kind of emotion representation is called categorical. Distinguishing between so many emotion categories is very challenging to model and implement since there are so many possible emotions. As noticed on Fig. 1 the emotions are somehow ordered in the wheel of emotions. In the second smaller circle the basic emotions are shown: joy, trust, fear, surprise, sadness, disgust, anger and anticipation. Also, the emotions above the biggest circle are similar to the emotions near them. This indicates that some other more ordered emotion representation is possible where emotion categories could be compared by some specific quantity. Different emotion representation in which emotions are assigned with values for a given quantity also exist (Wong, 2006). These quantities enable emotions to be represented in a multidimensional space. There can be one, two or more dimensions. In this representation emotions are shown as points or surfaces in a given multidimensional emotion space. Given the values for all the dimensions, one specific emotion can be determined. The problem with this manner of representation is that this is not precise. This means that for example the emotion happiness cannot be clearly placed in the multidimensional emotion space. As a result, the main focus for many researches is representing specific emotions in an emotion space (Wong, 2006; Feifakis, Daradoumis. and Caballe, 2011).

Another difficulty that arises in perceiving emotions is due to human's individual and cultural differences. There could be differences in the emotion manifestation in human speech and in other biological signals among people from different cultures. But also, each person has an individual mark in expressing emotions. If one is angry he/she might speak louder, while another might be quiet. There are many factors that influence emotion manifestation. The environment has some influence, but also genes factors are important. This problem must be considered when creating emotion aware robots.

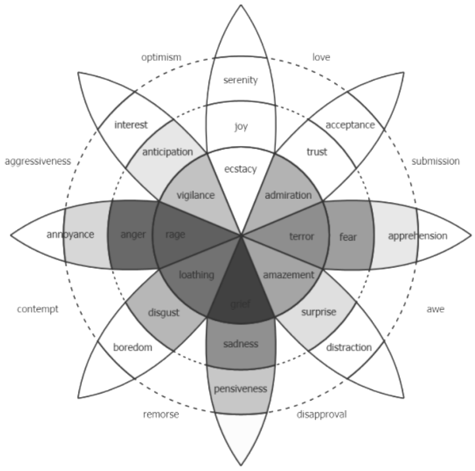


Figure 1. Plutchik's wheel of emotions (Plutchik, 2001).

According to some psychological researches like the research from Klaus et al. (1991), one person could have many emotions simultaneously. As a result different people can perceive different, but still true emotions concerning that particular person. This is very serious problem named emotion ambiguity. Consequently, a well chosen emotion representation, like the representation in dimensional spaces, should be used instead of the categorical representation.

This text elaborates on one concept for building emotion aware robots to which humans react positively. In the next section the main challenges in the human- robot interaction for social robots are explained. Next, the idea and the implementation for biologically driven emotion perception are described. Also the justification for this kind of emotion evaluation perception modeling in human-robot interaction is elaborated. An example implementation of emotion perception in a robot is given in the fourth section. In the discussion, a deeper look at the usage of these emotion aware social robots is given and their effect on the human state is presented. Even more so, some ethical issues in human-robot interaction are presented. At the end, the possible directions for future work along with the conclusions are given.

# 2. CHALENGES IN HUMAN-ROBOT INTERACTION FOR SOCIAL ROBOTS

Today's robots, especially social robots, are constructed following some preferable guidelines and functionalities. There are several aspects of robotic behavior that can be considered. Executing a practical task for the human needs is one of many possible robotic actions. Robot's functionality can be limited by some specific task or can have clearly defined functionality, like vacuum-cleaning, that is given without specifying simple tasks (for example walk straight ahead). Even more, robots should adapt and learn from real world situation. For example, robots that move to different environments could learn and adapt to the new environment in order to be better in executing its task.

Along with executing practical tasks, robots could have some social skills. The requirement for social skills in robots depends on the robot application (Fong, 2003). In some robots social skills are not required. One example is a remote controlled robot used in space. On the other hand, for some robots the existence of social skills is a valuable robot features. For example, vacuum cleaning robots and robots- firefighters need to move in the same environment with the humans and as a result some specific skills are required. For example, for a cleaning robot it would be useful saying "have a good day", "can you let me pass please" and even asking for more tasks to be done. Social features are most important for service or assistant robots because their goal is to actually communicate with humans. These robots need to possess a wide range of social skills in order to be acceptable for humans.

An illustration of a social robot is given in Fig. 2. The robot is under constant influence of the environment and it interchanges signals with humans. Robots get different human signals and perform actions in their environment. The primary goal of the robot's actions is a more human-like interaction with humans.

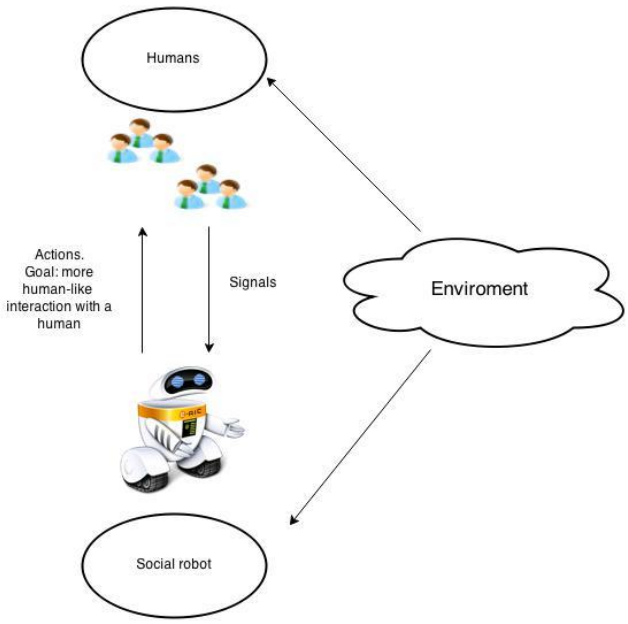


Figure 2. Social robot in a human – robot interaction

Having all this in mind, one could argue that important characteristics for social robots are to be considerate, proactive and non-intrusive. Robots and humans should coexist in the same space, but each must have their own personal space disabling intrusion. Also, these social robots should work towards a relationship of trust and confidentiality with the humans. One way to accomplish this is by successfully doing its tasks. Humans would trust a person, as well as a robot, that acts according to the situation and that accomplishes the given tasks. Natural or almost natural communicative skills are important for the interaction. Understanding the human is one primary task for a robot whose goal is to be a companion to a person. Without understanding the person's needs, the robot could misbehave, since the input information it gets is noisy.

For long-term interaction with humans, the robot needs to be flexible and to adapt to specific humans and also to different human behavior. Robots sometimes should act in a completely new situation and a good assumption about its action should be made. Constant learning must be applied to robots in order for them to fulfill human requests and consistent interaction. In order a robot to learn it must have some feedback from its environment about its manifestation. Robots should act differently in a new situation, given they have some new feedback information to process.

More importantly, the robot needs to ensure the human is satisfied and happy, so that human could have a positive experience in its presence. This concept is not new. It actually dates from 1942. Indeed, in one of the three laws of robotics, Asimov (1942) stated the rule that a robot may not injure a human being or, through inaction, it may not allow a human being to come to harm. According the second law, robots should not cause negative emotions in humans. One way to enable robots to understand whether a human is satisfied or not, is by using emotion perception.

As argued by Dautenhahn, (2007) in the future of human-robot interaction new theoretical foundations and modes need to be found in order to improve the researches. More scenarios and methodologies for obtaining results in experimental environment should be composed since today no standard procedure for data collection and evaluation is introduced. This is of great importance in comparing different research techniques in human-robot interaction. Evaluation of the robot social skills asks for different approach that depends on different application domains. Also, new methodological approaches used in human-robot interaction will be appreciated for improving the interaction. In the direction of new concepts for building social robots, information from human-human interaction can be used as a role model for improving human-robot interaction. This idea was presented, but not implemented, by Fong in 2003. Nevertheless, there are not many researches that follow this line of reasoning. However, in this paper the idea of utilizing human- human interaction in order to build more successful human – robot interaction is used. Also a new concept based on human- human interaction is proposed and implemented in a social robot. In addition to the information extracted from human-human interaction, features from human-computer interaction might be used. But this is not in the scope of the research presented here.

Implementing and taking information from human-human interaction should be done with precaution. On one hand robots are not human, so the models used in human-human interaction and studies in many social sciences should be rather changed and modified. On the other hand robots are not computers, and embodiment and the social features of the robots are additional possibilities that have to be taken in consideration.

From the human perspective, how humans perceive and respond to social robots is also important. This interaction in some way influences humans and the goal is this influence to be positive. One way in which the robot could make decisions that the human is satisfied with this interaction is to be able to perceive emotions. Making decision based on human emotions could change the general robot performance and even more, it could improve its social skills.

According to Dautenhahn (2007) it is unclear whether the emotional component in human–human interaction can be fulfilled by robots. This paper hypothesizes that it is truly possible to transfer, at least to some extent, human-human emotion perception features in human-robot interaction by robot emotion perception.

# 3. THE CONCEPT FOR CREATING SOCIAL ROBOTS THAT PERCIEVE EMOTIONS

One valuable social robot characteristic, as argued in the previous Section, is for the robot to be able to perceive emotions. This feature makes the robot empathic. It means that after perceiving (sensing) some emotion it can be programmed to act accordingly. The general goal is the robot to be accepted by the human it interacts with, while it works on its given tasks, but also to take care of the human's emotional state. In order to make the robot emotion aware, it should have an implemented system for emotion detection and classification.

Emotion classification is a process of distinguishing an emotion form given input. Emotion classification, from robotic point of view, is an algorithm that enables a robot to decide the emotional state of the human. The input in this algorithm is data that can differ by its nature. For example, visual and sound signals are used in the systems for perceiving human characteristics. Examples are speech recognition and facial recognition. These signals are processed and afterwards algorithms for feature extraction are used in order to extract relevant data. Facial features and movement features, as well as sound and speech features are some examples of relevant data. In this paper the input data will be extracted from human sounds.

Emotion classification can be achieved using different classification techniques. Supervised methods have training data based on which the classification model is built. Test data is used to validate the model.

The models for emotion perception can target a different goal. So, models could support different concepts. Next, the concept used in other researches is summarized and later the concept proposed in this research is described.

## 3.1 Concepts used in Other Researches

There are many researchers that have created social robots that perceive emotions (for example, Huang, Zhang and Da, 2011). Many researchers, for example Vogt et al. (2008), tried to make the best emotion classifier compared to the perfectly correct emotion detector. This means that the goal of the classifier is to have the highest precision with the new test data. Usually, in other classification problems, such as face recognition, symptoms analysis in sick patients etc., this is the main goal. However, emotion classification is different since emotions are difficult to understand and model, as explained earlier. The question that arises is whether it is possible to make a very precise model of emotions in real life situation. Even humans have difficulty when perceiving other people's emotions. This was precisely investigated using a survey in the next subsection.

Robotics researchers in human emotion perception had achieved a percentage of accuracy from 70 % to 90%, or even more (Cichosz and Ślot, 2010; Dai, Fell. and MacAuslan, 2008.). This is a relatively high percentage given the emotion characteristics. However, this is not strange when the goal of the model is to minimize the errors. Another thing that explains this relatively high percentage in the accuracy is how the databases used for training and testing of the model was build.

In order to make a model for emotion classification perception and then validate it, databases of human signals are used. It is truly hard to make this kind of database, since a great amount of data is needed. Even more, real life situations where human express emotions are hard to capture. And also it is hard to recognize which emotion is expressed by a human in each moment. In lack of real life databases, other kinds of databases were built.

Some databases are created from acted recordings of human sound and video. There are several publicly available databases of this kind. These are most often used in researches for emotion perception. One is the audio-visual database eNTERFACE'05 presented by Martin, Kotsia, Macq and Pitas (2006). This database consists of videos that are recorded in such a way that actors act on specific emotions. Usually one or more predefined sentences are acted. In real world situations the humans do not reveal their emotions as expressive as actors do. Actors tend to over express emotions.

Some other databases are constructed from the recordings of non-actors. These databases should have much more samples in order to build a valid model. But the variety in how people express different emotions makes this model not so accurate in the process of model validation where new test data are used.

The problems derived from this concept for emotion perception was the motivation to investigate deeper the human-human emotion perception.

## 3.2 Human-human Emotion Evaluation Perception

In order to get the sense of how well humans perceive other human's emotions, practical experiments about human emotion perception were conducted. One question that should have been answered was weather emotional states can be actually classified with great precision by other humans. In (Kirandziska & Ackovska, 2013 - 2) a study has been conducted to partially answer this question. The results showed variety in human precision of detection of emotional states. Some results are presented in the sequel.

Since there are more than 20 different emotions, as discussed earlier, a study for recognizing all these emotions is immense to perform. Consequently, a much simple emotion representation was used in the study. The human emotional state was represented via emotion evaluation. It is a measure that represents the "color" of the emotional state. The color of an emotional state can be positive or negative. Positively colored emotional states represent good and pleasant internal human state. On the opposite side, negatively colored emotional states represent bad and unpleasant internal human state. Since the color of the emotional state represents emotion evaluation, emotions can be categorized to positively or negatively evaluated emotions. For example happiness is positively, while sadness negatively evaluated emotion.

In this study the human-human emotion evaluation perception was investigated experimentally. The emotion evaluation classifier created for this research and used in the experiments that support this study is based on human sounds perception. Therefore, the experiments were done using sound signals only.

For the experiment, sound signals of one person expressing fourteen different emotions were recorded. This person was not an actor and was not dramatically expressive. Afterwards, the sound signals which were unprocessed were played to selected group of people, called evaluators, who did not know the speaker. Also, for validating purposes, a smaller group of people who did know the speaker was included. Their task was to try to guess the speaker's emotion evaluation.

The objective of this experiment was to investigate how well a person could distinguish emotion evaluation in another person that he/she knows or doesn't know. Also, is there any difference in the accuracy of perceiving known and unknown people? And last, which acted emotions are easier and which are harder to distinguish and classify correctly in one of the two classes: positive or negative.

Table 1. Average accuracy of the evaluators' emotion evaluation classification for different emotions

| Positive emotion | Percentage | Negative emotion | Percentage |
|---|---|---|---|
| **Optimism** | 100 | **Guilt** | 90 |
| **Happiness** | 86.6 | **Disgust** | 86.6 |
| **Satisfaction** | 80 | **Fear** | 86.6 |
| **Joy** | 80 | **Embarrassment** | 73.3 |
| **Surprise** | 80 | **Boredom** | 66.6 |
| **Pride** | 50 | **Rigidity** | 66.6 |
| | | **Despise** | 60 |
| | | **Sorrow** | 50 |

The average percentage of the evaluation accuracy of the evaluators' perception is presented in Table 1. The percentages are different for different emotions. Some emotions, like optimism and guilt, had very high precision of recognition of their evaluation – positive and negative, accordingly. But, there were some emotions, like sorrow, that 50% of the evaluators estimated as a positive emotion. This shows a very poor evaluation perception in some emotions, even by humans. Several reasons may cause this result. One is the quality of the acted emotion; another is the similarity of the manifestation of one emotion with another emotion with opposite evaluation. Yet another could be that these emotions in general give less information in the sound signals, so it is difficult for a human to make a correct evaluation.

It is noticeable that positive emotions are perceived with a higher percentage than negative emotion. This could show that positive emotions have more valuable sound features that human can hear and that helps in emotion evaluation. On the other hand, negative emotions have less valuable features for sound emotion perception. Maybe if visual signals are included, the result could be much better for these negatively evaluated emotions.

Overall, the experiments showed an average percentage of accuracy of 71.8033%, both for positively and negatively evaluated emotions. This percentage illustrates the human precision to perceive others emotion evaluation. As a result, the model built for the robot created based on sound features used in human-human emotions is expected to be accurate around this, human evaluated, percentage. Compared with the emotion evaluation models explained in the subsection 3.1., the percentage obtained in this research is in the lower bound (of the 70 % to 90%, or even more).

The evaluator percentage of truly perceiving emotion evaluation based on the recorded sound features is represented by the histogram on Fig. 3. It can be observed that the distribution seems almost uniform and ranges from 50%-90%. In the experiments conducted in this research, there was no evaluator that had a precision of more than 90%. Note again that these evaluators did not know the speaker.

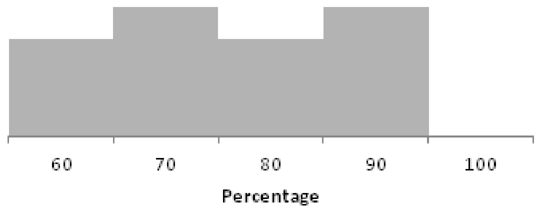


Figure 3. Histogram of the human emotion evaluation percentage for evaluators who do not know the speaker

The next experiment gives insight whether the emotion precision changes if the evaluator recognizes the voice of the speaker. This actually shows the difference of the precision of the emotion detection if the evaluator actually knows the speaker. Fig. 4 presents a histogram for evaluators who did know the speaker. The resulted distribution looks like a normal one with an average value between 80% and 90%.

This indicated that humans better perceive other humans emotions by their speech if they know the speaker. This result was expected because humans learn from experience. And in this case they have learned how their acquaintances express their emotions.

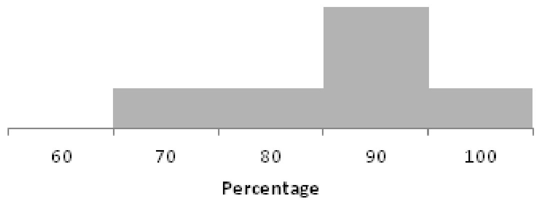


Figure 4. Histogram of the human emotion evaluation for humans who do know the speaker

This very important result was included in the concept presented here, for building a classification model for emotion classification in a robot. The implementation of this result is done by creating a learning module that can be implemented in a robot. The robot can adapt its algorithm for emotion classification from its own experience, gained in the interaction with the humans. The classification model for emotion evaluation in social robots used in this research is presented in the fourth section.

## 3.3 The Newly Proposed Concept

Another concept for building a classifier of emotions includes biologically driven knowledge from human-human interaction. Indeed, this concept includes the knowledge we have on how humans evaluate other humans emotions. If one could implement such a classification system in a robot, it would have more human-like characteristics. This is the goal of the research presented. As stated before the goal of the concept described in Section 3.1 was to reduce the error in emotion evaluation classification.

This idea can be included in the model in many ways. Human-human interaction characteristics can be used to represent emotions. Up to today most representations of emotions are based on what emotions are or how they are expressed. But, if one includes the knowledge based on how humans perceive other humans emotions, maybe another emotion representation will be created.

A different perspective of this idea is to include information from human-human interaction in finding valuable human features that humans use to perceive emotions. One example of a valuable human feature in human emotion perception is a human smile. We often perceive that when someone smiles, he/she is happy. Note that someone could smile and still be sad. Smile could be an act to cover up his/hers true emotions. What is true is that this person would be perceived as happy by most humans. In this case humans would not perceive his/hers emotion correctly. If this knowledge about human-human emotion perception based on smile is used in robot-emotion perception, then the robot would also be wrong in perceiving the emotion of a person that smile. Note that the assumption that a human mostly perceives a human to be happy only by his/hers smile, should be proven. Statistical analysis of data extracted from human-human interaction should be done and then used.

In this paper, we give an example of the concept for modeling emotion classification for robots whose main goal is making the classifier more similar to human’s emotion perception in other humans. Here, the selection of important human features from a given set of human features is done with previous background knowledge from human-human interaction.

A schematic view is given on Fig. 5 illustrates of this concept. As shown in the upper right part of the illustration the information for valuable features was included in modeling the robot emotion classification module. Prior to that the model was build for all features. The result of the information added is a new classification model created from the selected features only (left-bottom in Fig. 5).

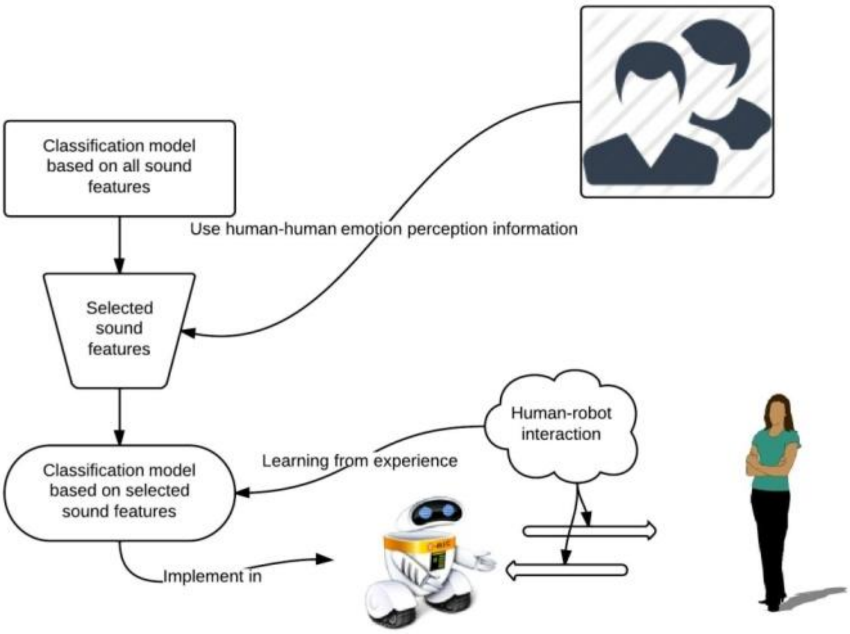


Figure 5. The concept of including human-human emotion perception information in feature selection

In the presented research, as it will be explained in the next section, sound features were used. As a consequence the concept presented in Fig. 5 specifies that the features are sound. In general, any other feature can be used in this concept.

The concept also suggests that the classification model build is used in a robot. This robot could learn from experience. New data from the robot's interaction with a human change the classification model. This changed model is later implemented in the robot.

A practical usage of this concept in an application of human-robot interaction is presented in the following section.

## 4. EMOTION CLASSIFICATION MODEL IMPLEMENTED IN A ROBOT

Emotion perception in robots can be implemented with machine learning classification algorithms. However, due to the unclear definition of emotions and the variety of different emotions, emotion classification is a difficult problem. There are varieties of approaches that are used in building the classification model. Beside the varieties in emotion representations stated in Section 1, the classification models can use different input data, different techniques for feature selection, different classification algorithms and different on-line learning techniques.

One valuable input data used for emotion perception are sound signals from human speech. Apart from the visual signals, these are important in emotion expression. In cases where good visual information cannot be extracted, sound signals could be used. In the research presented in (Kirandziska & Ackovska, 2012) only sound signal were used as input data.

Several frameworks for automatic emotion classification have already been created (Vogt et al. 2008; Mower, Mataric and Narayanan, 2011). These frameworks combine input data, feature extraction algorithms, feature selection algorithms and also classification algorithms, and for a given input, an output is presented. The output is one class of the emotional state, given some emotion representation. However, some researches try to solve the problems on a smaller scale. They focus on separate parts of the emotion classification model and try to improve this part only (Oudeyer, 2003).

Some researches aim at finding valuable sound features (Klaus et al., 1991) or extracting the best combination of existing sound features (Picard, 1995). Others, like Vogt, André and Bee (2008) presented a research for real-time emotion recognition from speech.

Many different classification algorithms known in computer science are being used in different researches. Neural networks, Support vector machines, Bayesian networks are examples of classification algorithms.

## 4.1 The Emotion Evaluation Classification model implemented in a Robot

This section presents an implementation of the emotion evaluation classification system implemented in a robot. The concept used for the implementation was explained in Fig. 4.

The classifier in this research uses neural networks as the core algorithm of the classification model. As input data sound features are used and the output is the emotion evaluation class. Prior to the modeling, the sound signals were preprocessed and more sound features were extracted. More than 30 sound features were extracted using PRAAT - software for feature extraction in sound signals (Boersma. and Weenink, 2009). These features were all base on pitch, amplitude and tempo. The feature selection component, as indicated in the concept presented on Fig. 1, was obtained using information from human-human emotion evaluation perception.

The governing assumption for the research states that some sound features, which are perceived consciously by humans, have a great effect on perceiving some emotional state. For example, humans can perceive consciously that another person is speaking loudly and fast. Even more, this characteristic may indicate to one that this person is angry. Because certain emotions are correlated with the values of some sound features extracted from human speech, the information which sound features are more correlated with emotion evaluation can be used for feature selection. Examples of this kind of human sound features are pitch mean, amplitude, pitch standard deviation or tempo. Following the presented line of reasoning, the knowledge gained from human emotion evaluation was included in the approach for feature selection presented in (Kirandziska & Ackovska, 2013).

The description of the human emotion perception was taken from a psychological research made by Picard (1995) in which a survey about important sound features for emotion detection and their relation to specific emotion was investigated. Since this emotion classifier is based on the information about how human perceives other human, this emotion classifier is said to be biologically driven.

The classification model built was trained on a collected database of sound signals that was recorded especially for this research. This database contains recordings of a speaker that pronounces one sentence expressing different emotions that are labeled with positive or negative evaluation.

The trained classifier gives a perception for the emotion evaluation – positive or negative evaluation. After the model was built, it could be changed by adding new information to the model from new experience. This is called real time learning because the model is changing in real time. This kind of learning was evaluated in the results.

The model for emotion evaluation classification was in the end implemented in a robot. In order to get some insights of how well the robot implements the classifier an application in was created. The Lynx5 robotic arm robot made my Lynxmotion was used. The human-robot interaction application was called "Wordless call for help" (Kirandziska & Ackovska, 2012 - 2). In this application, a robotic arm should simulate the hand giving gesture when the speaker has negative emotions expressed by his/her speech. The robot actually straightens its hand, goes in a handshaking position and puts the arm back in the starting position. The automatic emotion evaluation system built in the robotic arm gives the most probable emotion evaluation (positive or negative) from the features extracted.

It is expected that this emotion evaluation perception model is not so precise, but closer to human-human emotion evaluation perception. The tradeoff between the accuracy of the model and the similarity of the model with human-human interaction is on the side on similarity. This approach is expected to accomplish better result in the application for human-robot interaction.

## 5. RESULTS

In order to properly evaluate the emotion evaluation classification model and its implementation in a robot described in Section 4.1, various experiments have been conducted.

The first experiment was made to evaluate the emotion evaluation classification model. In this experiment the classification model was tested on new test data. The new test data are new recordings from the speaker.

Experimental results showed a precision of around 70% of the robotic classifier compared to the true emotion evaluation of the speaker's recordings. The results also showed that more than 78% of the positively classified emotions by humans, were classified the same by the robot. From this perspective, true positively evaluated emotions were classified better than true negatively evaluated emotions. A similar result for human-human interaction was presented in Section 3.2. This once again raises the question whether negatively evaluated emotions can be perceived correctly only from sound signals. Another option is that the feature selection algorithms did not select some valuable sound features for negatively evaluated emotions.

In the second experiment the robot emotion evaluation perception was evaluated. According to our prior knowledge, these kinds of experiments have not been conducted in other studies. The idea was to compare the robot emotion evaluation perception with human emotion evaluation perception. The recordings in the test database ware played to human evaluators who had the task to classify the speaker's emotion without visual contact with the speaker or the robotic arm. The idea was to find if there is a correlation between the emotion detection done by a human and the one done by the robot.

In Table 2 some results of this experiment are shown. The evaluators had the precision of 71% in perceiving the speaker's emotion evaluation. What is even more important is that on average 68.4% of the evaluators evaluated the same as the robot classification. So, there exists a slight correlation between the emotion evaluation done by a robot and by the human evaluators.

Table 2. Average accuracy of the evaluators' emotion evaluation perception. (Kirandziska & Ackovska, 2013 - 2)

| **Average accuracy of the evaluator's emotion evaluation perception compared to** | **Accuracy** |
|---|---|
| True speaker evaluations | 71% |
| Robot's classification | 68.4% |

The last experiment was motivated by the experiments shown in Section 3.2. As seen in Fig. 3 and Fig. 4 humans can perceive emotions of another human more precisely if they know, or are acquainted to, each other. As a result, robots should be given a learning period to improve their precision for a specific human. The results (Fig. 6), after several learning periods, show some improvement of the precision on the classifier as well as on the similarity with the human perception. The precision grows up to 90% after 15 learning steps. Each learning step introduces feedback result given by the human for the emotion classification. This states the great role of the learning phase in robot emotion perception.

The results obtained in the experiments are truly expected in the human – human interaction. However, in these experiments the concept of "getting acquainted to" a specific human, only by using sound features has also been shown for human – robot interaction. The robot learned how to recognize specific emotions, given "some time spent" with a specific human.

To summarize, the overall goal was to build a robot that perceives human emotions more like humans. The result suggests that the goal was accomplished. Even more it has been shown that if the robot makes mistakes it should be able to learn from them, and correct its behavior in order to improve later the precision of the evaluation classification model.

This supports the concept for creating social robots described in Section 3.3. And it might change the way the robots are seen in the future. New experiences of the robot for a specific human, improves its emotion perception for that particular human. The following section elaborates on the usage of this model in the future and its possible impact on human-robot interaction. The ethical implications are also discussed.

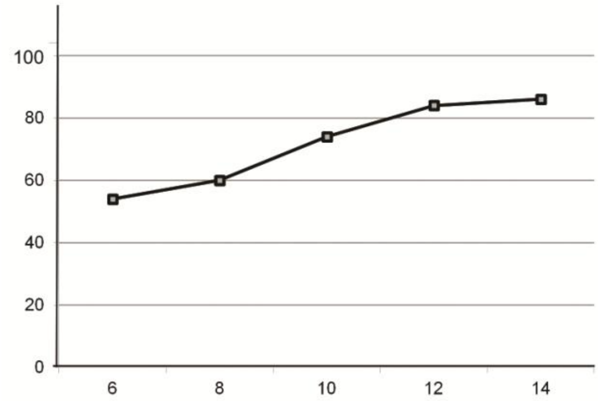


Figure 6. The change of the robotic emotion perception with respect to the learning phase

## 6. DISCUSSION ON THE ETHICAL ISSUES

Emotion aware robots are becoming more included in everyday human life. However, emotion awareness in robots can have a positive or negative effect on humans. The negative effects raise some ethical issues in building emotion aware robots. Some examples are given in the sequel.

In working environments, especially when working with clients, robots can control the communication process. Emotion aware robots could make sure the clients are well served. In this way the administration can be controlled and improved. The negative effect is that humans could feel they are being manipulated in the interaction with a robot, because robots could be programmed to do what the clients want them to do in order to get their task accomplished.

Some social robots are used as companions to humans. This is especially true for elderly people and children. One good robot characteristic would be to have a positive effect on the human it interacts with. Indeed, the robot shouldn't cause fear, anger, nervousness and other negatively evaluated emotions on human. One way to accomplish this is the robot to be emotion aware. Thus, perceiving emotions may accomplish the wanted robot behavior. The downside to this behavior is that human may create an emotional connection with these robots. The emotion aware property of a robot can cause creating a false relationship between the human and the robot. This can have a great impact on the human, for example, when the robot is broken, or for some other reason cannot be used. People can get very emotional when losing someone or something they care about. This point must be taken in consideration when building emotion aware robots. On the other hand, some humans wouldn't want to be emotionally evaluated by robots. Thus, a privacy issue is in question. As one possible solution, a policy for usage of the emotion information should be taken in consideration.

Health informatics is an emerging scientific field. Using robots sensitive to emotions in hospitals for patients that have difficult temper or in psychological institutions is one possible useful application of emotion aware robots. Here, human-robot interaction must be open in the sense that the human must know what are the possibilities and tasks of the robot. Also, the human must not take advantage of this knowledge. For example, people in hospitals should not think that the robot could make them healthy. It is not ethical for a robot “to make patients believe” that they are recovering if they are not. But also, humans should not act to have negatively evaluated emotions in order to get better treatment by robots.

One problem that can arise in the society in the future is finding the guilty party when there is a situation in which robot’s actions are involved. The situation can be caused due to a hardware fault of the robot, due to a software fault or because there was misleading in the learning phase of the robot. If a hardware or software mistake has occurred, an engineer can be found partially guilty. Many factors are included so that engineers should not be the only ones to blame. The question is whether or not a robot can be held responsible for its actions that led to some unwanted situation. A robot can be held responsible if it is a moral machine. Moral decision of the robot can be guided by emotions. Thus this is an important usage of emotion aware robots in the future.

All of these examples show some ethical issues that can arise from including emotion aware robots in the life of the human population. Some questions are left open to be discussed in the future.

# 7. CONCLUSION

The motivation for the work done here was to improve the eligibility of the emotion aware social robots. An investigation about the existing researches for social robots was done prior to this work. This investigation showed that although a variety of researches have been done so far, their results are not satisfactory in the sense of completeness, precision and application.

In order to better understand how human perceive other human’s emotions a study about human-human emotion perception was done. It showed that humans are not so precise in perceiving other human’s emotions. This result brought the idea of a new concept for making social emotion aware robots.

The concept presented here argues that some knowledge from human-human interaction should be transferred to human-robot interaction in the robot model of emotion perception. In addition according to this concept, new knowledge from the robot’s experience should be used to improve the model for emotion perception in human-robot interaction. It is expected that this concept could contribute to the human acceptance of the robots, in which the presented module is implemented. The idea behind the presented concept is that the robot emotion classifier must not only have a satisfying precision, but it should be made more humanlike in the sense of emotion perception. To prove that this concept has a positive influence on human-robot interaction, a practical implementation of this concept was done.

In this research an emotion evaluation classification model was created. The model was done based on human sound input data. The sound feature selection algorithm was based on the knowledge from human-human emotion perception. The model used those sound features that are valuable for humans for emotion evaluation detection in other humans. Even more, a learning module was implemented in the model, so the classification model could adapt to new situations.

The classification model was implemented in a robot in an application for human-robot interaction. The evaluation results showed a similarity between the robot’s and the evaluators’ emotion perception. The precision of the emotion evaluation model of the robot was around

70%. A balance between the precision of the robot and the similarity of the robot with human-human emotion perception was done in our human-robot interaction application. The learning module implemented in the robot contributes more to the similarity with human-human interaction. As the study on human-human interaction showed, humans are able to perceive better the emotions of a person they know, rather than the emotions of a person they do not know.

The research opens some important perspectives, such as the importance of the ability of both robot and human to perceive positive or negative emotions similarly. This feature improves the notion of human-robot interaction. The researches in the future could work more on increasing the number of emotion categories that can be perceived by robots with satisfactory eligibility. However, in order for this to become reality, a better representation of emotions should be done. Emotions differentiation in more categories would be essential for getting deeper perception of the human emotion.

As discussed, the future with emotional robots could also create some inconvenience. Bringing robots that perceive emotion in the environment should be considered carefully. From social and ethical perspective, guidelines on how a robot should behave and communicate with humans should be done. This is crucial for creating more social robots and involving them in the real-life environment with humans, where they truly belong.

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